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Patient Scheduling System for Medical Treatment Using Genetic Algorithm

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ABSTRACT
The manual scheduling of medical treatment in a health center is a complex, time consuming, and error prone task. The system takes into account various constraints such as patient preferences, physician availability, and resource allocation. The GA is used to optimize the scheduling of patients to physicians and to allocate resources to minimize the waiting time. The proposed system is tested using real-world data, and the results demonstrate that it can effectively reduce the total waiting time of patients and improve the efficiency of healthcare providers. This study contributes to the optimization of patient scheduling systems in the healthcare industry, and provides a valuable tool for healthcare providers to improve patient satisfaction and operational efficiency. Furthermore, there is no guarantee a manually generated schedule maximizes the operational efficiency of the center. Scheduling problems have seen extensive research across several domains. The current work presents a novel genetic algorithm for the scheduling of repetitive Transcranial Magnetic Stimulation (rTMS) appointments.

Keywords: *genetic algorithm, rTMS, list scheduling, partially mapped crossover*

INTRODUCTION
Scheduling is a day-to-day activity everyone performs. It is a process of arranging similar or heterogeneous types of jobs in order to optimize work. We schedule in our life to prioritize what to do next etc.. Industries use scheduling to allocate plant and machinery resources. Similarly for companies also. In all those years before computers we used manual scheduling wherever it's needed.

Manual scheduling is a very cumbersome process, it can also lead to a lot of mistakes. Sometimes those mistakes cost a lot of time or resources for the organization. If the number of jobs or items to be scheduled is increasing then manual scheduling is impossible to do. In this work we are trying to find a solution for one such scheduling problem using genetic algorithms

Depression is a mental state of aversion to activity. It affects a person both mentally and physically. In the current society depression among people tends to increase day by day. According to some resources it is said that even children under age 10 are also starting to show a large number of symptoms of depression. So we cannot simply avoid depression anymore. There has to be proper treatments for depression. One such treatment is TMS. Transcranial magnetic stimulation (TMS) is a procedure that uses magnetic fields to stimulate nerve cells in the patient's brain to improve symptoms of depression in them. TMS is used as an alternative treatment that comes into action when other treatments are quite ineffective. Since it involves giving repetitive magnetic pulses, it's called rTMS which means repetitive TMS. Hence in an health center there will be some set of rTMS machines (instruments used for TMS treatment) which will be used for finding the symptoms for depression among people. So, we are trying to devise a genetic algorithm-based solution for rTMS machines allocation. This is an allocation-based algorithm that is we know the number of patients and their respective details before scheduling so that we can use this information to allocate the rTMS machine in an optimized order to these known number of patients. For this algorithm to work basically we need the number of rTMS machines and the number of patients and their information prior to performing any process. We can define the scheduling of rTMS appointments as a parallel machine problem of unrelated jobs with preemption is not allowed. And our objective is to minimize the overall makespan. This type of scheduling comes under NP-Hard problem Since we cannot do a job piece by piece, once a job is started it has to be completed before moving to the next one. Genetic algorithms are suitable for search, optimization and machine learning problems.

Genetic algorithms are adaptive procedures for optimization and search oriented problems inspired by the mechanism of the natural selection process. It is suitable for problems with more than one solution. This way it can search for an optimized solution in the search space (search space is the set of all possible solutions we can form) . In GA we initially have a set of solutions from search space. We pass these solutions to a fitness function which calculates the fitness value of the solution. The higher the fitness value the better is the solution. Then we select the best solution from them and applying crossover and mutation we can generate new offspring (new set of solutions from search space) . This process continues for a definite number of iterations or until an acceptable optimized solution is obtained.

LITERATURE REVIEW

In a world of 7.97 billion people with the amount of healthcare/virus breakout problems going on recently for the past 2 years the assistance and need for hospitals have skyrocketed more than we can ever think of. It once was at a point where many major leading hospitals did not have enough manual labor to support the amount of people who were begging for help outside of the hospitals. Looking back from what we've gone through it is clear that we cannot always be dependent on manual labor because it is limited and available only for a certain period of time.

Griffiths et al. (2012) did work on automated scheduling for physiotherapy appointments and has shown to save about 6 hours per week of manual labor. There have been many other techniques used such as mathematical programming by Braaksma, A., Kortbeek, N., Post, G., & Nollet, F. which focused on rehabilitation planning, heuristics by Petrovic, S., Leung, W., Song, X., & Sundar, S. which attempted to solve this issue for radiotherapy treatment booking. Pedgorelec and Kokol further worked on using genetic algorithms for physical therapy.

There has been plenty of work done on parallel machine problems using genetic algorithms. Golgoun and Sepidnam used a genetic algorithm for patient priority scheduling and Zhao, Chien, and Gen used it for rehabilitation scheduling. Many different approaches have been done for the subprocess of GAs. Petrovic et al used elitist selection with linear order crossover whereas Chien et al. used roulette wheel selection and preserving order-based crossover. Besides the Healthcare industry there have been many research projects done on using genetic algorithms for list scheduling. However very few of them provide insight into the runtime needed for the process. While Aickelin and Downland mentions that the run time is under 10s, they don't mention how that runtime scales with larger dataset and input provided.

Jiang et al., recently used data mining and heuristics to predict the demand for MRI procedures. They compete with empirical data gotten from clinics. Therefore, it is optimal to always check the working of any algorithm on real life scenarios and datasets. but due the nature of medical treatment we chose, there is a lack of readily available data.

There are multiple other techniques used but these four are the most used and are the most successful. As time goes these techniques will be implemented more and more widely around the world which will help the betterment of the people.

Problem Definition

Since we know how long each process is going to take and the fact that we can't stop the process in the middle and replace it with another process this problem can be called a runtime minimization of parallel machines problem with deterministic time with no preemption.

Let the number of rTMS machine available be m = {m1,m2,...} and the set of patients be p = {p1,p2,...} and the completion time be C. Our goal is to minimize C by altering the order in which patients go in thereby saving time and manpower.

METHODOLOGY

Chromosome Representation

Genetic Algorithms work on fixed length chromosomes. To have a consistent length of jobs for each machine, we populate the chromosome with "dummy jobs", represented by negative numbers. Each chromosome will be of length JxM, where J is the number of jobs and M is the number of machines. This methodology has taken inspiration from Ak and Koc (2012) and Matthew Squires a , Xiaohui Tao. To explain this representation further, each chromosome can be split into M segments, each representing a machine and the number of jobs it can take, and each of these have J genes which can be taken up by either a job or a dummy job, this represents the order in which the machines will do said jobs. Dummy jobs are represented with -1 whereas jobs will be represented by a positive number according to their ID.

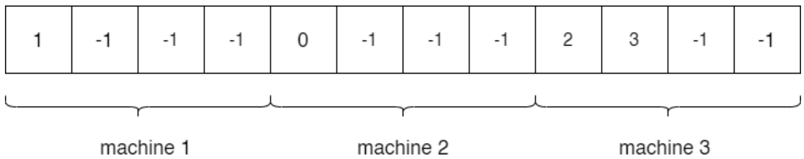


FIG.1: Chromosome representation

Dataset

In this paper we deal with psychiatric conditions faced by patients, we use an artificial dataset, due to the sensitive nature of the information. We used the python faker and random packages to create the dataset. Following the guidelines set by the Matthew Squires a , Xiaohui Tao we have imitate the results from 2 psychiatric diagnostic questionnaires; the Montgomery–Asberg Depression Rating Scale (MADRS) (Montgomery & Asberg, 1979) and the Depression Anxiety Stress Scales (DASS) (Lovibond & Lovibond, 1995).

The MADRS is a semi structured interview, held by a clinician, and gives a score ranging from 0 to 60, a higher number would indicate a higher level of depression. Conversely the DASS is a self-report test, which generates 3 scores, each ranging from 0 to 42, for mental health, depression and anxiety.

Furthermore, each machine might have a different downtime for maintenance purposes.

So, we have generated a certain time for each machine along with how often it has to happen. Along with this some patients may be given some preference according to their status with the hospital, therefore we accounted for 2 classes that patients can belong to, the general and preferential. if they are a preferential patient their final priority level is increased by 1.

Each result was then generated using the python random number generator, which their respective constraints placed. We then normalize each score and sum them up and then split the patients into quartiles and assign a priority level according to which the algorithm will be penalized for wait time. This is done so that people with a generally higher score in both the tests, which would imply that they are facing forms of severe depression, would be treated with more priority than those who have low test scores.

Population initialization

While completely random initialization is possible, it may lead to poor results and therefore it may be advantageous to initialize the population by sorting the jobs in priority first

Selection

The selection method used is fitness proportionate roulette wheel selection algorithm. This method involves choosing a parent based on the probability proportional to the fitness of the individual.

To evaluate the fitness of an individual we use the below formula

$Fitness = 1 / (C * W)$

where W is the penalization from the weights and C is the completion time of the given individual. The weights are calculated according to the priority of the patient. Therefore, if a patient has higher priority the fitness will be penalized more for each minute of wait. The weights go as follows. The final completion time will have to include the downtime for the machines as well.

TABLE I

Patient Priority	Weight per minute wait
4	15
3	10
2	5
1	1

Crossover

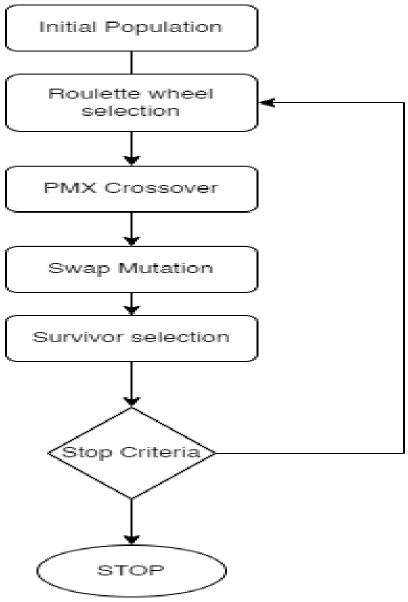
Since the offspring after crossover must be valid for enumerated chromosomes, we use Partially Mapped Crossover (PMX). This was proposed by (Goldberg & Lingle, 1985) and was originally used for the Traveling salesman problem. It works just like a regular 2 points crossover but if we were to just use a 2-point crossover there would be a problem with repetition. PMX solves this problem by using a “map” to find these replacements by adding all values from within the crossover zone as keys and what they replace as values.

Mutation

We use a modified version of the swapping mutation, where 2 random jobs are chosen and their values are exchanged. The modification done is to make sure that at least one of the jobs is changed and it's not just a dummy job. This is done to ensure that the mutation has an effect as swapping dummy jobs makes no difference to the fitness of the individual.

Survivor selection

While traditional GA, for example the works of Ahmed(2010), the old population with the addition of the offspring population will be sorted based on their fitness and the top few will be taken into the next generation. While this might seem ok at first glance, other studies show that this method leads to quick convergence at local minima and has a high mean fitness. Therefore, it is crucial to include a larger scope of the population for the sake of diversity therefore our selection method includes a check where the highest rated offspring is only included into the population if its fitness is higher than the least fit individual in the current population.



Comparison With Heuristic Algorithm

To check the effectiveness of our model we have to compare it to models or methods currently available. To do this we have chosen the First Come First Serve (FCFS) method. This is one of the methods most commonly used by systems around the world. It works by assigning the first machine to the first patient available and the next machine if there is a patient waiting. While this method might not be the most efficient, it makes up for the lack of starvation as every job will be done in due time irrespective of their priority.

TABLE II

Generation Number	Which algorithm is faster
1	FCFS
5	FCFS
10	FCFS
20	GA
30	GA

RESULTS AND DISCUSSION

In this paper we present a genetic algorithm solution for optimization of schedule for rTMS treatments. Our goal was to minimize the makespan of the system ensuring a model that works better than systems that currently exist. Instead of just using the time, we include the priority of patients using multiple other considerations such as their DASS score, and patient preference to give an optimal schedule for those that need treatment first. From the comparison we determine that our model is faster than a simple list scheduling algorithm.

If optimal patient priority is to be achieved then Matthew Squires a , Xiaohui Tao suggests using genetic algorithms for the list scheduling and then using SWPT(shortest weighted processing time) for each machine. As we are using a synthetic dataset, there might be more considerations that need to be made that are available to the clinics, adding those to the dataset might ensure a more accurate result.

Compliance with Ethical Standards

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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Conflict of interest

The authors declare that they have no conflict of interest.

Informed Consent

Not applicable

Authorship Contribution

Not applicable

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