Techniques for Improving Genetic Algorithms in Solving Operating Room Scheduling Problems: An Integrative Review

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ABSTRACT

Operating room scheduling is a complex process that involves various resources and takes the interests of many parties into consideration. The genetic algorithm is the frequently used metaheuristic algorithm to solve a large-size operating room scheduling problem. Many techniques have been developed to improve the genetic algorithms' performance in dealing with the operating room scheduling complexity. In this paper, we survey available literature to identify improvement techniques used at each stage of the genetic algorithm and capture the underlying problems. This review provides a mapping of improvement techniques in genetic algorithms correlating with the considered problems. The results can be employed by other researchers as a guide for future research in integrating a genetic algorithm or other population-based metaheuristic algorithm with a recent heuristic algorithm following the future directions of operating room scheduling research.

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1. INTRODUCTION

An operating room is typically an essential facility in a hospital that requires complex resources and high costs. The hospital management needs to maintain the service quality provided to patients, which directly relates to the efficiency and effectiveness of resource usage. An inaccurate operating room schedule influences the timeliness of surgery starting time and the queue of patients waiting for surgery. Surgery requires not only the accuracy of the medical treatment for a disease but also the certainty of the accurate surgery starting time. Delayed surgery, consequently, can affect the patient's condition or safety.

Operating room scheduling is an activity of sequencing surgeries in the available operating rooms and allocating the resources needed for the surgeries. Operating room scheduling is a complex problem because it must synchronize various resources for the surgeries. The complexity of operating room scheduling has encouraged the development of operating room scheduling research with various considered factors and techniques in solving the problem. Mathematical programming and heuristics are the frequently used methods for solving operating room scheduling problems (Samudra *et al.*, 2016; Zhu *et al.*, 2019). However, mathematical programming is not able to obtain solutions with acceptable computation time, especially for large-size problems. Therefore many published papers have proposed the use of heuristic techniques. Zhu *et al*. (2019) divided the heuristics in the operating room scheduling literature into six categories: exact-method based heuristics, constructive heuristics, improvement heuristics, metaheuristics, linear programming-based heuristics, and dispatching-rule based heuristics.

Solving the optimization problem using the heuristic technique does not guarantee to obtain an optimal solution. However, the solution is good enough or close to the optimal with acceptable computation time (Hillier and Lieberman, 2010). Abdalkareem *et al*. (2021) report in their review that the major successful heuristic algorithms for solving healthcare scheduling problems are from nature-inspired algorithms. The genetic algorithm is a more widely used nature-inspired algorithm to solve operating room scheduling problems compared to other metaheuristic algorithms (Samudra *et al.*, 2016; Zhu *et al*., 2019).

Genetic algorithms have been widely used to solve various scheduling problems. Xing *et al*. (2013) conducted a literature review to investigate the development of operation research applications in service industries. They identified that genetic algorithms were also used to solve the scheduling problem in service industries, such as schedules flights, trains, logistics transportation, and ambulances. In manufacturing industries, a literature review by Allahverdi (2016) identified that genetic algorithms were intensively employed to solve scheduling problems with no-wait in process. However, the operational characteristics of the service industries are more complex than the manufacturing, thus providing opportunities for researchers to conduct broader investigations (Xing *et al*., 2013). Moreover, Abdalkareem *et al*. (2021) revealed in their review that one of the challenges in healthcare scheduling is integrated scheduling especially for the operating room due to high operational cost with limited resources.

Some studies have improved the classic genetic algorithms to obtain a good solution with less computational effort due to the complexity of the operating room scheduling problem. To the best of our knowledge, no review papers have investigated the improvement of genetic algorithms in the context of scheduling, for either manufacturing or service industries. Therefore, this review aims to categorize the developed improvement techniques at each stage of the genetic algorithm and to identify the motivation for designing the improvement. The results provide a guide to integrate the genetic algorithm with the recent heuristic algorithm in solving the operating room scheduling problem, which expected to be applied also for scheduling cases in other fields. The remaining of this paper is organized as follows. Section 2 presents an overview of operating room scheduling problem complexity and section 3 describes the methods in conducting the review. The following section outlines the improvement techniques conducted at each stage of the genetic algorithm while section 5 briefly discusses the results. Finally, Section 6 presents the conclusion and future work directions.

2. OVERVIEW OF OPERATING ROOM SCHEDULING PROBLEM COMPLEXITY

The operating room scheduling problem constitutes a combinatorial optimization model for allocating given resources considering specific objectives. The objectives involve the interest of the parties: the hospital managers, the surgeons, and the patients. Therefore, the operating room scheduling problem is a complex and challenging task (Zhu *et al.*, 2019). The primary decisions of operating room scheduling problem show the allocation of patients to operating rooms and time slots in conducting the surgeries. There are three patient allocation strategies: open strategy (Fei *et al*., 2010; Hamid *et al*., 2019), block strategy (Guido and Conforti, 2017; Lee and Yih, 2014), and modified block strategy. The open strategy is more flexible in allocating surgery into the operating room and time slot, but the surgeon's schedule becomes uncertain. With the block strategy, the surgeon's schedule becomes steadier, and the availability of time slots and operating rooms to conduct surgery becomes limited. The modified block strategy combines the benefits of open and block strategy by providing particular operating rooms and time blocks for any surgery type if its blocks are insufficient.

The complexity of the operating room scheduling problem also relates to the three stages of the surgical procedures known as pre-operative, intra-operative, and post-operative. Research articles on operating room scheduling problems consider single-stage or multi-stage surgery procedures. The considered resources will comply with the consideration stage of the surgery procedure. For a single-stage surgical procedure problem, the consideration stage is the intra-operative stage as the main stage of the surgery procedure (Marques *et al*., 2014; Wang *et al*., 2015). Two-stage surgical procedure problems take the intra-operative and post-operative stages into consideration (Latorre-Núñez *et al*., 2016). Some research articles have discussed the three-stage surgical procedure problem and the availability of the wards and intensive care unit (ICU) (Belkhamsa *et al*., 2018; Vali-Siar *et al*., 2018). The second stage is the most complex since it needs various resources and a surgeon assisted by several nurses as the principal actors to conduct the surgery on top of the tools and equipment. Operating room scheduling problem considering the medical staff also considers its various related factors, which are available in number (Vali-Siar *et al*., 2018), surgeon specialty (Belkhamsa *et al*. 2018), compatibility level of the surgical team (Hamid *et al*., 2019), maximum working hours (Vali-Siar *et al*., 2018), medical staff tiredness (Wang *et al*., 2015), or nurse scheduling (Guo *et al*., 2016).

Surgery duration is one of the uncertainty factors to address in the operating room scheduling problem (Hooshmand *et al*., 2018), in addition to the patient pre-condition, postoperative recovery time (Souki, 2011), and arrival time of the emergency patient (Latorre-Núñez *et al*., 2016). The operating room scheduling research that does not take the uncertainty of surgery duration into consideration uses the average surgery duration of the same surgery type based on the hospital historical data. Actual longer surgery duration can cause postponement, cancelation, and overtime. However, shorter actual surgery durations will result in longer waiting time as the resources in the next stage are still in use.

The various factors considered in the operating room scheduling problem determine the scheduling performance measure to evaluate the developed schedule. The objective functions of the optimization model represent the scheduling performance measure. The waiting time (Santoso *et al*., 2017) and surgery tardiness/cancellation (Vali-Siar *et al*., 2018) represent the patient's perspective of expecting good service quality with the service time certainty. Whereas the hospital management expects the efficiency and utilization of resources, which is shown in the total time to complete all surgeries (Latorre-Núñez *et al*., 2016), overtime of resource usage (Fei *et al*., 2010; Lin and Chou, 2020; Lu *et al*., 2019), resource idle time (Vali-Siar *et al*. 2018; Lin and Chou, 2020), or resource cost (Wang *et al*., 2015). Nurses have a different perspective compared to hospital management and patients. They are concerned with their workload. Overtime (Santoso *et al*., 2017) and variation in working hours (Belkhamsa *et al*., 2018) are the common presentations of nurses' workload. The performance measures of operating room scheduling models from different perspectives are conflicting and contributing to the problem's complexity.

The performance measure selection must be relevant to the real-world condition and accommodate the objectives of the most related parties (Samudra *et al*., 2016). The complexity of the considered factors in the operating room scheduling problem will motivate the design of methods in solving the problem. Likewise, the complexity level of the problem will influence the optimal solution searching process.

3. REVIEW METHODOLOGY

The integrative review methodology which systematically searches and qualitatively synthesizes existing articles (Whittemore and Knafl, 2005) is applied. The integrative review combines data from the theoretical and empirical literature. Therefore, it is generally applied to examine studies that use similar methodologies (Whittemore and Knafl, 2005; Souza *et al*. 2010). In this study, Whittemore and Knafl's framework (Whittemore and Knafl, 2005) is applied to conduct the integrative review. The steps in the framework include problem identification, literature searching, data evaluation, data analysis, and presentation. The introduction and background as the problem identification step are discussed in Sections 1 and 2. Figure 1 shows the screening process in literature searching and data evaluation to select articles for review.

3.1. Literature Search

In the literature searching process, the search engine of our university library is used and it shouts out using reputable electronic journals and publication databases, such as Scopus, Science Direct, Springer Link, ProQuest, EBSCO, Emerald, Sage, the MBJ, IEEE Xplore, and AIP Publishing. The articles searching process uses “operating room scheduling”, “operating theater scheduling”, “surgery scheduling”, and “genetic algorithm” as the keywords by using the Boolean operator “AND” and “OR”, for an unlimited year. The search resulted in 149 articles. Samudra *et al*. (2016) and Zhu *et al*. (2019) conducted a literature review to classify the problems in operating room scheduling and the methods for solving

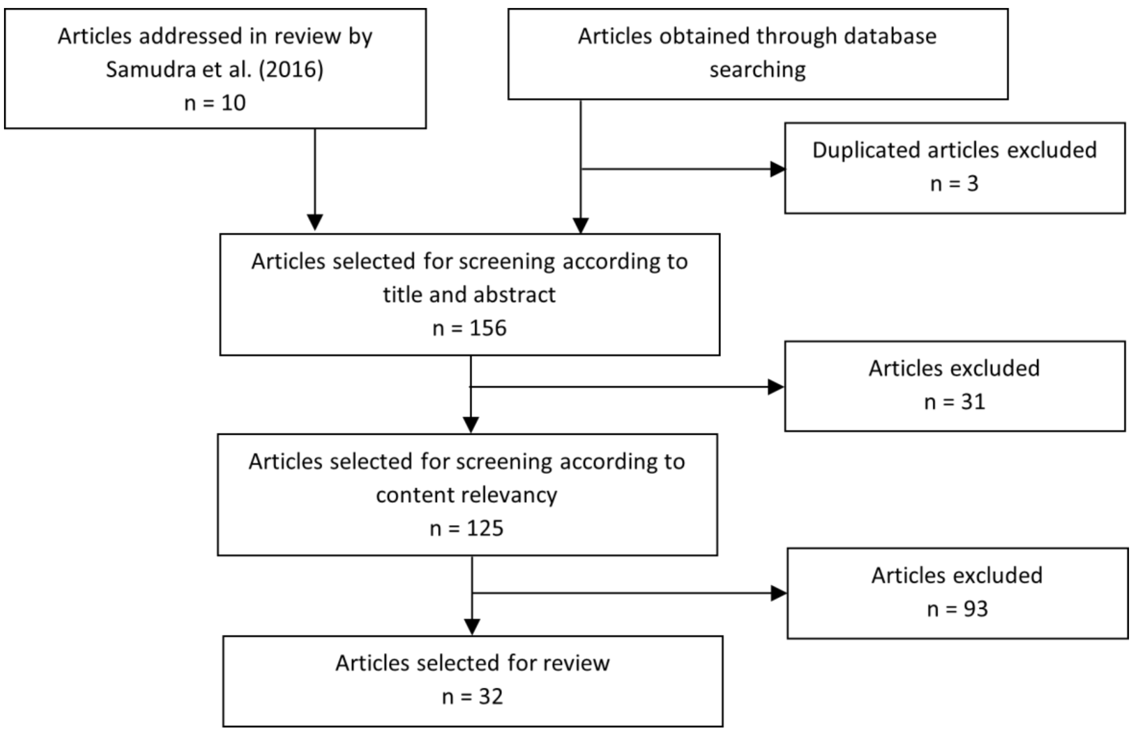

Figure 1. Flow chart of articles selection

the problem. Therefore, this study also identifies articles addressed in both studies but not obtained by this searching process. This process identified ten additional articles from the review by Samudra *et al*. (2016).

3.2. Data Evaluation

Duplicate articles are eliminated from the database searching process and three duplicates are excluded. The screening process is conducted according to the title and abstract of the remaining 156 article, resulted 125 articles remaining. Then the screening is carried out again according to full-text content relevance for eligibility, leaving 32 articles in the list. The publishing years of the articles are between 2006 and 2022. Each screening process uses inclusion and exclusion criteria. The articles need to meet the following inclusion criteria: (1) written in English, (2) reviewed journal or conference proceeding, (3) applied the improved genetic algorithm for operating room scheduling, (4) described the technique in improving the genetic algorithm, and (5) reported the quality solution of the improved genetic algorithm. The articles are excluded if they met any of the following criteria: (1) not coverage of the operating room scheduling, (2) applied classical genetic algorithm without improvement, and (3) the genetic algorithm is on the comparison method for solving the problem.

Whittemore and Knafl (2005) state that there is no gold standard for evaluating the quality of selected articles for research review. For an integrative review that the primary sources have similar research designs, the quality appraisal can be calculated according to inclusion and exclusion criteria. As the objectives of our study are to identify and summarize the improvement techniques in genetic algorithms to solve the operating room scheduling problem, the quality of eligible articles is not assessed.

3.3. Data Analysis

There are some strategies for data analysis and comparison in the integrative review and one of them is themes and relations (Whittemore and Knafl, 2005). Therefore, the data analysis process starts by classifying the discussed problems in the selected articles by using six fields to categorize the problems: (1) patient characteristics, (2) patient allocation strategy, (3) surgical procedure stage, (4) considered resource, (5) aspect of uncertainty, and (6) model objective function (performance criteria). Section 2 presents the problems summary. Corresponding to the developed genetic algorithm, the statements that described the chromosome structure, technique for initial population generation, parent selection, technique for developing next generation (crossover and mutation operator, additional technique if any), fitness evaluation, and obtained solution (quality and computation time) are extracted. The extracted statements are examined to identify similar improvement techniques conducted at each stage of the genetic algorithm. Similar improvement techniques are grouped into the same category (themes). The relations between the improvement technique in each category with the emphasized problem are identified to investigate the motivation in developing the improvement. Each Subsection of Section 4 discusses the identified improvement techniques.

4. IMPROVEMENT TECHNIQUES OF GENETIC ALGORITHM FOR OPERATING ROOM SCHEDULING

The natural phenomenon of the biological evolution process formulated by Charles Darwin is fundamental in the genetic algorithm. Each individual has variations represented by chromosomes. The reproduction process generates children that share some of the features (genes) of the parents' chromosomes. Individuals with an ability to adapt to the environment are most likely to survive into the next generation. The genetic algorithm adapts this natural process to solve the optimization problem. Chromosome fitness is the representation of the solution objective function value. It is a primary parameter to survive into the next generation. The population in each iteration of the genetic algorithm is a group of individuals (or chromosomes) representing the trial solutions. The chromosome structure consists of genes that comprise the decision variables. Some of the chromosomes in the population will be randomly selected as parents and paired up to generate children through the crossover procedure. Each pair of parents will give birth to two children. The children's genes comprise a random combination of the parents' genes. The genetic algorithm also explores new solutions by generating children through mutation. The process randomly chooses a chromosome and interchanges the genes within it. A particular crossover and mutation process may result in infeasible solutions that need a procedure to resolve.

The iteration represents a generation with a fixed population size. The next generation will retain the best individuals in the current population into a new one. The commonly used stopping rules are a fixed number of iterations or a fixed amount of CPU time. An additional stopping rule is a predetermined number of consecutive iterations without improvement with the best solution found so far. The final solution is the best solution found on any iteration.

Abdalkareem et al. (2021) conducted a comprehensive review of healthcare scheduling. They organized the articles using four essential components in solving optimization problems: problem definition, formulations, data sets, and methods. It was identified that the common healthcare scheduling problems discussed in the recent papers were patient admission scheduling, nurse rostering, and operating room scheduling. Their review also revealed the genetic algorithm as the frequently used method in solving operating room scheduling problems. However, Ab Wahab *et al*. (2015) identified that the main drawback of the genetic algorithm was the lack of fast convergence to obtain optimal solutions due to the random mechanisms. Therefore, many studies have proposed techniques to improve the performance of the genetic algorithm. The following subsections will discuss the improvement techniques of genetic algorithms for operating room scheduling problems covered by the selected articles as mentioned earlier.

4.1. Initial Population Generation

The traditional genetic algorithm randomly generates the initial population that can increase the number of infeasible solutions for a complex problem and affects the solution searching time. However, maintaining the random generation technique will ensure solution diversity to avoid being trapped in a local optimum Wang *et al*., (2015). The improvement of the genetic algorithm at the initial population generation stage aims to improve the convergence level of the solution Vali-Siar *et al*. (2018). Therefore, the idea for improvement is combining the random generation technique with a procedure to obtain high-quality individuals. These individuals usually are also named elitist individuals. The high-quality individual is a sub-optimal or, at least, a feasible solution. There are three techniques for generating high-quality individuals in the reviewed articles: a procedure to generate chromosome that partially optimize the multi-objective function, a procedure of resources allocation for generating chromosome by combining sequential and random selection, a procedure to generate chromosome based on priority dispatching rules.

Guido and Conforti (2017), Marques *et al*. (2014), Wang *et al*. (2015), Lu *et al*. (2019), and Marques and Captivo (2015) discussed operating room scheduling model with a multi-objective function. The decision variables of the model were in the opposite conditions. They developed a procedure to generate chromosomes that partially optimized the multi-objective functions. The motivation is the conflicting multi-criteria performance measure of the developed model. Marques *et al*. (2014) and Marques and Captivo (2015) developed an operating room scheduling model with two conflicting objective functions, which were maximizing the operating room occupation and maximizing the number of scheduled surgeries. A surgery with longer duration is preferable than a shorter for maximizing operating room occupation. However, the opposite condition is preferable in maximizing the number of scheduled surgeries. The developed genetic algorithm independently considers the two objective functions by applying a two-phase heuristic procedure. The first phase provides an initial solution, and the second one will improve the solution. The heuristic procedure in both two-phases will schedule surgeries according to their priority level and results in a certain percentage of elite individuals of the initial population. The surgery priority level in this model represents the due date to accomplish the surgery. The remaining individuals are randomly generated.

Guido and Conforti (2017) also developed an operating room scheduling model with conflicting objective functions, maximizing the number of scheduled patients and minimizing operating room overtime. However, increasing in scheduled patients might result in the possibility of operating room overtime. The developed procedure of generating the initial population combines two types of individuals. The first type comprises feasible solutions for all constraints, but only one objective function is optimized. The second type is semi-feasible solutions and randomly generated. These solutions only satisfy the operating room block constraint for patients' and surgeons' allocation. Lu *et al*. (2019) also applied the objective function of maximizing the number of scheduled patients and minimizing operating room overtime. The developed procedure for generating the initial population imposes constraints on randomly generated individuals to improve the performance of Non-dominated Sorting Genetic Algorithm II (NSGA-II). This procedure guarantees the surgeries will be scheduled but cannot restrain the operating room overtime.

Wang *et al*. (2015) addressed the surgery duration as a non-decreasing function of the surgery starting time, which represents surgeon and surgical staff fatigue as the surgeries continue. The optimization model also has two conflicting objective functions, total completion time and resource cost. The surgery duration is controllable by allocating extra resources. It means that shortened surgery duration, which simultaneously reduces the completion time and increases the resources cost. The developed genetic algorithm has a procedure to generate two optimal solutions based on the resource allocation extreme condition. The initial population comprises the obtained optimal solutions and randomly generated solutions.

The decision of the operating room scheduling problem indicates two conditions, surgery sequence and allocation into all the considered resources. The developed chromosome structure represents only the surgeries sequence but indirectly signifies the resource allocation. However, operating room scheduling with resource-constrained problems generally constructs the chromosome structure representing resource allocation. Therefore, the complexity of chromosome structure motivates the development of procedures in generating "good" solutions as an initial population. The identified improvement technique for the resource-constrained problem is combining sequential and random selection to allocate the considered resources to each part of the chromosome structure. This technique is applicable for single or multi-stage surgical procedure problems. For a single stage with a multi-resource problem, the considered resource beside the operating room is the surgeon (Hooshmand *et al*., 2018) or nurse (Guo *et al*., 2016). Therefore, chromosome structures are developed in that some parts represented the medical staff allocation and their schedule. For the weekly scheduling period, the chromosome structures in Roland *et al*. (2006, 2010) represent the day and operating room allocation for scheduled surgeries. The availability of medical staff and material resources corresponds to the surgery day.

Fei *et al*. (2010) and Vali-Siar *et al*. (2018) discussed the operating room scheduling model for a multi-stage problem with a different focus on the decision of the developed model. Vali-Siar *et al*. (2018) considered more complete resources needed for the surgeries and focused on the surgeon allocation, operating room allocation, and the day to perform surgeries. The chromosome structure complies only with these three allocations since the model only considered the number of other resources. Fei *et al*. (2010) considered the operating room and recovery bed allocation for two-stage surgical procedure problem. The developed procedure sequentially chooses resource type among all the considered resources and then randomly chooses within the resources of the same type (Fei *et al*., 2010; Vali-Siar *et al*., 2018; Guo *et al*., 2016; Hooshmand *et al*., 2018; Roland *et al*., 2006, 2010). The resource allocation order conforms with the gens arrangement in a chromosome structure representing each resource type.

Wang et al. (2022) discussed surgical scheduling with inpatient beds shortage. The developed chromosome represents the operating room assignments, scheduled surgery days, and bed assignments. The operating room day assignments are randomly generated for the initial population. A heuristic algorithm is applied for operating room and bed allocation. Rivera *et al*. (2020) considered the operating rooms as the containers with heterogenous capacity. Each gene in the chromosome represents an operating room with its surgery allocation according to the surgery duration. For the initial population, the First-Fit algorithm firstly allocates surgery with a duration of more than 50% of the operating room capacity and then randomly select the remaining surgeries.

The characteristic of operating room scheduling problem with the single-stage surgical procedure is similar to parallel machine scheduling. Whereas the multi-stage operating room scheduling problem is similar to a flow-shop scheduling. Parallel machines and flow-shop scheduling problems generally utilize performance measures related to resource utilization that schedules all jobs as soon as possible. The commonly applied method to solve the parallel-machines and flow-shop scheduling problems is the priority dispatching rules. The jobs are sequenced and allocated in resources according to the priority dispatching rule. Therefore, parts of the chromosome structure need to represent the jobs sequence in manufacture scheduling or surgeries sequence in operating room scheduling.

Souki (2011), Santoso *et al*. (2017), Lin and Chou (2020), Souki and Rebai (2010), and Souki *et al*. (2009) utilized a procedure based on the priority dispatching rule to generate some solutions for the initial population combined with random generation. Souki (2011), Santoso *et al*. (2017), Souki and Rebai (2010), and Souki *et al*. (2009) discussed two-stage surgical procedure. The problem is analogous to the two-stage flow-shop scheduling problem. The patient will be transferred to the post-operative stage if the recovery bed is available and the surgical procedure in the intra-operative is completed. The surgery duration and patient recovery time will influence the flow of the patients to complete all the stages of the surgery procedure. The priority dispatching rules will sequence the surgeries according to the surgery duration and patient recovery time. Souki (2011), Souki and Rebai (2010), and Souki *et al*. (2009) applied five two-step heuristics based on the dispatching rules aside the random technique to generate the initial population. The five two-step heuristics are SPT-SPT, SPT-LPT, LPT-SPT, LPT-LPT, and Johnson's Rule. The surgery sequence in the chromosome structure also indicates the order of surgery allocation into the resources. The developed chromosome structure in Santoso *et al*. (2017) shows surgery starting time, operating room allocation, and nurse allocation for each patient. The operating room allocation and surgery starting time in the initial population are constructed by separately utilizing SPT, LPT, and random mechanism, following the clustering process of surgery durations. A part of the chromosome structure represents the surgery starting time and according to the surgery's sequence. The clustering process is the pre-processing stage to classify the surgeries based on the average and the standard deviation of surgery duration.

Lin and Chou (2020) discussed the single-stage surgical procedure to minimize overtime and unproductive time in the operating room. The generated initial population comprises the randomly generated and four good solutions. The four good solutions are resulted by the proposed heuristics based on the shortest processing time (SPT), longest processing time (LPT), earliest due date (EDD), and the ratio of LTP/EDD rule. The studied problem in Lin and Chou (2020) is multifunctional operating rooms. This problem has similar characteristics to the parallel machines scheduling to minimize the makespan, the total time to complete all the jobs. The LPT rule has been extensively used and can obtain optimal solution for parallel machine scheduling problems to minimize the makespan. Whereas the SPT rule is optimal for single-machine scheduling problems to minimize total completion time and total lateness, likewise the EDD rule to minimize maximum lateness.

Table 1 summarizes the techniques to improve the genetic algorithm at the initial population generation stage. Almost all reviewed articles show that the improved genetic algorithms result in superior solution quality and more efficient computation time. Souki (2011), Vali-Siar *et al*. (2018), Lin and Chou (2020), and Souki and Rebai (2010) developed another heuristic algorithm besides the improved genetic algorithm. The model evaluations show that the heuristic is better in the objective function value for the large-scale problem (Souki, 2011; Vali-Siar *et al*., 2018; Souki and Rebai, 2010). However, the improved genetic algorithm is still efficient in computation time for a good solution (Lin and Chou, 2020).

4.2. Population Reproduction in The Next Generation

The traditional genetic algorithm generally uses mutation, crossover, or both to produce chromosomes of a new population in the next generation. The improved genetic algorithm at this stage is expected to expand the solution-searching process and not be trapped in the local optimal (Fei *et al*., 2010; Wang *et al*., 2015). Two improvement techniques of population reproduction are identified in the reviewed articles: a procedure based on local search to expand diversity in a population and a correction operator to obtain feasible solutions in a population. The motivations of the improvement techniques at this stage are the chromosome structure itself.

Lin and Chou (2020) studied the operating room scheduling model for a single-stage surgical procedure with a deadline to accomplish the surgeries. The developed chromosome structure directly represents surgeries sequence but indirectly represents the operating room allocation and the day to conduct the surgery. Whereas the constructed chromosome structures in (Fei *et al*., 2010; Wang *et al*., 2015; Fei *et al*., 2006; Ewen and

Table 1. Improvement techniques for initial population generation

Improvement Technique	Motivation	Research
A procedure to generate chromosome that partially optimize the multi-objective function	Conflicting multi-criteria performance measure	Guido and Conforti (2017), Marques *et al*. (2014), Wang *et al*. (2015), Lu *et al*. (2019), Marques and Captivo (2015)
A procedure of resources allocation for generating chromosome by combining sequential and random selection	Resource constrained problem (multi-resource or capacity constrained problem) with chromosome structure representing resource allocation	Fei *et al*. (2010), Vali-Siar *et al*. (2018), Guo *et al*. (2016), Hooshmand *et al*. (2018), Roland *et al*. (2006), Roland *et al*. (2010), Wang *et al*. (2022), Rivera *et al*. (2020)
A procedure to generate chromosome based on priority dispatching rules	Chromosome structure represents surgery sequence	Souki (2011), Santoso *et al*. (2017), Lin and Chou (2020), Souki and Rebai (2010), Souki *et al*. (2009)

Mönch, 2014) represent the sequence of all surgeries and the resource allocation. The developed chromosome structure in (Wu *et al*., 2018) represents operating room allocation for a three-stage surgical procedure. Belkhamsa *et al*. (2018), Souki *et al*. (2009), Britt *at al*. (2021), and Wang *et al*. (2021) developed the chromosome structure representing the sequence of all surgeries that serve as the basis for resource allocation. Belkhamsa *et al*. (2018) applied a local search algorithm as an improvement technique after the mutation process. The algorithm sequentially uses the insertion move and swap mechanism for generating other possible improvement solutions. The local search algorithm applied in Ewen and Mönch (2014), Wu *et al*. (2018), Britt *at al*. (2021), and Wang *et al*. (2021) was variable neighborhood search (VNS), whereas Souki *et al*. (2009) applied a variable neighborhood decent (VND), a variant of VNS.

Wang *et al*. (2015) also applied a local search algorithm to accomplish the population reproduction of the NSGA-II algorithm. All new individuals from crossover and mutation are combined with the current population and sorted based on their fitness using the non-dominated sorting procedure. The insertion and exchange move is the sequentially used local search technique for randomly selected individuals to obtain new local optimums. Lin and Chou (2020) developed four local search procedures: internal reassignment, internal exchange, external insertion, and external exchange which are combined into a greedy search and accomplished with an elite procedure search to escape from local optimal. Wang *et al*. (2022) applied crossover, mutation, and a heuristic algorithm using the swab rule and greedy search. The crossover and mutation are applied for part of the chromosome representing the operating room day assignment, while the heuristic algorithm is for the other parts representing the operating room and bed assignment.

The searching process in local search algorithm may return to the previously obtained local optimum. Therefore, Fei *et al*. (2006) and (2010) applied a tabu search procedure as a local improvement in the developed genetic algorithm to generate individuals. The procedure is performed for the resulting individuals from the crossover mechanism. Compared to a random technique, the searching process ensure that all possible alternative solutions have been included. The tabu search algorithm is a metaheuristic algorithm that uses a local search procedure. The advantage of tabu search is the use of a memory named tabu list, which records forbidden moves that would return to the solution recently visited. The tabu search algorithm also expands the searching process using intensification and diversification (Hillier and Lieberman, 2010).

The developed chromosome structure in multi-resource problems may represent other resource allocations besides the operating room. The resource allocation is associated with operating room allocation. Hooshmand *et al*. (2018) discussed single-stage and multi-resource problems. The developed chromosome structure consists of two parts representing operating room allocation and a sequence of surgeons. The surgery sequencing in the operating room is determined by examining the sequence of surgeons. This developed chromosome structure is very likely to produce the same solution. This condition will stop the solution-searching process, even though there are possible better solutions on the top the obtained solutions. Therefore, Hooshmand *et al*. (2018) proposed a symmetry-breaking operator, a correction procedure that guarantees the diversity of chromosomes in the population. The symmetry-breaking operator has a distinctive mechanism for each part of the chromosome structure that identify the similarity of each newly produced chromosome in the current population and replace the similar one to the new chromosome.

Erdem *et al*. (2012) studied the rescheduling of elective patients upon the arrival of emergency patients. The developed chromosome structure consists of five parts: the surgery sequence, operating room, number of open time slots before the patient’s surgery, number of surgeries in each operating room, and the admission of an emergency patient with the operating room assigned. Parts of the chromosome structure influence each other. The random mechanism in the crossover and mutation operator for generating the next population can result in infeasible solutions due to allocation into the operating room time slot. Therefore, the developed genetic algorithm is improved using a correction operator to decrease infeasibility. Timucin and Birogul (2018) also utilized a correction operator after the crossover and mutation operator. The developed chromosome structure represents operating room allocation with the surgeon assignment and patient's priority status while the correction operator prevents infeasible solutions which violate surgeon availability and patient's priority status constraint.

Expanding the solution-searching process logically affects the computation time. However, the reviewed articles reported that the improvement techniques for population reproduction in the next generation produce superior solutions quality and computation time. The improvement techniques accelerates the convergence level of the solution compared to the random mechanism. Table 2 shows the improvement techniques summary for population reproduction in the next generation.

4.3. Fitness Evaluation

The genetic algorithm encodes solutions into chromosomes to represent the surgery sequence or resource allocation. So that in the fitness evaluation stage, which is to calculate the value of the performance measure (objective function of the optimization model), chromosomes must be in the form of an operational schedule. The schedule shows the resources allocation to all surgeries while the operating room scheduling problem with conflicting multi-criteria performance measures increase the complexity of objective function evaluation. Therefore, the improvement for the fitness evaluation stage aims to maintain the quality of the obtained solution. The identified factors to apply the improvement techniques are the objective function and the surgical procedure stage with its chromosome structure to represent the resource allocation.

Hamid *et al*. (2019), Guido and Conforti (2017), Wang *et al*. (2015), Lu *et al*. (2019), Ewen and Mönch *et al*. (2019), Conforti *et al*. (*2010)*, and Wu *et al*. (2021) applied the NSGA-II in handling the multi-objective problem. The procedure sorts all individuals based on the dominant level of fitness values. The individual with better objective function value is placed in the lower rank and dominant than others. The evaluation for individuals in the same domination rank uses a crowding distance, the distance to their neighbors, the procedure assigns a higher fitness value for the one with a higher crowding distance. This procedure will maintain solutions diversity and emphasize the non-dominated solutions. Marques *et al*. (2014) and Marques and Captivo (2015) applied a two-phase heuristic procedure that independently evaluates the conflicting objective functions. The heuristic is similar to the one for generating elitist individuals in the initial population with a difference in the mechanism of allocating the surgical specialty.

Another motivation for improvement techniques in the fitness evaluation stage is the developed chromosome structure. Wang *et al*. (2015), Guo *et al*. (2016), Hooshmand *et al*. (2018), Lin and Chou (2020), Roland *et al*. (2006, 2010), Erdem *et al*. (2012), and Timucin and Birogul (2018) discussed the single-stage surgical procedure problem. Whereas Wang *et al*. (2022) also considered the beds in the downstream unit. The constructed chromosomes in those articles also represent resource allocation. The individual generation through a random mechanism for the resource allocation in the chromosome structure may result in infeasible solutions due to a capacity or non-overlapping constraint violation. Therefore, Wang *et al*. (2015) also applied the penalty procedure for solutions violating the capacity constraint before the non-dominated sorting procedure. The motivation for the improvement technique is the necessity of the model to control surgeon and surgical staff tiredness by adding extra resources to minimize the total completion time and resource cost. Guo *et al*. (2016) utilized a penalty procedure for solutions violating the non-overlapping constraints of operating room blocks and nurse allocation. This individual is a deceptive solution in minimizing the number of surgical nurses and operating rooms used, which is practically an infeasible solution. Whereas the developed algorithm by Lin and Chou (2020) penalizes the surgery scheduled later than the deadline and the operating room exceeds daily operational hours (regular plus overtime). Fitness function calculation by Roland *et al*. (2006, 2010) and Wang *et al*. (2022) penalizes the solution for violating resource availability, while a penalty score is applied for each hard constraint solution in Erdem *et al*. (2012) and Timucin and Birogul (2018).

Hooshmand *et al*. (2018) considered the uncertainty of

Table 2. Improvement techniques for population reproduction in the next generation

Improvement Technique	Motivation	Research
A procedure based on local search	Chromosome structure representing surgeries allocation into ORs	Fei *et al*. (2010), Wang *et al*. (2015), Belkhamsa *et al*. (2018), Lin and Chou (2020), Wang *et al*. (2022), Souki *et al*. (2009), Fei *et al*. (2006), Ewen and Mönch (2014), Wu *et al*. (2018), Britt *at al*. (2021), - Wang *et al*. (2021)
A correction operator	Chromosome structure representing surgeries allocation into ORs and other allocation associate to OR	Hooshmand *et al*. (2018), Erdem *et al*. (2012), Timucin and Birogul (2018)

surgery duration and modeled it by generating various scenarios of surgery duration. The occurrence probability of surgery duration is based on consultation with the surgeon and the hospital's historical data. The objective function of the optimization model is to minimize the total expected cost of the operating room and surgeon idle times. So that one of the decisions is the surgeon's arrival times. The proposed procedure approximates the fitness value in a hierarchical approach covering four sequential steps. The surgeon's arrival times estimation is the first step. The next step utilizes the obtained value in the previous one for calculating the objective value. The procedure also checks the constraints and adds a penalty for the chromosome fitness value violating operating room overtime constraints.

Latorre-Núñez *et al*. (2016), Belkhamsa *et al*. (2018), and Vali-Siar *et al*. (2018) considered the multi-stage surgical procedure problem. Latorre-Núñez *et al*. (2016) and Belkhamsa *et al*. (2018) modeled a chromosome structure as an integer array that only represents surgeries sequence. Therefore, a procedure is developed to allocate the resources and calculate the objective function value, that is minimizing the makespan. For operating room scheduling problems, makespan is the total time to complete all surgeries. The developed evaluation procedure in Belkhamsa *et al*. (2018) transforms the surgery sequence into a feasible solution. The evaluation procedure sequentially assigns the surgeries into resources in each stage of the surgical procedure while complying with the resource constraints. A similar allocation procedure is applied in Latorre-Núñez *et al*. (2016), namely the constructive heuristic. Because the developed model considers sequence-dependent setup times and no-wait move from the intra-operative stage to the post-operative, the procedure enables delay in the starting time of surgery due to the availability of the resources and the surgery starting time to minimize the maximum waiting time for emergency surgery.

Vali-Siar *et al*. (2018) considered the uncertainty of surgery duration, patient recovery time, and post-surgery length of stay. However, the chromosome structure only specifies the allocation of the surgeon, the operating room, and the day of the surgery. Therefore, the fitness evaluation in the developed heuristic algorithm allocates the surgery into a time axis and simultaneously examines all resource constraints to avoid infeasible solutions as much as possible. Zhang and Su (2021) discussed dynamic scheduling for elective surgeries on the day of execution. The surgeons are not available before their assigned appointment times. Therefore the objective of the model is to minimize surgeon waiting time and operating room idle time. The chromosome structure represents the surgery sequence, so a translation process decodes the operating room allocation and the planned starting time of the remaining surgeries.

Table 3 is the summary of improvement techniques at the fitness evaluation stage. The reviewed articles report high-quality solutions and efficient computation time obtained by the improved genetic algorithm. However, the improved genetic algorithm can have a less superior objective function value compared to the constructive heuristic (Vali-Siar *et al*., 2018) and the multi-objective particle swarm optimization (MOPSO) (Hamid *et al*., 2019).

4.4. Optimal Solution Improvement

The genetic algorithm does not guarantee to produce a globally optimal solution. Therefore, limited studies have proposed additional procedures to improve the solution quality after the stopping rule. Lee and Yih (2014) considered the uncertainty of the surgery duration and modeled it as a triangular fuzzy number. The chromosome in the developed genetic algorithm consists of two-string vectors representing the surgery sequence and resource allocation. The genetic algorithm provides the surgeries' starting times sequence in triangular-fuzzy numbers. Accordingly, Lee and Yih (2014) proposed several heuristic procedures to acquire a schedule with operational times (a crisp-time schedule) according to the

Table 3. Improvement techniques for fitness evaluation

Improvement Technique	Motivation	Research
A procedure of evaluating multi-objective function	Multi-criteria performance measure	Hamid *et al*. (2019), Guido and Conforti (2017), Marques *et al*. (2014), Wang *et al*. (2015), Lu *et al*. (2019), Marques and Captivo (2015), Ewen and Mönch (2014), Conforti *et al*. (*2010)*, Wu *et al*. (2021)
A penalty procedure for solutions violating the resource allocation constrains	Chromosome structure representing resource allocation	Wang *et al*. (2015), Guo *et al*. (2016), Hooshmand *et al*. (2018), Lin and Chou (2020), Roland *et al*. (2006, 2010), Wang *et al*. (2022), Erdem *et al*. (2012), Timucin and Birogul (2018)
A procedure to obtain feasible solution by complying all the resource constraints	Multi-resource problem with uncomplete resource allocation represented in the chromosome	Latorre-Núñez *et al*. (2016), Belkhamsa *et al*. (2018), Vali-Siar *et al*. (2018), Zhang and Su (2021)

obtained fuzzy-set-based. Those procedures determine the completion time of all surgeries structured in a chromosome to calculate the exclusive relationship of the objective function, patient waiting time, and resource idle time. Because of the nature of fuzzy numbers, the heuristic decision procedure does not guarantee to produce the optimal decisions but the implemented operational solutions.

As discussed in the previous subsection, Hooshmand *et al*. (2018) addressed the uncertainty of surgery duration to minimize the total expected costs, the operating room and surgeon idle times. The developed genetic algorithm has an additional procedure to generate neighborhood solutions for the best ten from the population in the last generation. The objective is to improve the performance measure value. Since the first stage of the fitness evaluation procedure is the estimation of surgeon' arrival time as one of the model decisions, the improvement procedure slightly changes the value of the surgeon's arrival time to minimize the surgeon's idle time. The modification is repeated until the step size reaches less than 10 minutes. Table 4 summarizes the improvement techniques at the optimal solution improvement stage.

5. DISCUSSION

Many studies have discussed various techniques to improve the performance of the genetic algorithm to solve operating room scheduling problems. This review provides a map of the improvement techniques utilized in each stage of the genetic algorithm. Operating room scheduling problem involves complex decision variables and constraints. Therefore, this review identifies that the performance measure and considered resources are the basis of developing the improvement techniques. A chromosome structure in a genetic algorithm represents a solution that directly or indirectly represents the considered resource allocation. The chromosome structure commonly relates to the considered resources and performance measures. The considered resources will comply with the consideration stage of the surgical procedure. Resource allocation to each surgery as one of the decisions of the operating room scheduling problem will determine the developed chromosome structure, the mechanism for generating individuals, and the calculation of the model objective function (performance measure). Therefore, the designed chromosome structures also motivate the development of improved techniques, especially in the stage of next-generation reproduction. The developed genetic algorithms for multi-resource or multi-stage surgical procedure problems should complement the initial population or fitness evaluation stage with an additional procedure to improve the solution. The improvement design aims to maintain the solution diversity with a random mechanism and, simultaneously, to obtain feasible solutions that fulfill the resource allocation constraints.

Hamid *et al*. (2019), Guido and Conforti (2017), Wang *et al*. (2015), Lu *et al*. (2019), Ewen and Mönch (2014), and Conforti *et al*. (*2010)* discussed multi-criteria performance measure. They applied the NSGA-II, an intensively applied algorithm to resolve optimization problems with multi-criteria performance measures. Hamid *et al*. (2019) and Conforti *et al*. (*2010)* utilized a classic NSGA-II as the improvement only for the fitness evaluation stage while others also designed the improvement technique for other stages in the genetic algorithm. Even though the studies discussed similar problem, the improvement could be designed for different stages of the genetic algorithm. This situation can occur because each researcher may emphasize different factors in the scope of similar discussed problems.

The reviewed articles discussed the final performance of their improved genetic algorithm. Most articles with improvements in more than one stage of the genetic algorithm did not deeply examine which significantly improved the schedule performance in detail. However, Lin and Chou (2020) developed improvement techniques for the three stages of the genetic algorithm. They discussed a heuristics for the initial population stage and local search procedures embedded in population reproduction for the next generation stage. The evaluation shows that the proposed local search procedures significantly improve the schedule performance. The developed improved genetic algorithms in the reviewed articles obtain promising results in good solutions or efficient computation time. Some of them report less superior solutions compared to other heuristic algorithms, such as Variable Neighborhood Search (Souki, 2011; Souki and Rebai, 2010), constructive heuristic (Vali-Siar *et al*., 2018), and MOPSO (Hamid *et al*., 2019). These flaws are possibly due to the random mechanism in mutation and crossover (Ab Wahab *et al*., 2015). However, our findings may contribute to further study as a guide to develop improved genetic algorithms, and very likely other population based metaheuristic algorithm, following the future directions of operating room scheduling research.

6. CONCLUSION

This review addresses the improvement techniques in

Table 4. Improvement techniques for optimal solution

Improvement Technique	Motivation	Research
A heuristic procedure to obtain a schedule with operational times	The uncertainty of the surgery duration modeled as fuzzy-set number	Lee and Yih (2014)
A neighborhood generation procedure	Estimation value for the decision variable in fitness evaluation stage	Hooshmand *et al*. (2018)

genetic algorithms to solve the operating room scheduling problem. Articles with a similar problem are identified designing the improvement techniques at different stages of the genetic algorithm. The improvement techniques are categorized to find the motivation for developing. The identified motivations in developing the improvement techniques are model performance criteria, considered resources, and the chromosome structure. This review provides a map to facilitate researchers to select the appropriate improvement technique for their problem. The improved genetic algorithms result in promising solutions quality, even though some are less superior than variable neighborhood search, constructive heuristic, and MOPSO. Solution quality is dependent upon the utilized performance criteria (Abdalkareem *et al*., 2021).

Chromosomes of a population in the genetic algorithm represent a group of solutions in an iteration. The solution provides the surgery sequence, resource allocation, or both. A multi-resource problem needs a complex chromosome structure. Therefore, future research on solving operating room scheduling needs to investigate the relationship between the developed chromosome structure and the ability of the improved genetic algorithm to search for new feasible solutions. As well as a future investigation is necessitated to identify which improvement techniques significantly contribute to improving the schedule performance.

Abdalkareem *et al*. (2021) reported that the successful algorithms for solving healthcare scheduling problems were from nature-inspired algorithms. Korani *et al*. (2021) identified more proposed nature-inspired algorithms in recent years. They also suggested that the relations between the components in the proposed algorithm with those in existing techniques such as genetic algorithm or particle swarm optimization should be well defined. Meanwhile, we only identified the tabu search algorithm integrated with the genetic algorithm (Fei *et al.*, 2006; Fei *et al.*, 2010). Therefore, the findings of the improvement techniques at each stage of the genetic algorithm and its relation to the considered problem may contribute as a guide for further discussion of integrating the genetic algorithm with the recent heuristic algorithm to obtain a better solution in the objective value and computation time. An efficient computation time will support the development of an operating room schedule information system.

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