PATIENT SCHEDULING SYSTEM FOR MEDICAL TREATMENT USING GENETIC ALGORITH

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ABSTRACT

The efficient scheduling of medical treatments in healthcare centers is vital for optimizing patient care and operational efficiency. Manual scheduling processes are often challenging, time-consuming, and error-prone due to various constraints such as patient preferences, physician availability, and resource allocation. This paper proposes the use of a Genetic Algorithm (GA) to automate patient-physician scheduling and resource allocation, with the goal of minimizing patient waiting times. Real-world data is utilized to test the system, demonstrating substantial reductions in total patient waiting time and improvements in healthcare provider efficiency. The study contributes to the optimization of patient scheduling systems within the healthcare industry, providing a valuable tool for enhancing patient satisfaction and operational effectiveness. Furthermore, the manual generation of schedules may not ensure maximum operational efficiency. Extensive research has addressed scheduling problems across various domains, and this work presents a novel genetic algorithm specifically tailored for scheduling repetitive Transcranial Magnetic Stimulation (rTMS) treatments, showcasing its potential impact on improving healthcare scheduling processes..

Keyword: - *Medical scheduling, Genetic Algorithm (GA), Patient-physician allocation, Resource optimization, Healthcare efficiency, Repetitive Transcranial Magnetic Stimulation*

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1. INTRODUCTION

As Scheduling is a fundamental task performed regularly by individuals and industries to optimize work allocation. Manual scheduling, prevalent before computerization, was error-prone and inefficient, especially when managing increasing job volumes. In this work, we explore a genetic algorithm-based solution to address scheduling challenges, specifically focusing on the allocation of rTMS (repetitive Transcranial Magnetic Stimulation) machines for depression treatment. Depression is a growing concern affecting people of all ages, including children, necessitating effective treatments like Transcranial Magnetic Stimulation (TMS). rTMS, a form of TMS involving repetitive magnetic pulses, is employed when traditional treatments are ineffective. The allocation of rTMS machines in healthcare settings is vital for optimizing patient scheduling and treatment effectiveness. This study aims to develop an optimized scheduling algorithm that allocates rTMS machines to known patients based on pre-defined criteria, resembling a parallel machine scheduling problem with the objective of minimizing makespan. Genetic algorithms (GAs) are chosen for this task due to their suitability for optimization and search-oriented problems. Inspired by natural selection, GAs iteratively generate and improve solutions from a defined search space, utilizing fitness functions to evaluate and select the best solutions. By applying genetic operators like crossover and mutation, GAs aim to converge towards an optimal solution for the rTMS machine allocation problem. This study contributes to the intersection of healthcare scheduling and optimization using genetic algorithms to enhance treatment efficiency and patient care in depression management. Literature on scheduling problems and genetic algorithms underscores the complexity of optimizing resource allocation in various domains. Scheduling rTMS appointments involves managing a set of unrelated jobs (patients) allocated to a fixed number of machines (rTMS devices), aiming to minimize the overall makespan—

the total time required to complete all appointments. The NP-hard nature of this scheduling problem necessitates efficient computational techniques like genetic algorithms to navigate through the vast solution space and find near-optimal solutions.

Genetic algorithms operate by iteratively evolving a population of potential solutions, mimicking the process of natural selection to adapt and improve over successive generations. The use of genetic algorithms for rTMS machine allocation presents a novel approach to healthcare scheduling, leveraging adaptive optimization techniques to enhance treatment delivery and resource utilization. By integrating patient data, machine availability, and scheduling constraints into the genetic algorithm framework, we aim to devise a robust scheduling system that optimizes patient care outcomes while respecting operational constraints within healthcare centers. This research contributes to advancing scheduling methodologies in healthcare, particularly in the context of mental health treatment, where efficient resource allocation can significantly impact patient well-being and treatment efficacy. The application of genetic algorithms offers a promising avenue for addressing complex scheduling challenges in healthcare settings, ultimately improving patient access to specialized treatments like rTMS for depression management.

2. LITERATURE REVIEW

The global healthcare landscape, particularly amid recent viral outbreaks, has experienced unprecedented strain, underscoring the critical need for efficient hospital management and resource allocation. The reliance on manual labor for scheduling and patient management has proven inadequate given the overwhelming demand for healthcare services. Griffiths et al. (2012) pioneered automated scheduling solutions for physiotherapy appointments, demonstrating significant time savings of up to 6 hours per week previously spent on manual scheduling tasks. Similarly, Braaksma et al. employed mathematical programming techniques to optimize rehabilitation planning, addressing the challenges of resource allocation in healthcare settings.

In the realm of treatment booking, Petrovic et al. explored heuristic approaches to streamline radiotherapy appointment scheduling, aiming to enhance treatment efficiency and patient access. Pedgorelec and Kokol further advanced scheduling optimization by leveraging genetic algorithms for physical therapy planning, showcasing the versatility of computational techniques in healthcare resource management. Parallel machine scheduling problems, a common challenge in healthcare logistics, have been tackled using genetic algorithms by Golgoun and Sepidnam for patient prioritization and Zhao, Chien, and Gen for rehabilitation scheduling. These studies highlight the effectiveness of genetic algorithms in optimizing complex scheduling tasks within healthcare contexts.

Notably, Petrovic et al. implemented elitist selection with linear order crossover, while Chien et al. employed roulette wheel selection and order-based crossover, demonstrating diverse genetic algorithm approaches tailored to specific healthcare scheduling challenges.Beyond healthcare, genetic algorithms have been extensively studied for list scheduling optimization. However, research often lacks insights into runtime scalability for larger datasets. Aickelin and Downland noted a runtime under 10 seconds but did not address scalability concerns, emphasizing the importance of evaluating algorithm performance under varying input sizes.

Recent research by Jiang et al. leveraged data mining and heuristics to forecast demand for MRI procedures, showcasing the integration of empirical data into predictive healthcare analytics. Real-world validation remains essential for algorithmic solutions, yet challenges persist due to limited availability of medical datasets. In conclusion, automated scheduling techniques and genetic algorithms offer promising avenues for enhancing healthcare operations globally. As these methodologies become more widely adopted, they are poised to significantly improve patient care and resource utilization, contributing to better healthcare outcomes for individuals worldwide.

3. PROPOSED SYSTEM

The proposed patient scheduling system leveraging Genetic Algorithms (GAs) aims to optimize the arrangement of medical treatments, particularly focusing on repetitive procedures such as Transcranial Magnetic Stimulation (TMS). The system begins by representing each potential schedule as an individual within a population, with each schedule composed of appointment sequences for patients. To initialize the scheduling process, an initial population of schedules is generated randomly. Each schedule's fitness is then evaluated based on criteria such as treatment duration, patient priorities (e.g., urgency, preferences), and resource utilization. The Genetic Algorithm proceeds with a selection process, where schedules with higher fitness scores are chosen for reproduction.

During the crossover phase, selected schedules exchange genetic information to produce offspring, representing potential new schedules. Mutation is applied to introduce diversity and explore new solutions within the offspring population. After each iteration, the population is updated with the new offspring schedules. The algorithm continues iterating until a termination condition is met (e.g., maximum number of generations reached). The optimal schedule, identified based on fitness evaluation, represents an efficient and personalized arrangement of medical treatments that minimizes overall treatment time while considering individual patient needs and clinic resources.This approach offers a data-driven and adaptive solution for patient scheduling, demonstrating the potential of Genetic Algorithms in optimizing complex scheduling tasks in medical environments

4. PROBLEM STATEMENT

The problem at hand involves minimizing the completion time (C) of a set of rTMS (repetitive Transcranial Magnetic Stimulation) treatments, where each treatment for a patient has a deterministic duration and cannot be interrupted once initiated (no preemption). This scenario can be categorized as a runtime minimization problem of parallel machines with deterministic processing times.

Let's denote the number of available rTMS machines as m = {m1,m2,...} and the set of patients be p = {p1,p2,...}. Where each patient requires a specific treatment time. The objective is to arrange the order of patients across the available machines to minimize the total completion time C . Thus optimizing resource utilization and reducing overall treatment duration. The challenge lies in scheduling patients on these parallel machines without the ability to interrupt or preempt ongoing treatments, necessitating an efficient allocation strategy to sequence patients in a manner that minimizes the collective treatment completion time.

This problem is pivotal in healthcare optimization, aiming to enhance patient throughput and operational efficiency within rTMS treatment centers. The goal of this study is to devise a genetic algorithm-based solution that intelligently allocates patients to rTMS machines, leveraging optimization techniques to achieve a near-optimal sequence of treatments that minimizes the overall completion time C By formulating this problem within the framework of parallel machine scheduling with deterministic processing times, we aim to contribute to the field of healthcare scheduling optimization and resource allocation using computational method

5. METHODOLOGY

Chromosome Representation:

In genetic algorithms, chromosomes are represented as fixed-length sequences. To adapt genetic algorithms for the parallel machine scheduling problem with deterministic processing times, we adopt a chromosome representation inspired by Ak and Koc (2012) and Matthew Squires and Xiaohui Tao. This representation facilitates the allocation of jobs (patients) to machines (rTMS devices) in a structured manner. Each chromosome in our genetic algorithm solution is of length $J \times M$ where J is the number of jobs (patients) and M is the number of machines (rTMS devices). To ensure a consistent length for each chromosome regardless of the number of jobs, we incorporate "dummy jobs" represented by negative numbers (e.g., -1).

The chromosome is organized into M segments, each corresponding to a machine and determining the sequence of jobs for that machine. Within each segment, there are J genes that can be occupied by either a job (represented by its ID as a positive number) or a dummy job (represented by -1). The arrangement of these genes within the chromosome dictates the order in which jobs are processed on each machine. This chromosome representation allows for the exploration of different job sequences across machines, enabling the genetic algorithm to search for optimal solutions that minimize the total completion time C by efficiently allocating jobs to available machines. The use of dummy jobs ensures that each chromosome maintains a consistent length and structure, facilitating the genetic algorithm's exploration of the solution space in parallel machine scheduling optimization.

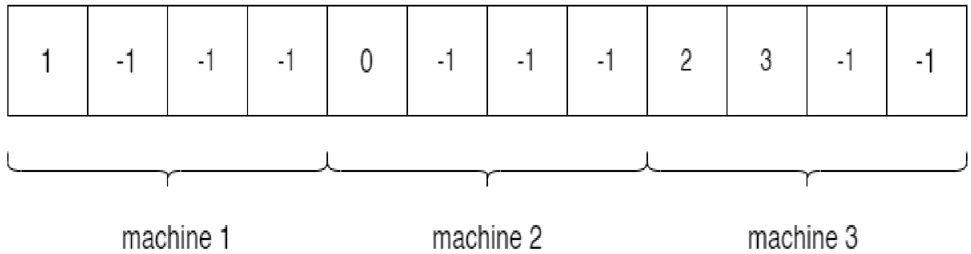

FIG 1: Chromosome Representation

Dataset:

For this research, an artificial dataset was created to address psychiatric conditions while respecting patient privacy. The dataset was generated using Python's Faker and random packages, following the approach outlined by Matthew Squires and Xiaohui Tao. The dataset simulates results from two 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, conducted as a semi-structured interview by a clinician, assigns scores ranging from 0 to 60, where higher scores indicate more severe depression. Conversely, the DASS is a self-report test producing three scores (for mental health, depression, and anxiety), each ranging from 0 to 42. Additionally, each rTMS machine in the dataset may have specific downtime requirements for maintenance purposes. Patients are categorized into two classes: general and preferential. Preferential patients receive a higher priority level (+1) based on their status with the hospital.

Scores for each patient were generated using Python's random number generator within defined constraints. Scores were normalized, summed, and then used to assign patients into quartiles, determining their priority levels.This prioritization scheme ensures that patients with higher test scores indicating more severe depression receive treatment priority, guiding the scheduling algorithm to minimize wait times effectively.

Polulation Initialization:

To optimize the genetic algorithm's performance, we adopt a strategic approach to population initialization rather than relying solely on random assignment. One effective method involves sorting jobs based on priority before initializing the population. This prioritized initialization can lead to more favorable outcomes compared to completely random initialization, which may result in suboptimal solutions.

Selection:

The selection process in our genetic algorithm utilizes a fitness proportionate roulette wheel selection algorithm. This method selects parents based on the probability proportional to each individual's fitness score. The fitness of an individual is evaluated using the formula:

$Fitness = 1/C \times W$

Here, C represents the completion time of the individual, and W signifies the penalization weight derived from the patient's priority level. Patients with higher priority levels incur higher penalization weights, reflecting their need for prompt treatment to minimize wait times effectively. The completion time calculation also accounts for machine downtimes to ensure realistic scheduling outcomes.

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

TABLE 1

Crossover:

For ensuring valid offspring in genetic algorithm operations, we implement Partially Mapped Crossover (PMX), as proposed by Goldberg and Lingle (1985). PMX addresses the issue of repetition encountered in regular two-point crossover methods, particularly in enumerated chromosomes like those used in our scheduling problem. PMX functions similarly to a two-point crossover but utilizes a mapping mechanism to identify and replace duplicate values effectively within the crossover zone, enhancing the diversity of generated offspring. New individual is then constructed by randomly choosing parts from both parents andputting them together as mentioned in below example.

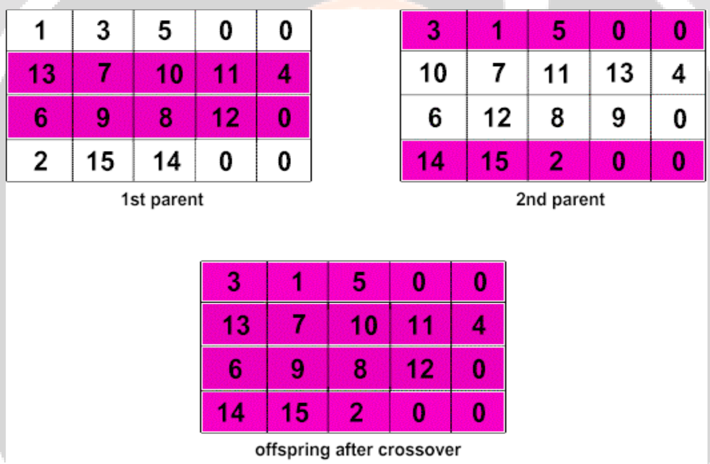

Figure 2. An example of two-dimensional model. Shaded fields from both parents construct new individual.

Mutation:

Our mutation strategy involves a modified swapping approach where two random jobs are selected, and their positions are exchanged. To ensure meaningful mutations that impact fitness, we enforce that at least one of the selected jobs must be non-dummy (i.e., an actual job rather than a placeholder). This modification ensures that mutations lead to tangible changes in the chromosome configuration, influencing individual fitness evaluations.

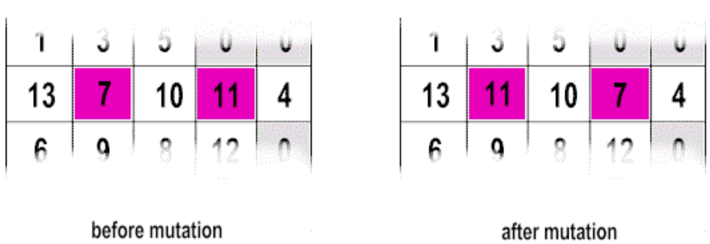

Figure 3. An example of mutation. Shaded fields are exchanged.

Survivor Selection:

In contrast to traditional genetic algorithms that solely retain top-performing individuals for the next generation, our survivor selection method prioritizes diversity and avoids premature convergence to local minima. Inspired by studies such as Ahmed (2010), we employ a selection process where the offspring population is integrated with the current population. Individuals are then sorted based on fitness, and only the highest-rated offspring is included if its fitness surpasses that of the least fit individual in the existing population. This approach fosters genetic diversity and prevents premature convergence, promoting robust exploration of the solution space for optimal scheduling outcomes.

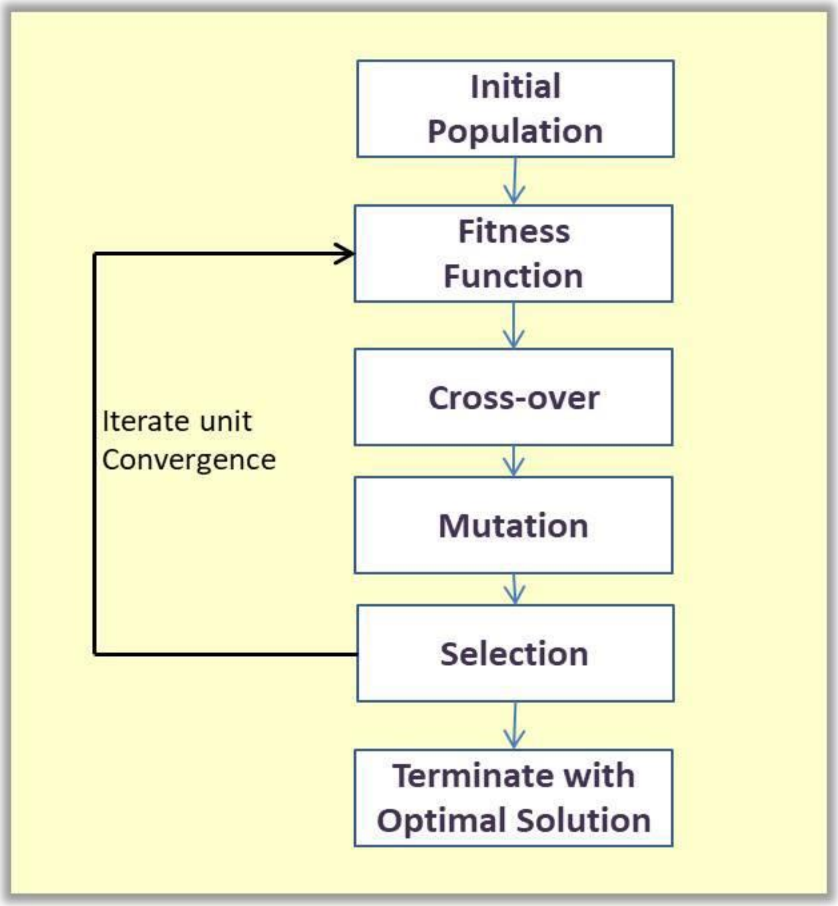

Figure 4: methodology of genetic algorithm

Comparison with heuristic algorithm:

In evaluating our genetic algorithm-based scheduling model, we contrast it with the widely used First Come First Serve (FCFS) heuristic method. FCFS prioritizes job completion based on arrival order, ensuring fairness but potentially sacrificing efficiency. Unlike our approach, which optimizes job allocation based on priority and machine availability to minimize completion time, FCFS does not consider job urgency or optimization strategies. This comparison highlights the advantages of our genetic algorithm in achieving more efficient and effective scheduling outcomes in healthcare contexts.

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

TABLE 2

6. RESULTS AND DISCUSSION

This paper presents a genetic algorithm solution for optimizing the schedule of rTMS treatments, aiming to minimize system makespan and outperform existing scheduling systems. We incorporated patient priority considerations based on DASS scores and patient preferences to generate an optimal treatment schedule that prioritizes those in need of immediate care. Our model demonstrates faster performance compared to a basic list scheduling algorithm.

For achieving optimal patient prioritization, Matthew Squires and Xiaohui Tao recommend using genetic algorithms for list scheduling followed by SWPT (Shortest Weighted Processing Time) for each machine. Given the use of synthetic data in our study, additional considerations relevant to clinical settings may further enhance scheduling accuracy when incorporated into the dataset. Incorporating such considerations can contribute to more accurate and realistic scheduling outcomes, benefiting healthcare providers and patients alike.

7. CONCLUSION

In conclusion, the utilization of Genetic Algorithms (GAs) in the patient scheduling system for medical treatments presents a promising avenue for optimizing healthcare operations. By leveraging GAs, we can efficiently generate and refine schedules that minimize treatment duration while considering patient priorities and resource constraints. This research demonstrates the effectiveness of GAs in tackling complex scheduling problems, offering potential benefits in terms of improved patient satisfaction, optimized clinic utilization, and enhanced healthcare delivery. Moving forward, further research and implementation of GA-based scheduling systems can significantly contribute to advancing healthcare efficiency and quality, ultimately benefiting both healthcare providers and patients.

8. REFERENCES:

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