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SCHEDULING CASE SIMULATION TO PERFORMANCE EVALUATION OF HOSPITAL PRODUCTIVITY

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ABSTRACT

The block is a strategic and complicated system in the hospital. It uses diversified and expensive human resources, material and information flow. In this field which investments are very expensive, simulation is a tool for decision-making to analyze the operation and detect malfunctions for dimensioning the system and obtaining the performance. We develop in this article a C++ simulation with a theory of queues based on the optimum of the proposed scheduling model. This model consists of a new approach. For scheduling model, we propose a new production model related to the hybrid flow shop hierarchy manufacturer. We solve the scheduling problem using the discrete particle swarm optimization with travelling salesman problem approach. The case study of our approach applied to the national Institute of Oncology in RABAT, Morocco, allowed us to measure the maximum of patients that can be accepted in a day and the allocation of the three machines queues stretchers, Operating rooms and beds among the scheduled elements involved.
Keywords: *Case Simulation, Hospital, Scheduling, Production Model,* Hybrid Flow Shop Hierarchy Manufacturer

1. INTRODUCTION

The operating room is a strategic sector of a hospital. It's the most important and complicated entity as far its technical platform, risk and generating costs. Profitability is linked to its efficiency, the quality of its organization for better attractiveness, and the fluidity of its processes given by the critical issue reflected on human life. An operating room consists of a set of local sights of invasive aseptic procedures and operates logically 24h/24h (operations room, post-interventional monitoring room and logistics adjoining). It is difficult, even risky, to intervene in the operating blocks system upon which human lives depend, then we must be able to assess a priority of the operation system re-structuring. Hence the need to use simulation.

The latter persists to estimate the behavior of the system under extreme operating conditions evaluates and compares various scenarios to identify the most sensitive system changes components and visualizes the system behavior during its design and even before its implementation.

Our paper is Organized as follows: After literature overview in the second part, we present a simulation model developed in C++ which has, as an entry point, the scheduling optimum result obtained by the algorithm of particle swarm optimization, in order to see the maximum number of patients who can pass the current day and the allocation of various resources required for its operation. This gives us the flexibility to evaluate possible solutions for improving and scaling the current system block.

In the third part, we present our scheduling model concerning the problem with a machines classification based on the new concept of hierarchical hybrid flow shop configuration type. In the fourth part, we solve the scheduling problem while presenting a new resolution process based on the use of discrete particle swarm optimization algorithm developed in C++ of traveling salesman

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problem approach, with a new definition of the distance concept from the operating time of each machine.

2. LITERATURE OVERVIEW

Several research studies have investigated the hospital management issues in general and the operating room in particular.

The modeling and simulation subject:

They were applied to emergency services [1] [2].They used a discrete event simulation to solve dimensioning resources problem. Besides, [3] used a simulation model that seeks to provide an optimal location for emergency teams and a better distribution of personnel and equipment, which means the distribution that minimizes the time unit response of emergency services for a given time value of the desired service.

[4] proposed an agent based simulation model to examine twelve different policies for assigning casualties to destination hospitals following an improvised explosive device explosion in downtown Pittsburgh (USA).

[5] Presents the use of a DES model to simulate the number and costs of hospital emergency services delivered to the population in one Polish region.

The scheduling operating rooms subject:

Planning is to allocate time in the "operating room" for a practitioner or a group of practitioners to enable them to care for their patients while ensuring the satisfaction of human resources in their interaction with the system (patient, doctor and paramedical staff), the availability of equipment and various hazards.

We find in the literature three programming models that are as follows [5]:

1- The programming opening (Open Scheduling) share a common principle of planning without prior decision where the surgeons place their interventions either chronologically or periodically by challenging previous investments. This technique has the advantage to be centralized and easy to organize. However, it can cause malfunctions [6] as the resources under-utilization, a greater rate of deprogramming, time overruns, when performed empirically.

2- Programming by prior allocation ranges (Block Scheduling) is a policy based on the prior allocation of time slots to surgeons for a given period, usually a week. Then, surgeons will just place their interventions within these ranges. It is therefore the technique that has been most commonly used in North America [7],[8],[9]. The difficulty with this type of programming is in the management plane construction of the slots allocation time.

3- Programming prior allocation ranges adjustment process (Modified Block Scheduling). The concept of lost time becomes soft with a possibility of extension. The Manager block has the possibility to act on the time slots that are previously assigned and based on monitoring the progress of a surgical program. The adaption time scale can be adjusted according to the actors will. [10].

3. SIMULATION BY THE QUEUES MANAGEMENT

We have developed a simulation program using a C++ based on queues to check the feasibility of the schedule obtained by the discrete particle swarm optimization of our system on three phases:

- Phase 1: a team of stretchers carrying the patient to the operating room.
- Phase 2: The procedure is performed in an operating room.
- Phase 3: When the operation is completed, the patient was immediately transferred to an awaking bed.

As soon as the patient is fully awake, the stretcher carries him to his room. At the same time, the operating room cleaning begins.

This simulation also allows us to inject scheduling process determined in the model in order to simulate the number of patients accepted in a day and the allocation of resources of different sequenced interventions. The surgeries are placed first in the order obtained by DPSO, first on the machine (stretcher), then on the machine (operating room) and in the end on the machine (awaking bed). When an intervention arrives on a machine that is not available, the job is placed in a queue; and when the resource becomes available - if the queue includes multiple operations - a priority rule is used to resolve the conflict.

A priority rule is a formula that associates a value to each operation of a queue, usually calculated on the parameters of the operation. [11]. The queue operation to be placed on the machine is the one which value is the lowest or the highest. Numerous priority rules exist, using various criteria: [12], [13] or [14]. Many studies have been done to try to determine the impact of these rules on the scheduling and overall performance compared to some criteria.

As a result of all these analyses, it

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basically shows that no rule outperforms the other at all the objects or workshops [15].
The effects of a priority rule on the scheduling are difficult to predict as it heavily depends on the workshop.

We study the real case of the National Institute of Oncology, Rabat, Morocco as well as we introduce the following as an input of our program:
The optimum scheduling we received during the execution of the algorithm
Stretcher duration.
Surgical intervention duration.
Awaking bed spent duration.
Operating block Stretchers number (2).
Operating rooms number (three operating rooms).
Awaking beds number (3 beds Wake).

We defined the following functions: stretchering, stretcher liberating, intervention, free operation room, waiting bed, awaking bed, liberating awaking bed.

We also defined a set of structures to follow the clock and the number of stretched patients, operating rooms, awaking beds…etc.
The patient structure is as follows:

```
typedefstruct patient
{
indint; / / optimum scheduling DPSO
inttb; / / stretcher duration
toint; / /  Operating Room duration
inttr;/ / Time awaking Room
intbr;/ / stretcher assigned to patient
int n;/ / Operating room assigned to patient
lrint; / / awaking bed assigned to the patient
};
struct patient patients[N];
```

« N » patient number (surgeries generated from the DPSO).

We've defined 3 queues: stretcher's Operating room and awaking bad.

4. MODEL OF THE PROPOSED PROBLEM SCHEDULING

The flow shop problem receives the attention of many researchers. Solution begins when [16] has found a solution in the case of two or three machines. The objective is to find the maximum flow time (makespan), which is a model of hierarchical hybrid flow shop with three floors, especially if the job shop with duplicate machines: each floor K Mk parallel machines with Mk> 1.

Five set for intervention I = {P1, P2Pn}, not preemptive interventions: they run uninterruptedly assigning to this day scheduling.

The model proposed scheduling problem is as follows (Figure 1):

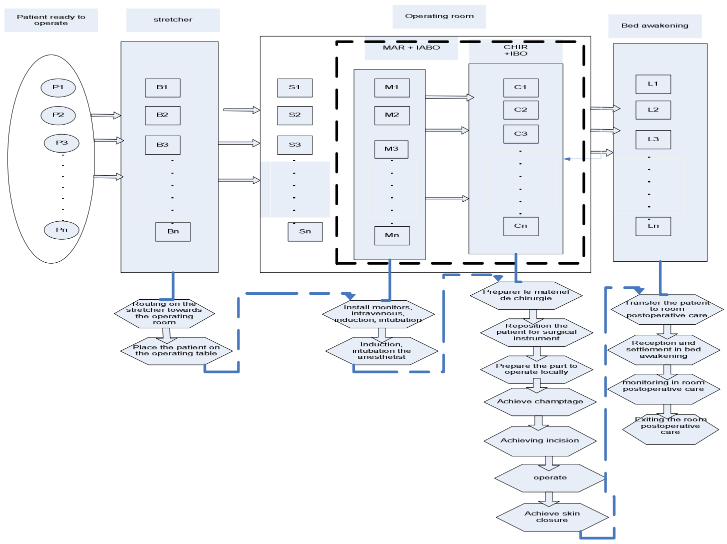

Figure 1: hierarchical hybrid flow shop proposed

This problem is NP-hard, we can define it with the notations of rinnooy [17]. (1)

$$\textbf{FH3}\ ((P_n^{(1)}, P_n^{(2)}, P(t)_n^{(3)}\ /\ /T_{max} \qquad (1)$$

For the first time, this is an extension for the operating block problem which is generic and represents the different possible interactions within and between machines. It has been identified and presented in quéré [18] and oriented to the modeling and optimization of manufacturing systems as follows: (each floor or machine can be a flow shop or a hybrid flow shop). This model represents the operating room as a hybrid flow shop (stretcher, operation room, awakening bed) and the operating room in hybrid flow shop too (Mar, Chir).

5. DESCRIPTION OF THE SCHEDULING PROBLEM

The objective of scheduling problem is to minimize the total length of scheduling, denoted T max is equal to the date of the last intervention completion during the scheduled day in the operating room.

Considering the fact that we held a modeling simulation for the best configuration of operating rooms and recovery rooms, we suppose in this case that all machines are available: T max= max{T (Pi)} with T (Pi) is the patient (Pi) surgery end date.
The objective function: (2)

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$$\text{Min Max } (T (Pi), PTS (Pi, Ti, Si)) \quad (2)$$
$$\forall Pi \in P, \forall Ti \in T, \forall Si \in S.$$

The process of solving this scheduling problem is as follows:

Step 1: Calculation of distance.

Step 2: Calculation of a unique solution after scheduling this set by OEP.

Step 3: Simulation and C++ queues.

Problem assumptions are as follow:

- Each intervention was assigned a prior to a surgical team (surgeon and anesthetist).
- Material resources are always available during the scheduled day.
- All surgeons are available at all times.
- A priority is given prior to each intervention.
- Operating time is given.
- All operating rooms are similar.
- All awakening beds are similar.
- All operating rooms and SSPI open simultaneously at 08:00.
- No pre-emption in the operating room and SSPI.
- Resources are disjunctive (non-shareable) and perform a task at the same time.

Our problem is as follows:

We have a set of planned interventions for the day J and we should schedule their passage through the machines we took into account in our system modeling, which are: stretcher, operating room and recovery room. In each machine, the procedure takes a duration defined as “ti” depending on its type.

The interventions durations listing is taken into consideration in the algorithm, consequently the average length is used at NIO (table 1).

Table 1: The interventions durations listing

Designation of the act	Mean TROS/act
Patey	150
ovary	230
Breast conservative treatment	160
Tumeurectomie	100
colpohysterectomy	222
soft parts	126
Laying implantable	93
jejunostomy	75
axillary	83
Total vulvectomy	186
cervicotomy	145
mammaplasty	100
Hystéroctomie	126
colostomy	145
Liver + VB	220
gastrostomy	125
Anterior resection of the rectum	495
Laparoscopy (laparoscopic)	245
laparotomy	75
laryngectomy	520
SpNIO'sear	115
Tumor of the ear	205
thyroidectomy	205
occlusion	160
leg amputation	190
peritonitis	380
lymphnodebiopsy	60

Note that TROS include:

T1 * (patient preparation time)

T2 * (" Time of induction)

T3 * (Duration of the surgery itself)

T4 * (Duration of bandage)

T5 * (Time restoration of the room)

TROS intervention: Begins with the patient entry into the operating room and finishes with the end of the reinstatement of the room.

We can obviously see that the intervention time is varied:

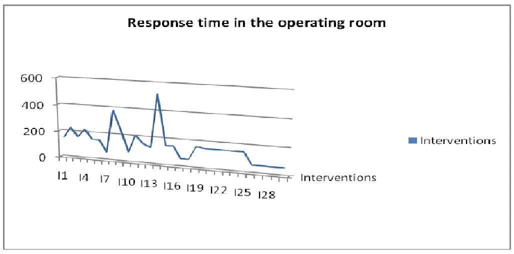

Figure 2: Response time in the operating room

➢ <u>Step 1:</u>

An initial population is chosen either randomly, by heuristics, by specific methods to the problem, or by a mixture of random and heuristic solutions. The population must be sufficiently diversified so that the algorithm does not remain blocked in a local optimum. This is what happens when too many people are alike. The OEP generate new individuals so that they are more efficient than their predecessors. The process of improvement of individuals is done with the following rules: separation, alignment and cohesion. Scheduling heuristics are characterized using combinations of basic rules. They will then be multi-criteria and will

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be able to help the decision maker in relation to respect of deadlines, current level, and the workshop charge. They are dynamic and will allow the simulation of physical flows.

In our case, the initial population will be selected RAND: random order.

- Step 2:

We first solve this problem by an extension of the meta-heuristic optimization introduced by Eberhartand Kennedy [19] in 1995 in the United States which is the discrete particle swarm optimization (DPSO).

The basic principle of the OEP is a technique based on the concept of cooperation between agents (particles) with rather limited capacities; and the exchange of information in between allows them to solve difficult problems.

At the beginning, a swarm that contains a set of particles enters in a search space. Each particle in the swarm has the following five characteristics:

1. Position.
2. Speed.
3. Its current position and the value of the objective function for this position.
4. The value of the best position of its neighbors and the corresponding objective function.
5. Its best previous position.

In the discrete case:

A position X: a sequence of operations: potential schudeling, $(x_1, x_2, \ldots x_n)$

A speed V is a list of transposition $((x_{i\text{-}k}, x_{j\text{-}k}))_{k=1,\ldots\|V\|}$

F (x): The value of the objective function in the X position: Fitness

Operators in the discrete OEP are as follows:

- Subtraction (position, position) = speed
- External Multiplication (real, speed) = speed
- Addition (speed, speed) = speed
- Move (position, speed) = position
- Addition (position, speed) = position

The algorithm is as follows:

Initialization

Xi// Generate initial particles of the swarm randomly

Vi // generate the initial velocity of the particles

X besti // Identify the best position of the particle

Xgbesti// Identify the best position of the swarm

X Nbesti // Identify the best positions of the neighboring

Repeat

Loop i = 1 .... N (all particles in the swarm)

Fitness i (t) // Evaluate Fitness (Xi)

If

Fitness i (t) <Fitness Xbesti (t)

Xbesti // Xi attractor particles

end IF

Loop i = 1 .... M (M number of neighbor in swarm)

X Nbesti// Define best position in the neighborhood

end Loop

If

Fitness i (t) < Fitness Xg best (t)

X gbesti// Xi best attractor particles

end IF

For i1 .... N

Update velocity V id (t +1)

Vi $\longleftarrow$ Vi+ p1 (X best i-Xi) + p2 (x i g best-Xi)

Update position id X (t +1)

Xi $\longleftarrow$ Xi + Vi

To end

Until the process converges

We will propose a generalization of the distance notion between jobs that must be defined in our hybrid hierarchical flow shop model. [20]

One of the basic ideas of our solving approach is to solve scheduling surgeries problem in analogy with the classical traveling salesman problem approach to obtain interventions scheduling and then study their assignment with a simulation of queues.

For the first problem, it is necessary to define the notion of distance between two interventions. This distance is of course based on the transit times between the three machines of our system, which are:

- The patient transport duration from the hospitalization bed by the porter to the operating room.
- Surgery duration in the operating room depending on the invention type.
- The awaking bed duration.

This distance takes into account only two interventions Ij and Ij+1. The distance between the last and the first job in the sequence is not considered. Indeed, we must find a sequence that minimizes the total time wasted and that is given by the shortest path from the initial intervention. This distance definition consists of a weighting of difference between the two surgeries processing duration taking place simultaneously. The weighting gives a higher penalty for differences on

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the first machines. (3)

For (k=0; k<n-1; k++)
For (l=k+1; l<n; l++)

d= $T_{k\ branc\ i} + abs\ (T_{k\ sale\ j} - T_{l\ branc\ i'}) + T_{l\ lit\ h}$ (3)

∀ i∈ [1, m], with m number of stretcher
j∈ [1, m'], avec m number of operating room
∀ h∈ [1, m''], avec m number of awakening beds

And assuming that:
- All rooms are available
- All awakening beds are available
- All stretcher are versatile
- A FIFO rule is used in the floors: the first machine available is the first served.

6. EXPERIMENTAL RESULTS

We will make a graph for 6, 8, 10, 12 and 14 interventions.

For 6 interventions: We use the surgical procedures as indicated in the table and the operating time as follows: (Table 2)

Table 2: surgical procedures used

	stretcher time DF (1) (i)	Designation of the act	Operating room time DF (2) (i)	Bed awakening time DF (3) (i)
I1	5	Patey	150	60
I2	5	ovary	230	60
I3	5	Breast conservative treatment	160	60
I4	5	Colpohst erectomy	222	60
I5	5	Patey	150	60
I6	5	Patey	150	60

The input graph of the DPSO algorithm with distances is:

We develop a C + + program to calculate the matrix of distance with the formula explained in the previous paragraph with the operating time of the previous table, then we get: (Table 3)

Table 3: Matrix of distance

	I1	I2	I3	I4	I5	I6
I1	0	210	210	210	210	210
I2	210	0	290	290	290	290
I3	210	290	0	220	220	220
I4	210	290	220	0	282	282
I5	210	290	220	282	0	210
I6	210	290	220	282	210	0

For 8 interventions:

We use the surgical procedures as indicated in the table and the operating time as follows: (Table 4)

Table 4: surgical procedures used

	stretcher time	Operating room time	Bed awakening time
I1	5	150	60
I2	5	230	60
I3	5	160	60
I4	5	222	60
I5	5	150	60
I6	5	150	60
I7	5	60	60
I8	5	380	60

The input graph of the DPSO algorithm with distances is: with C++ developed (Table 5)

Table 5: Matrix of distance

	I1	I2	I3	I4	I5	I6	I7	I8
I1	0	210	210	210	210	210	210	210
I2	210	0	290	290	290	290	290	290
I3	210	290	0	220	220	220	220	220
I4	210	290	220	0	282	282	282	282
I5	210	290	220	282	0	210	210	210
I6	210	290	220	282	210	0	210	210
	210	290	220	282	210	210	0	120
I8	210	290	220	282	210	210	120	0

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With the same reasoning, For 10 interventions: (Table 6)

Table 6: surgical procedures used

	stretcher time	Designation of the act	Operating room time	Bed awakening time
I1	5	Patey	150	60
I2	5	ovary	230	60
I3	5	Breast conservative treatment	160	60
I4	5	Colpohst erectomy	222	60
I5	5	Patey	150	60
I6	5	Patey	150	60
I7	5	lymphnodebiopsy	60	60
I8	5	peritonitis	380	60
I9	5	Laparoscopy (laparoscopic)	245	60
I10	5	laparotomy	75	60

The input graph of the DPSO algorithm with distances is: (Table 7)

Table 7: Matrix of distance

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
I1	0	210	210	210	210	210	210	210	210	210
I2	210	0	290	290	290	290	290	290	290	290
I3	210	290	0	220	220	220	220	220	220	220
I4	210	290	220	0	282	282	282	282	282	282
I5	210	290	220	282	0	210	210	210	210	210
I6	210	290	220	282	210	0	210	210	210	210
I7	210	290	220	282	210	210	0	120	120	120
I8	210	290	220	282	210	210	120	0	440	440
I9	210	290	220	282	210	210	120	440	0	305
I10	210	290	220	282	210	210	120	440	305	0

With the same reasoning, we also define a set of intervention for 12, 14 and 16 patients. After the execution of the DPSO algorithm, we have the following results that represent the optimum schedules for 10 iterations, the value of the objective function and the CPU used when compiling the program.

Table 8: Scheduling obtained

PB num	Patient Intervention Pi	Number of iteration	function objective value	CPU	scheduling obtained Ω
PB1	6	10	1140		Ω = {P3, P1, P2, P4, P5, P6 }
PB2	8	10	1752	22.379000	Ω = {P2, P1, P3, P4, P5, P16, P7, P8 }
PB3	10	10	2100	25.430000	Ω = {P1, P5, P6, P10, P3, P4, P2, P8, P7, P9 }
PB4	12	10	2517	19.259000	Ω = {P1, P5, P6, P8, P3, P4, P9, P2, P11, P7, P10, P12 }
PB5	14	10	2967	28.340000	Ω = {P1, P5, P6, P8, P3, P4, P9, P2, P12, P11, P7, P10 , P13, P14 }
PB6	16	10	1462	42.125000	Ω = {P2, P1, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12 , P13, P14, P15, P16}

The simulation has become indispensable to solve complex problems in the systems of production of goods or services such as optimization of physical flows and information flows, understanding the operation of systems and compare several scenarios to select the best configuration that achieves the objectives.

With the simulation, we had the results as follows:

For 6 interventions: (Table 9)

We have the optimum scheduling generated by the algorithm of particle swarm optimization, which is: Ω = {P3, P1, P2, P4, P5, P16}.

We affect the necessary means for this scheduling in order to operate the patients; we get as a result, and the optimum assignment throw the queues management and we find out that all the patients could pass a current day.

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Table 9: Result of simulation for 6 interventions

	stretcher time	Designation of the act	Operating room time	Bed awake ning time	Num br	Num so	Num lr
I3	5	Breast conservative treatment	160	60	br0	so0	lr1
I1	5	Patey	150	60	br1	so1	lr0
I2	5	ovary	230	60	br0	so2	lr2
I4	5	colpohysterectomy	222	60	br1	so1	lr1
I5	5	Patey	150	60	br0	so0	lr0
I6	5	Patey	150	60	br1	so2	lr2

For 8 interventions: (Table 10)

The same for this configuration, we used the optimum scheduling that we got by using the method described in the paragraphs below and which is Ω = {P2, P1, P3, P4, P5, P16, P7, P8} to serve 8 patients during a day time, we see that we can satisfy all patients presented in the scheduling and who are assigned to different machines (medic, operating room and bed)

Table 10: Result of simulation for 8 interventions

	stretcher time	Designation of the act	Operating room time	bedawakening time	numbr	numso	numlr
I2	5	ovary	230	60	br0	so0	lr2
I1	5	Patey	150	60	br1	so1	lr0
I3	5	treatment	160	60	br0	so2	lr1
I4	5	colpohysterectomy	222	60	br1	[illegible]	lr1
I5	5	Patey	150	60	br0	so2	lr0
I6	5	Patey	150	60	br1	so0	lr0
I7	5	lymphnodebiopsy	60	60	br0	so2	lr2
I8	5	peritonitis	380	60	b1	so1	lr0

For 14 interventions: (Table 11)

We note that the 13 th is the last Intervention affected. From the 14 th interventions, the patient is denied in the system. Resources (surgeons, anesthetists, nurses ....) should work extra hours to make interventions require further study to diagnose other criteria such as: the cost to add and prioritization of interventions that needs to be done for better organization.

Table 11: Result of simulation for 14 interventions

	stretcher time	Designation of the act	Operating room time	bedawakening time	Num br	Num so	Num lr
I1	5	Patey	150	60	br0	so0	lr0
I5	5	Patey	150	60	br1	so1	lr0
I6	5	Patey	150	60	br0	so2	lr1
I8	5	peritonitis	380	60	br1	so0	lr2
I3	5	treatment	160	60	br0	so1	lr0
I4	5	colpohysterectomy	222	60	br1	so2	lr2
I9	5	Laparoscopy (laparoscopic)	245	60	br0	so2	lr1
I2	5	ovary	230	60	br1	so1	lr0
I12	5	Patey	150	60	br0	so2	lr2
I11	5	thyroidectomy	205	60	br1	so0	lr1
I7	5	lymphnodebopsy	60	60	br0	so1	lr1
I10	5	jejunostomy	75	60	br1	so1	lr0
I13	5	gastrostomy	125	60	br0	so2	lr2
I14	5	laryngectomy	520	60	-	-	-

7. CONCLUSION:

In this paper, we developed a C++ program to be simulated by queues, number of patients that can be accepted during a day, and studied the real case of the National Institute of Oncology, Rabat-Morocco, as well as the allocation of resources sets we've defined already in the modeling of our scheduling system that are (stretcher, operating room and awaking bed). Being used as a program input, the optimum scheduling result of DPSO.

We formulated the scheduling problem with a new approach; we first set a new model of our scheduling system using the hierarchical hybrid flow shop model. After that, we introduced a new design to our scheduling problem that is based on the travelling salesman problem approach issue in which we have developed a new concept of distance suiting this type of system. The scheduling issue was then solved with the discrete swarm particle optimization.

In addition, and in our sense, this work paves the way to other research perspectives. We quote some ideas as an example: A benchmark with other existing algorithms in literature, add contingencies …etc.

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