A Review of Evolutionary Algorithms for Integrated Healthcare Scheduling Problems

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***Abstract*—This review explores the use of evolutionary algorithms in integrated healthcare scheduling, focusing on nurse and operation theatre scheduling. While various optimization methods are discussed, there is a notable gap in applying evolutionary algorithms. The study highlights the potential of Cooperative Co-Evolutionary Algorithms (CCEAs) to address complex scheduling challenges, including resource constraints and service integration. CCEAs are promising due to their adaptability and scalability. The review calls for more research and empirical validation to improve efficiency and patient care in integrated healthcare scheduling.**

Keywords—cooperative co-evolutionary algorithm, integrated healthcare scheduling, nurse scheduling problem, operation theatre scheduling problem

I. Introduction

Healthcare scheduling is crucial for coordinating medical activities efficiently [1], within timeframes [2], while considering resource limitations and organizational policies [3]. The growing global population emphasizes the need for an optimized healthcare system to meet rising demands, especially during challenges like the COVID-19 pandemic [4]. Addressing scheduling issues involving nurses and operation theatres together is vital for improving efficiency, resource utilization, and healthcare quality, moving beyond independent scheduling methods.

The Nurse Scheduling Problem (NSP) in healthcare management [5] coordinates resources [6] based on availability while meeting nurses' demands [2,7]. This involves assigning schedules to balance shifts, days off, staffing, skill sets, and regulations to ensure optimal staffing and efficient care, addressing organizational and staff preferences [8][9]. Understanding NSP constraints, like resource dependencies and skill restrictions, is essential for improving scheduling and avoiding worker dissatisfaction [7].

Operation Theatre Scheduling Problems (OTSP) involve allocating surgical rotations based on resource availability [10-14], such as patients, nurses, and medical tools, with dependencies varying by surgery type. For instance, patient numbers must not exceed available beds [3], and staff and equipment must be aligned during operations, differing from post-surgery needs. Existing multi-objective optimization methods [15-18] introduce bias and uncertainty, failing to address schedule dependencies, necessitating more advanced metaheuristic algorithms to manage shared and individual constraints effectively. Two key challenges for integrated scheduling are: 1) inter-dependencies within schedules, and 2) intra-dependencies between them. Cooperative Co-Evolutionary Algorithms (CCEAs) provide an integrated solution for both, improving efficiency and resource utilization.

II. Method

The literature review focused on English-language academic papers to ensure clarity in healthcare scheduling research, providing a foundation for further analysis. The integrated approach offers a comprehensive view for developing adaptable scheduling strategies in dynamic healthcare environments. The flowchart in Fig. 1 outlines the procedure for filtering and categorizing research papers on scheduling issues and cooperative co-evolutionary algorithms in healthcare. From 570 articles, 290 were removed as redundant, leaving 280. After authenticity checks, 76 articles were selected and categorized for analysis. Journal articles made up 73.7%, conference papers 18.4%, theses 2.6%, and websites 5.3%, highlighting the supplementary role of online resources.

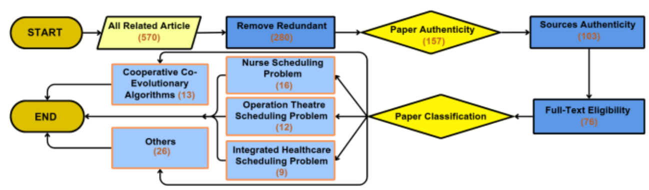

Fig. 1. Systematic Literature Review (SLR) Flow Chart

III. Related Work With Evolutionary Algorithms Solution For Healthcare Scheduling

A. Nurse

The literature on nurse scheduling covers a variety of studies but lacks depth in certain areas. Azimi et al. [2] discuss the shift from manual to computer-based methods, while Youssef and Senbel [8] highlight the Skill-Based Nurse Scheduling System, but neither evaluates its practical use in hospitals. The slow progress of Metaheuristic Algorithms, noted by Ngoo et al. [19], is mentioned without suggesting improvements. There's a brief mention of the differential evolution algorithm [20] but no in-depth comparison or discussion on optimization. Hybrid algorithms like the scout bee strategy [21] are praised but overlook practical implementation challenges. Duka [22] recognizes the adaptability of Evolutionary Multi-Objective (EMO) algorithms in cloud computing but doesn't address the challenges in nurse scheduling. The review also refers to studies in local hospitals [23] without clear findings or insights. A more thorough analysis of each approach's practical implications would improve the review.

B. Operation Theatre

The literature on operating room scheduling offers a comprehensive view but has some gaps. Bolaji et al. [10] emphasize economic importance but lack implementation strategies. Azimi et al. [2] note the potential of Evolutionary Algorithms (EAs) like Genetic Algorithms (GAs) but do not explore their integration into systems. Wang et al. [11] present a fuzzy model with a GA-based hybrid algorithm (GA-P) for uncertain surgical durations, yet real-time data integration is not discussed. The hybrid genetic algorithm (HGA) by Lin and Chou [13] improves operating room utilization, but its applicability across healthcare environments needs validation. Spratt and Kozan [14] introduce a rolling horizon approach, but its long-term adaptability isn't assessed. Arab Momeni et al. [24] focus on COVID-19 scheduling without analyzing its routine application. Najjarbashi and Lim [25] introduce a two-stage model for balancing costs and wait times, but its patient-centered impact is overlooked. Wang et al. [26] apply a Resilient Optimization (RO) model to NORA scheduling, but integration with other scheduling elements is unexplored. In conclusion, the review highlights the effectiveness of evolutionary algorithms in surgical scheduling [27-30], but lacks discussion on real-time adaptation, multi-component integration, and patient-centered approaches. Table I simplifies the analysis and helps readers grasp the key ideas and practical use of each method in real healthcare situations.

TABLE I. SUMMARIZATION OF OPTIMIZATION MODEL

Optimization Method	Advantages	Limitations	Ref
Nurse Scheduling			
Computer-based Techniques	Improves efficiency by automating scheduling.	High initial cost for technology and training.	[2]
Skill-Based Nurse Scheduling System	Helps with better decision-making in management.	Lacks real-world testing in hospitals.	[8]
Metaheuristic Algorithms	Can optimize complex scheduling problems.	Slow progress and no improvements suggested.	[19]
Differential Evolution Algorithm	Works with fewer parameters, simplifying optimization.	Lacks comparison with other algorithms and no focus on parameter tuning.	[20]
Hybrid Algorithms (Scout Bee Strategy)	Efficient in finding optimal solutions.	Doesn't address real-world challenges in implementation.	[21]
Evolutionary Multi-Objective (EMO) Algorithms	Can manage multiple objectives, adaptable for complex cases.	Doesn't cover specific nurse scheduling issues like shift coverage.	[22]
Studies in Local Hospitals	Offers real-world insights.	Findings lack clarity and applicability to broader settings.	[23]
Operation Theatre Scheduling			
Evolutionary Algorithms (Genetic Algorithms)	Improves surgical scheduling, especially with large data.	Struggles with broader healthcare system integration.	[2]
Economic Importance of Efficient Scheduling	Helps reduce healthcare costs.	No clear strategies for applying this in practice.	[10]
Fuzzy Model with Genetic Algorithm Hybrid (GA-P)	Effective for uncertain surgical durations.	Doesn't integrate real-time data, limiting its use.	[11]
Hybrid Genetic Algorithm (HGA)	Enhances operating room utilization.	Needs further validation across different healthcare environments.	[13]
Rolling Horizon Approach	Dynamically adjusts schedules to improve patient flow.	Doesn't consider long-term adaptability or scalability.	[14]
COVID-19 Specific Scheduling Model	Provides solutions during crises like COVID-19.	Doesn't analyze use for routine, non-crisis scheduling.	[24]

C. Related Work with Evolutionary Algorithms for Integrated Healthcare Scheduling

Integrated healthcare scheduling has become a key challenge in optimizing healthcare operations, covering areas like hospital operating room planning [31], home healthcare staffing [32, 33], multi-resource capacity planning [34], and IoT-integrated task scheduling [35]. This complex problem requires advanced optimization methods to coordinate resources, personnel, and patients across different healthcare settings. Recent literature shows a variety of optimization techniques used to tackle these challenges, including integer programming [32, 33], stochastic modeling [34, 36], heuristic algorithms [37], and AI techniques [35, 38]. Xiao et al. [37]

proposed an integrated scheduling algorithm, while Fu et al. [36] developed a stochastic multi-objective model adaptable to healthcare contexts, highlighting the potential of hybrid approaches.

Despite this, there is a significant gap in the application of evolutionary algorithms to integrated healthcare scheduling problems. This is surprising given that challenges such as resource constraints [39], uncertainty [34, 36], multi-objective optimization [36], and service integration [40, 41] align well with the strengths of evolutionary algorithms. Zhang et al. [39] discussed the complexity of resource allocation in healthcare, while Stan et al. [40, 41] explored innovative scheduling solutions. Moerman's patent [38] and Senthil et al.'s work [35] on IoT-integrated systems illustrate the growing interest in leveraging technology for efficient scheduling.

D. Dependencies Between Schedule

Figure 2 illustrates the inter-dependencies and intra-dependencies between different types of scheduling. The Nurse Scheduling Problem (NSP) focuses on allocating nursing staff across shifts while considering factors like nurse specialty, working hours, and day-off rules. It is inter-dependent with the Operation Theatre Scheduling Problem (OTSP) since certain surgeries require specific nurses, requiring alignment between both schedules. Intra-dependencies within the NSP involve balancing nurse schedules, managing preferences, and ensuring coverage.

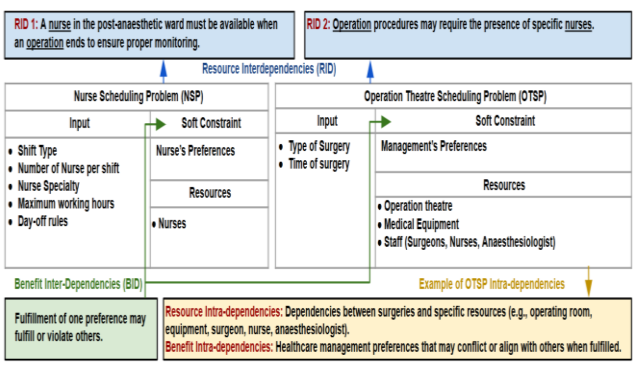

Fig. 2. Examples of the inter-dependencies and intra-dependencies of the resources and benefit between different types of scheduling.

The OTSP involves resources such as the operating theatre, medical equipment, and healthcare professionals like surgeons, nurses, and anesthesiologists. It depends on the availability of qualified nurses, linking it to the NSP. Within the OTSP, intra-dependencies include coordinating medical equipment and healthcare professionals for surgery, emphasizing the need for effective planning and resource management.

IV. Mathematical Formulation for Integrated Healthcare Scheduling

A. Objective Function

The objective is to minimize the total scheduling cost, considering resource availability, nurse preferences, and operation theatre constraints:

$$min\ Z = \sum_{n=1}^{N_N} C_{N_n} + \sum_{o=1}^{N_O} C_{O_o} \tag{1}$$

Z is the total cost function to be minimised. N_N , N_O are the total number of nurses and operations respectively, C_{N_n} , C_{O_o} are the cost associated with scheduling nurse n and operation o.

B. Constraints

The hard and soft constraints of each scheduling problem should be added in total as a single evolution before integrating them to be cooperative co-evolutionary algorithms.

Nurse Scheduling Problem

Hard Constraints:

1. Each shift should have at least one nurse. $\sum_{n\in N} x_{n,s,d,u} \geq 1, \forall s,d,u.$
2. Each nurse should have exactly one shift per day. $\sum_{s\in S} \sum_{u\in U} x_{n,s,d,u} \geq 1, \forall n,d,u.$
3. Specific roles must be included in shifts. $\sum_{n\in N:r=1} x_{n,s,d,u} \geq 1, \sum_{n\in N:r=2} x_{n,s,d,u} \geq 1,\ \forall n,d,u.$
4. Minimum working hours. $\sum_{s\in S} \sum_{d\in D} \sum_{u\in U} x_{n,s,d,u}.hours \geq W_{min}, \forall n.$

Soft Constraints:

1. Sisters should only be assigned to AM or PM shifts. $x_{n,s,d,u} = 0, \forall n: r = 0, \forall s \in \{2,3,4\},\ \forall d,u.$
2. Each shift must include at least one nurse and one healthcare assistant. $\sum_{n\in N:r=1} x_{n,s,d,u} \geq 1, \sum_{n\in N:r=2} x_{n,s,d,u} \geq 1, \forall s,d,u.$
3. Minimum working hours. $W_{max} \geq \sum_{s\in S} \sum_{d\in D} \sum_{u\in U} x_{n,s,d,u}.hours \geq W_{min}, \forall n.$
4. Each Nurse and Healthcare Assistant must work at most one night shift per week. $\sum_{d\in D} \sum_{u\in U} x_{n,2,d,u} \leq 1, \forall n: r \in \{1,2\}.$
5. Each night shift must followed by a post-night shift. $x_{n,3,d+1,u} \geq x_{n,2,d,u}\ \forall n,d,u.$
6. Each nurse must have at most one off-day per week. $\sum_{d\in D} \sum_{s\in S\setminus\{4\}} \sum_{u\in U} x_{n,s,d,u} \leq 6, \forall n.$
7. Sisters must be assigned off-days on weekends. $x_{n,s,d,u} = 0, \forall n: r = 0, \forall u, s\setminus\{4\}, d \in \{Saturday, Sunday\},$
8. Each nurse must work in the OT at least once per week.

$$\sum_{s\in S} \sum_{d\in D} x_{n,s,d,1} \geq 1, \forall n$$

Operation Theatre Scheduling Problem

Hard Constraints:

1. Room type matches surgery type. $y_{r,d,s,u,ts} = 0$, if r is not suitable for ts.

2. Three slots per day per room.
   $\sum_{s \in S} \quad y_{r,d,s,u,ts} = 3, \forall r, d.$
3. Each slot must include all staff types.
   $\sum_{st \in ST} \quad assigned(st, r, d, s) \geq 1, \forall r, d, s.$
4. Elective surgery matches department$y_{r,d,s,u,ts} \leq department(u, ts)$, if ts = Elective.

Soft Constraints:

1. Each staff type have 2 to 3 members per shift.$2 \leq \sum_{st \in ST} \quad assigned(st, r, d, s) \leq 3, \forall r, d, s.$
2. On-call emergency rooms staff best not work for two consecutive days.$assigned(st, r, d, s) + assigned(st, r, d + 1, s) \leq 1, \forall st{:}\, on - call, \forall r.$
3. Elective surgery assigned on weekends and office hours.
   $y_{r,d,s,u,ts} = 0, \quad \forall r \notin R_{Emergency} \quad \forall ts = Elective, \forall d \in D \backslash \{Saturday, Sunday\},$
4. Surgeons and Anaesthetists work only weekdays unless assigned to the emergency room.$assigned(st, r, d, s) \ = \ 0 \ , \ \forall r \notin R_{Emergency} \forall st \in \{Surgeons, Anaesthetist\}, \forall d \in \{Saturday, Sunday\},$
5. Each nurse must have at most one off-day per week.$\sum_{d \in D} \quad \sum_{s \in S} \quad nurse(n, r, d, s) \leq 6, \ \forall n.$
6. Each nurse must enter the OT at least once per week.
   $\sum_{r \in R} \quad \sum_{d \in D} \quad \sum_{s \in S} \quad nurse\ (n, r, d, s) \geq 1, \ \forall n.$

V. Discussion

Integrated healthcare scheduling presents challenges due to diverse constraints such as staff availability, patient needs, and resource allocation. Traditional methods struggle to handle these complexities, especially in dynamic healthcare environments.

Cooperative Co-Evolutionary Algorithms (CCEAs) offer a promising solution, excelling in multi-objective optimization by balancing goals like cost reduction and resource utilization. Their modular structure supports scalability, and their iterative nature enables real-time adaptation. However, more empirical research is needed to validate CCEAs across various healthcare settings. Case studies where CCEAs have been implemented in real-world healthcare environments, such as hospital nurse scheduling or operation theatre planning, would be invaluable in proving their effectiveness and adaptability.

Despite their potential, CCEAs face challenges in real-time applications. High uncertainty and dynamic changes, such as sudden staff shortages or patient surges, can affect performance. Thus, further refinement is needed to address these limitations. Fig. 3 illustrates a basic co-evolutionary model, demonstrating the potential of CCEAs in tackling integrated healthcare scheduling's complexities by managing inter-dependencies between resources.

VI. Conclusion

Healthcare scheduling involves balancing nurse allocations, operation theatre planning, and patient admissions, each with complex resource dependencies. CCEAs and other evolutionary algorithms show promise in addressing these challenges by optimizing across different scheduling domains. However, the full potential of these algorithms must be validated through real-world case studies and compared with traditional systems to assess their impact on efficiency and patient care.

Future research should focus on refining CCEAs to handle uncertainty and improve real-time adaptation in dynamic environments. Open challenges include addressing multi-objective optimization in unpredictable healthcare settings, such as sudden patient surges. A comparison of evolutionary algorithms and their performance in single- vs. multi-task scenarios will help guide their practical application.

In summary, while CCEAs offer a solid foundation for integrated healthcare scheduling, further research and validation are necessary to improve their applicability, scalability, and effectiveness in real-world healthcare systems.

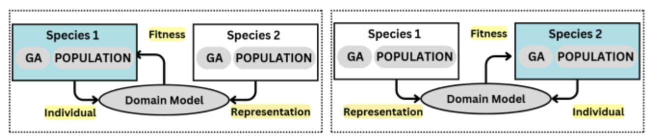

Fig. 3. Basic Co-Evolutionary Model with 2 Species

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