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Agent Based Patient Scheduling Using Heuristic Algorithm

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Abstract—**This paper describes about an agent based approach to patient scheduling using experience based learning. A heuristic algorithm is also used in the proposed framework. The evaluation on different learning techniques shows that the experience based learning (EBL) gives better solution. The processing time decreases as the experience increases. The heuristic algorithm make use of EBL in calculating the processing time. The main objective of this patient scheduling system is to reduce the waiting time of patient in hospitals and to complete their treatment in minimum required time. The framework is implemented in JADE. In this approach the patients and resources are represented as patient agents (PA) and resource agents (RA) respectively. Even though mathematical model give optimal solution, the computational complexity increases for large size problems. Heuristic solution gives better solution for large size problems. The comparisons of the proposed framework with other scheduling rules shows that an agent based approach to patient scheduling using EBL is better.**

Keywords-experience based learning; heuristic algorithm; scheduling; multi agent systems

I. Introduction

Patient scheduling is an inherently distributed problem and is a complex task. The dynamic nature of hospital patient scheduling, together with the decentralization of scheduling makes the tasks more complex. A more suitable approach to patient scheduling may be one that fits the problem domain better a distributed multi-agent system together with experience based learning technique would be a good choice. Here we consider each patient and resources as agents and they interact with each other [3], [12].

In multi agent System the patients are represented as Patient Agents (PA) and resources as Resource Agents(RA).The PA request for the resource. Other than PA and RA Common Agent is also included in the framework. It represents a general physician who decides on what tasks the patient has to undergo. The proposed framework trying to reduce the patients waiting time and tardiness. We can further reduce this by the introduction of experience based learning [13].

Most of the learning models in scheduling are based on the learning curve introduced by Wright[1]. In a scheduling problem with a new experience-based learning model, where job processing times are described by "S"-shaped functions that are dependent on the experience of the processor. In patient scheduling, decisions are made according to the learning model [1], [8].

A. Problem Domain

Hospitals have a distributed organizational structure being divided into several autonomous wards and ancillary units. Each department has the authority to take decision so it is decentralized.

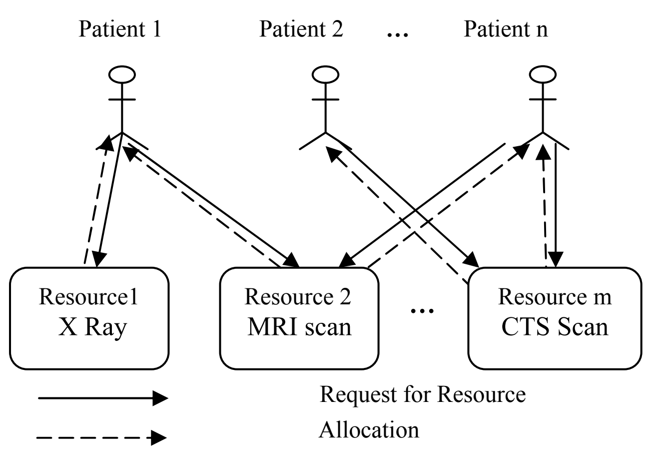

Figure 1. Agent view for a typical hospital patient scheduling

In addition to the complexity arising from the distributed structure of hospitals, patient scheduling has to be performed in the face of a high degree of uncertainty about the treatment pathways of patients within the hospital. Thus patients arrive continuously at the hospital and the necessary medical treatments are often not able to be completely determined at the beginning of the treatment process. Moreover the results of a diagnostic examination might change the (medical) priority of the patients, invoke additional activities and/or make other medical actions obsolete [3], [12]. Hospital patient scheduling can be implemented using agent based approach. Figure 1 shows the agent view for a typical hospital patient scheduling.

II. RELATED WORKS

Scheduling is concerned with the optimal allocation of suitable resources for a particular task.

A. Scheduling Techniques

The traditional scheduling technique in the field of operations research (OR) are effective for solving centralized problems. These algorithms provide an optimal schedule. It is not possible to use the OR technique to solve patient scheduling problem because of its highly decentralized nature. In patient scheduling there is a need for communication and coordination with different departments and is also not possible in case of OR [3].

Some procedures are designed to provide good solutions to complex problems in real time when scheduling problems are considered. These procedures are called scheduling rules. Some of the examples of such scheduling rules are those based on processing times (such as shortest processing time (SPT)), due dates (such as earliest due date (EDD)), and arrival times (such as first-in first out (FIFO)) etc [14].

An agent based approach is be used to solve the scheduling problems. Such systems allow the representation of every single coordination object as single autonomous agents with their own goals. Hospital agent based scheduling considers all the entities such as patients, doctors and other resources as agents. This reflects the decentralized structure of hospitals. This system also satisfies the dynamic nature of hospitals because of the proactive and reactive nature of agents. Each time a new patient came or the health state of a patient changes a new schedule is created. So creation of schedule is dynamic.

B. Scheduling with learning effect

Wen-Chiung [9] introduced a position based learning model. In this model the processing time of a task is depends on the position (that is at which time slot it is executed). He also introduced a group technology. In group technology the tasks are grouped according to their characteristics. So the processing time depends on position as well as the group in which the task belongs. Wen-Chiung concludes that the learning effect is seldom used in the context of group technology scheduling problem.

Edwin Cheng and Wen-Chiung Lee[10],[14] introduced the sum of processing time based learning model. In this model the actual processing time of a job as a function of total normal processing time of jobs that are already processed and of the job’s scheduled position.

The time dependent learning model [11] assumes that the learning effect of a task to be a function of total normal processing time of tasks that are scheduled in front of the specified task. The classical scheduling problem consider the processing time of task as constant. But the actual processing time become shorter due to the introduction of learning effect.

Adam Janiak and Radosław Rudek[1],[2] introduced an experience based learning model. Here learning factor is calculated and is used for the calculation of processing time. This can be applied for scheduling problem. A learning effect in the context of the scheduling theory assumes that the time required to perform a job decreases as an experience or a knowledge related to it increases. In patient scheduling the learning effect can be used .

Adam Janiak and Radosław Rudek [1],[2] proved that the experience based learning model is better. The proposed framework for patient scheduling make use of the experience based learning model for calculating processing time.

III. PROPOSED FRAMEWORK FOR PATIENT SCHEDULING

Agent based approach is suitable for scheduling patients in hospitals because of its reactive and proactive nature. The scheduling is done according to a heuristic algorithm.

A. Problem Description

The framework consists of Patient Agent (PA), Resource Agent (RA) and Common Agent (CA).The CA is a physician they collect and maintain information about patients and resources. It also determines the tasks that have to be taken, which consists of consultation of doctor, diagnostic procedures like MRI scan, CT scan lab tests etc. Now the PA knows what are tasks it has to perform and then it request for the resources. The Resource Agent may be X-Ray, CT Scan, Lab Tests, consultation with Physician etc. Each RA has multiple time slots. The PA request for this time slots. Multiple PA may request for the same slot. In this framework a agent called Learning Agent is included. The LA calculates the experience of each resource and find out the processing time according to the experience they possessed. As the experience increases the time required for processing a task is reduced.

In hospitals when patient comes for a test the required equipment and other resources has to be made ready. The time required for the preparation is called changeover time. It comprises of setup time and removal time. Setup time is the time span required to prepare the machine. The removal time is the time span needed to restore initial state of resource. In older patient scheduling systems this changeover is included with in processing time itself. For example during the task of CT scan an initial preparation time for patient and resource is needed.

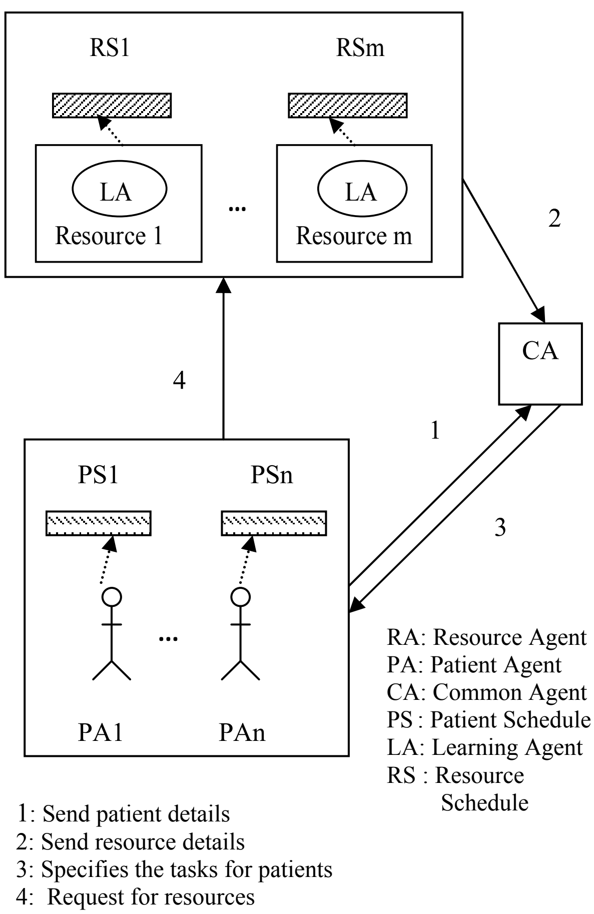

Figure 2. Framework for patient scheduling using experience based learning

After the scanning process is done return back to the initial state of scanning machine. If a person who is doing this have experience the setup and removal time can be reduced, that leads to the reduction of processing time. The framework for patient scheduling using experience based learning is shown in figure 2. Figure 3 shows the use case diagram for the framework, there are 4 main actors, the patient agent, resource agent , learning agent and the common agent.

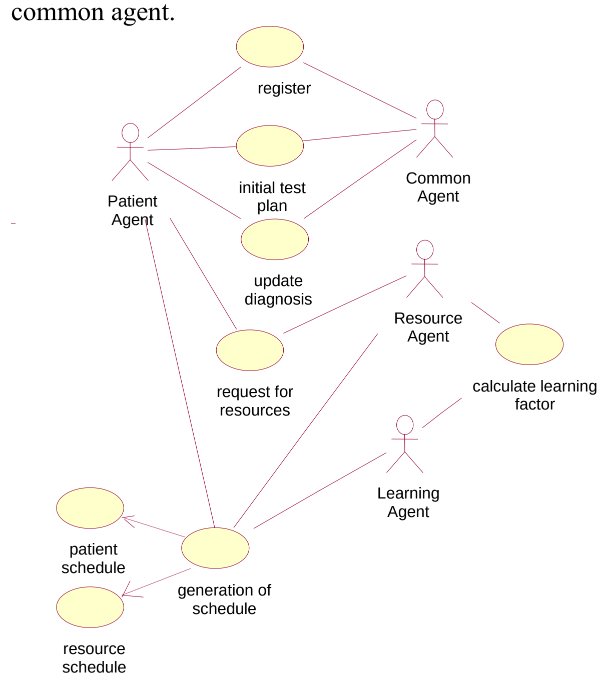

Figure 3. Use case Diagram for Patient Schedule with learning Agent

B. *Problem Formulation*

Patient are considered as jobs, each need to perform different tasks and it is processed by resource. The main objective scheduling problem is to find a sequence that minimizing the make span.

Let ni denote the number of tasks assigned to machine i, i = 1,2, . . . , m . The normal setup and removal times for job j on Mi are denoted $S_{ji}(=S_j)$ and $R_{ji}(=R_j)$. if S_{jir} and Rj_{ir} are the actual setup and removal times of job j scheduled in position r in a sequence, then $S_{jir} = S_{ji}r_a$ and $R_{jir} = R_{ji}r_a$ (where $a \leq 0$ is the learning effect, given is the logarithm to the base 2 of the learning rate) the objective is to find a schedule that minimizes the weighted sum of total completion time. The objective function is represented as to minimize

$$\alpha \sum \sum c_{ij} \qquad (1)$$

n the number of patients j = 1, 2,. . . ,n

m the number of resources $i = 1, 2, \ldots, m$
α the weight for total completion time $\alpha \geq 0$
n_i the number of tasks assigned to resource i $i = 1, 2, \ldots, m$
C_{ij} the completion time

It should satisfy the constraints .Only one task should be scheduled at a particular time slot for a resource and another constraint is a task should be scheduled only once.

First the completion time has to be find out. The completion time of a job placed in i^{th} slot is formulated as follows [1],[2]

$$C_i = C_{i-1} + P_i(E_\beta(v)) \tag{2}$$

The completion time is depends on completion time of jobs that are completed (C_{i-1}) and the processing time of current job($P_i(E_\beta(v))$). The processing time of job j scheduled in the v^{th} slot in a sequence is given as follows:

$$P_j(E_\beta(v)) = a_j - b_j(\min\{E_\beta(v), g_j\})^{\alpha j} \tag{3}$$

Where,
a_j is the normal (sequence-independent) processing time of task j,
α_j anb b_j are the exponential and linear learning ratios of task j
g_j is the learning threshold.

For the above model, the parameters $a_j > 0$, $b_j > 0$, $a_j > 0$, $g_j > 0$ and $\beta_j = [0, 1]$ are assumed to be rational since the job processing time is some positive value, it is assumed that $a_j - b_j g_j^{\alpha j} > 0$. The task processing time $p_j(E)$ formulated as a non-increasing positive function of the experience E possessed by the processor. If the processor does not possess experience (E =0), the processing time of a task (say j) is equal to its normal processing time a_j, i.e.,$P_j(0) = a_j$. Before calculating the processing time the learning factor is calculated [4], [5]. The learning factor is represented in terms of experience and is given as,

$$E_\beta(v) = \sum_{l=1}^{v-1} e_{[l]} + \beta_v e_{[v]} \tag{4}$$

$\sum_{l=1}^{v-1} e_{[l]}$ is the experience already possessed by the processor $e_{[l]}$ is the experience provided to the processor by a job scheduled in the l^{th} position $e_{[l]} \geq 1$. $\beta_{[v]}$ is the amount of experience (percentage of $e_{[v]}$) provided to the processor by job [v], $\beta_{[v]}$ [0,1].

C. Heuristic Algorithm

In traditional scheduling techniques all the possible schedules are considered. Calculates completion time of each of the schedule and find out the optimal schedule. For calculating the completion time the learning factor is considered. This model takes more time and the problem become very hard. So a heuristic method is considered. Here only some schedules are considered. The heuristic algorithm find out the optimal schedule from the selected schedules. In this patient scheduling system adopt a heuristic algorithm that is proposed by Tamer Eren . [7] there the experience based leaning is not used. But in proposed system this is also incorporated.

Let P_i denote the number of task assigned to machine i, $i = 1,2, \ldots, m$ and $j=1,2\ldots n$. where m is the total number of resources and n is the total number of tasks. The problem will be solved by using a heuristic algorithm.

Step 1.Obtain initial schedule for each of the resources by applying Shortest sum of Setup Processing and Removal time.

Step 2: Set i=1 ,p=2 and k=2.Pick the first two task from the rearranged task list of i^{th} machine and schedule them in order to minimize the weighted sum of total completion time and total tardiness.

Step 3: If the schedule is satisfied for the precedence constraint
(a) Update the selected partial solution as the new current solution otherwise
(b) Repeat the process with the next lowest value of weighted sum of total completion time and total tardiness.

Step 4: Check if p exceeds P_i If yes go to step 6
Otherwise increment k and p by one.

Step 5: Generate k candidate sequences by inserting the first task in the remaining task list into each slot of the current solution. Among these candidates select the best one with the least partial minimization of the weighted sum of total completion time and total tardiness and go to step3.

Step 6: Increment i and k and set p as 2, go to step 5 until i=m.

IV. RESULTS AND DISCUSSIONS

The agent based approach to patient scheduling using experience based learning has been implemented using JADE (Java Agent Development) platform. JADE is a middleware that facilitates the development of multi-agent systems. It is a software framework fully implemented in java language.

A. *Simulation in JADE*

The patient scheduling using multi agent and heuristic algorithm was simulated in JADE multi agent platform. When a new patient or resource entered they should register to the system. The schedule is created according to the diagnosis of all the patients [14],[15],[16].

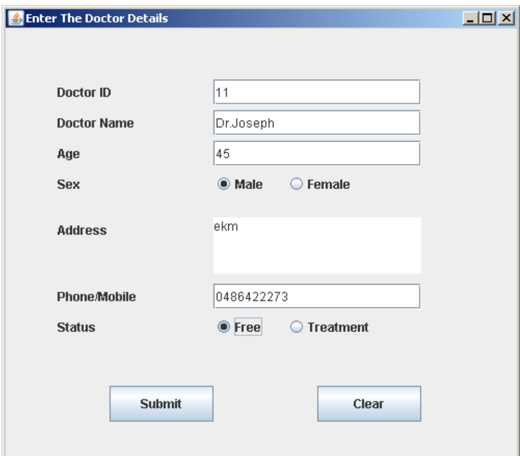

Figure 4. Patient Registration

The final schedule is shown in figure 5.

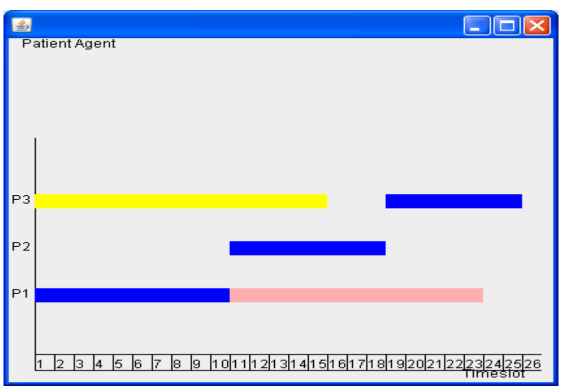

Figure 5. Final schedule

B. *Implementation of Heuristic Algorithm*

The heuristic algorithm is not considering all the possible schedules. It selects some possible schedules that are having shortest sum of completion time and this set contains the optimal one.

Consider the example of having three patients and three resources. Patient one(P_1) contains two tasks P_{11},P_{12},patient two(P_2) is having one task represented asP_{21} and patient three has to perform two tasks P_{31},P_{32}.The tasks of each resources are R_1 has to perform P_{11},P_{21}, R_2 has to perform P_{31} and task of R_3 is P_{12}. First consider R_1 ,take first two tasks from R_1 and consider the possible two schedules and find out weighted sum of total completion time as shown in table I. Consider first one is optimal. Second is not considered because its completion time is not more than first one. Check if any other task is remains in R_1 if yes add it to the optimal schedule and find out the optimal schedule (shown in Table II).

TABLE I POSSIBLE SCHEDULES(K=2)

No:	Tasks		Comp. Time	
1	P11	P21	18	Optimal
2	P21	P11	18	Not consider

TABLE II POSSIBLE SCHEDULES (K=3)

No:	Tasks			Comp. Time	
1	P11	P21	P32	24	Optimal
2	P21	P32	P11	24	Not consider
3	P32	P11	P21	24	Not consider

There is no other tasks in first resource so consider the second resource and do the same process done in R_1 (shown in Table III).Here the precedence constraints are also be checked that is the first task of a particular patient should complete before the second task. Do the same process for third resource R_3 (shown in Table VI).

TABLE III POSSIBLE SCHEDULES (K=4)

No:	Tasks				Comp.Time	
1	P11	P21	P32	P31	32.08	Prec not Satisfied
2	P21	P32	P31	P11	32.72	Prec not Satisfied
3	P32	P31	P11	P21	33.52	Prec not Satisfied
4	P31	P11	P21	P32	34.52	Optimal

TABLE IV POSSIBLE SCHEDULES (K=5)

No:	Tasks					Comp. Time	
1	P31	P11	P21	P32	P12	42.712	Optimal
2	P11	P21	P32	P12	P31	40.784	Prec not Satisfied
3	P21	P32	P12	P31	P11	42.576	Prec not Satisfied
4	P32	P12	P31	P11	P21	44.186	Not consider
5	P12	P31	P11	P21	P32	47.616	Not consider

The algorithm gives a schedule that having minimum completion time because our aim is to minimize the completion time of patient and hence reduces the ideal time of resources.

C. Performance Evaluation

Figure 6 and 7 shows the comparison of make span and total tardiness for 3x3 problem. It shows that the experience based learning model for patient scheduling using heuristic algorithm gives better results than EDD,SPT, FCFS etc.

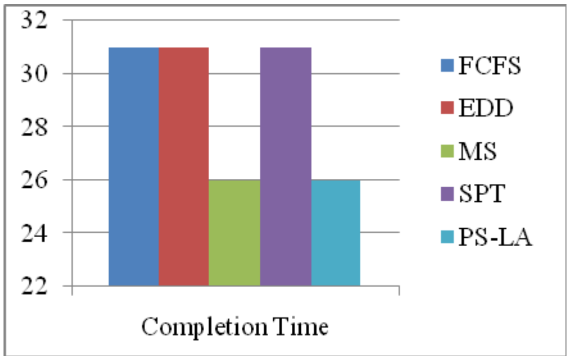

Figure 6. Comparison of Completion Time for 3X3 Problem

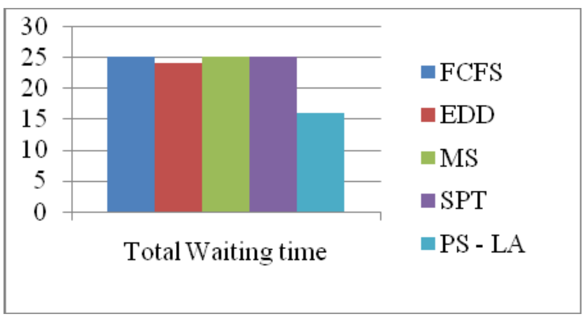

Figure 7. Comparison of Total Waiting Time for 3X3 Problem

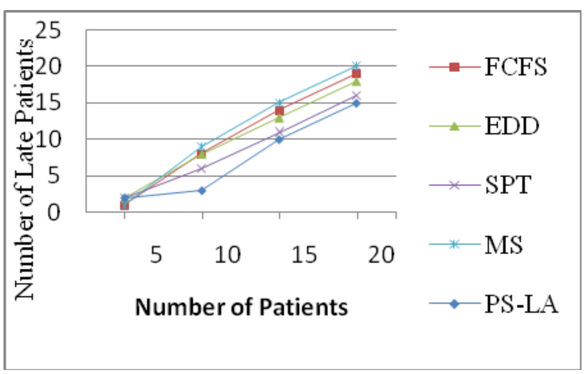

Figure 8. Total Number of Patient Scheduled Late

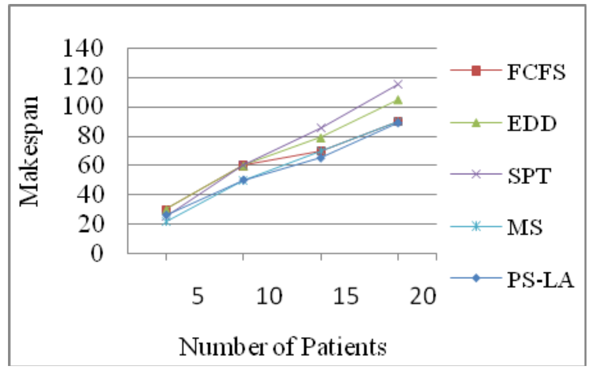

Figure 9. Comparison of Make span

The proposed framework produces the least number of patients scheduled late as seen in Figure 8. Figure 9 shows the comparison of make span. MS and PS-LA have less makespan as the number of patients increase.

CONCLUSION

This paper presents an agent based approach to patient scheduling for producing an optimal schedule. The main objective is to minimize the total completion time. It also reduces the patients waiting time in hospitals. The comparison of proposed framework with other scheduling rules has been done. This shows that this agent based approach is better.

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