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SURVEY

# Research Trends in the Optimization of the Master Surgery Scheduling Problem

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**ABSTRACT** The Master Surgery Scheduling Problem (MSSP) allocates operating theatre time to surgery groups such as medical specialities or surgeons, which is essential for daily operational planners. Many researchers have highlighted issues in the optimization of surgical scheduling problems. However, most recent reviews limited the issues at the operational level and excluded the problem characteristics such as surgery group type and schedule cyclicity. This study aims to review the state-of-the-art of MSSP and identify new trends in optimization strategies (problem characteristics and objective function), uncertainty scheduling factors (types and approaches), and solution and evaluation methods. These aspects are the key components in developing an effective MSSP optimization model. This paper reviews articles published between 2000 and 2021 that addressed the MSSP, concentrating on papers between 2016 and 2021. We underlined the popularity of medical specialities as the surgery group, one-week horizon length, a cyclic schedule, multi-objective optimization and evaluation by benchmarking. The analysis shows that surgery duration is the most prominent uncertainty type, whereas strategies for handling this are stochastic programming, robust optimization, and fuzzy programming. We highlighted the role of heuristic approaches in addressing the MSSP's computational complexity. This review's trends, challenges, and potential solutions are essential for future researchers in developing optimization models for MSSP.

**INDEX TERMS** Combinatorial optimization, healthcare management, master surgery scheduling, operating theatre planning, tactical level surgical scheduling.

## I. INTRODUCTION

Surgical scheduling entails selecting surgeries for operations, allocating resource time for the surgeries and sequencing them within the allotted time [1]. Surgical scheduling is crucial as it involves many stakeholders such as top managers, operating room personnel (surgeons, nurses, and anaesthetists), bed managers, and patients [2]. Furthermore, operating theatres (OT), including operating rooms, are a hospital's primary source of income [3]. Therefore, optimization is vital to ensure that the benefits to all stakeholders can be maximized. Surgical scheduling can be divided into three decision levels [4]. Each decision level focuses on different subproblems that make up a complete surgery plan and schedule. More information on the three decision levels can also be found in [5].

One of the decision levels is the tactical level which involves the Master Surgery Scheduling Problem (MSSP). MSSP involves the construction of a master plan that specifies the assignment of specialities or surgeons into the available OT time [4]. Optimization of surgical scheduling has been of interest to many researchers, as evidenced by 12 review papers on the subject [1], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13]. However, most of them did not focus on the MSSP. Some reviews did not use decision levels [1], [3], [6], [8], [12], whereas Cardoen *et al.* [9] defined

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the decision levels differently, excluding the MSSP. MSSP was not discussed in several reviews [7], [11], whereas in others, the discussions on the MSSP are very brief compared to the operational problems [4], [5]. Only two papers reviewed the MSSP in-depth [10], [13]. Oostrum *et al.* [13] compared the MSSP approach to centralized and decentralized planning systems, discussing the benefits and drawbacks, addressing implementation challenges, and examining the applicability. Guerriero and Guido [10] discussed the criteria and stochasticity in the construction of the master plan.

Our review differs from these reviews by focusing on the optimization of the master plan where the problem characteristics, objective functions, uncertainty, solution, and evaluation methods are reviewed. Furthermore, since the publications date back to 2010 and 2011, there is a need to refresh the review literature in the MSSP and include recent advances in the domain.

Optimization of the MSSP comprises several components such as objectives, uncertainty, solution methods, and evaluation methods. Previous reviews have highlighted the common types of these components. Zhu *et al.* [4] summed up that all objective functions fundamentally lead to maximizing the efficiency of OT usage and minimizing the cost of the resources involved. Besides, uncertainty is one of the most significant OT planning and scheduling issues [3]. OT planning and scheduling may include stochastic variables (stochastic approach) or neglects them (deterministic approach) [22]. The types of uncertainty identified are duration, arrival, resource and care requirement [5]. Zhu *et al.* [4] categorized solution methods for the optimization problem into exact algorithms, heuristic algorithms, simulations, and Markov decision processes. The methods used in each study are selected based on the researcher's view of the method's strength [3]. Meanwhile, the evaluation methods have not been reviewed before. Previous reviews only focus on the type of dataset used in the testing phase [3], [9], [12]. Master plan characteristics such as surgery group type and schedule cyclicity have never been discussed.

In order to establish a clear purpose for this review and answer questions that were not answered by previous reviews, a set of research questions was developed:

**RQ1:** How many studies have been conducted on MSSP optimization between 2016 and 2021?

**RQ2:** What optimization strategies (problem characteristics and objective function) are used in the MSSP?

**RQ3:** How are the uncertainty scheduling factors in the MSSP addressed (types and approaches)?

**RQ4:** How have the previous solution and evaluation approaches been implemented to deal with the MSSP?

**RQ5:** What are the challenges and recommendations for future studies in the MSSP?

The contributions of this review are as follows:

- A comprehensive analysis of the scientific work in the MSSP since 2000, with a particular focus on articles published between 2016 and 2021.
- Insights of the current trend and observation for problem characteristics (surgery group type, planning horizon length, schedule cyclicity) and evaluation methods of the MSSP.
- A summary of the latest trend and critical discussion of the objective function, uncertainty scheduling factors and solution methods in developing optimization models for the MSSP.
- Highlights of the key challenges and potential directions for tackling the unresolved issues in optimization of the MSSP.

Section II describes the background of the MSSP. Afterwards, each main section in this review answers one research question. Section III presents the steps taken in identifying the primary studies addressing MSSP optimization between 2016 and 2021 (RQ1). Section IV then discusses the optimization strategies, including the problem characteristics and objective functions of the primary studies (RQ2). The uncertainty scheduling factors, including their types and approaches, are addressed in Section V (RQ3), whereas Section VI analyses the solution and evaluation methods for the MSSP (RQ4). Next, Section VII outlines the challenges faced by the primary studies and suggestions to overcome these challenges (RQ5). This section also includes the summary of the analysis from Section IV-VI and our recommendations for MSSP optimization components. Finally, Section VIII concludes the review by summarizing the findings and future studies.

## II. BACKGROUND OF THE MASTER SURGERY SCHEDULING PROBLEM

The MSSP involves block scheduling, where OT times are divided into time blocks [14]. The availability of operating rooms in terms of quantity, type, and opening hours, and the surgery group allocated to the OT time blocks, are defined in a timetable called the master surgery schedule, which is referred to as the master plan [10], [15]. A master plan is a cyclic schedule repeated after a predetermined cycle time, often one week [16], [17]. Scheduling at the tactical level does not involve individual surgeries. Instead, they treat them as a surgery group. A master plan is essential as it links the long-term strategic and short-term operational decisions [18]. The operational-level schedules, which plan individual surgeries, are derived from the master plan. These schedules are the ones that determine the actual performance of the system [19]. A master plan has its advantages, as highlighted by previous researchers. Heider *et al.* [20] stated that a master plan offers planning certainty and minimizes the complexity of operational scheduling. Adan *et al.* [21] noted that a master plan brings a more balanced utilization of beds, OTs, and nursing staff. Balanced resource utilization is critical because surgeons and nurses may be unable to take appropriate rest if they are overutilized [22]. Sufficient breaks are essential in ensuring that hospital staff can provide high-quality medical care to patients [23].

The MSSP is an optimization problem, specifically the combinatorial variant. The solution of the MSSP is a two-dimensional master plan of size $M \times N$, where $M$ represents the planning days, whereas $N$ represents the OT at the hospital. Examples of the solution can be found in the literature [24], [25]. The MSSP involves assigning surgery groups to the master plan following the block-scheduling strategy [3]. Then, in the operational surgery scheduling, individual surgeries are assigned to the block that matches their associated surgery group [4]. Oostrum *et al.* [13] presented a seven-step implementation of the MSSP approach. The flowchart for the process is shown in Fig. 1.

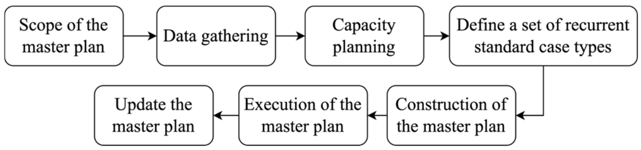


**FIGURE 1. Seven steps to implement the MSSP approach from van Oostrum *et al.* [13].**

Firstly, the scope of the master plan is defined, including the resources such as wards and organizational units such as medical specialities. Next, data on the processes and resources in the defined scope is collected. Capacity planning involves defining the availability and allocation of resources. Resources are either allocated to or shared among specialities or surgeons. Next, the surgeries with similar logistical characteristics (length of stay or surgery duration) or medical characteristics (diagnosis group or procedure type) are clustered to form surgery groups that will be assigned to blocks in the master plan. Then, the surgeries, including emergency, semi-urgent, and elective, are scheduled in the master plan subject to a set of hard constraints (which must be fulfilled) and soft constraints (which incur a penalty to the objective value if violated). The master plan is then executed, where the operational schedules are generated for all surgeries. The planning horizon length is determined based on a trade-off between utilization and waiting time. Finally, the master plan is revised as the timing for operation changes.

## III. PROTOCOL FOR IDENTIFYING STUDIES ON MSSP OPTIMIZATION

This review aims to revise the knowledge on the MSSP and recognize trends in key components of master plan construction. Components of the MSSP can be categorized into strategies, uncertainty, and approaches, as shown in Fig. 2.

To answer RQ1, a literature search was conducted using the systematic literature review technique by Denyer and Tranfield [26]. We decided to focus on publications from 1 January 2016 until 22 October 2021, when the literature search was done. We felt that a five-year time span would provide us with sufficient data to analyse the recent trends and come to a conclusion. A summary of the papers on MSSP published between 2000 and 2015 extracted from Rahimi & Gandomi [5] and Zhu *et al.* [4] is shown in Table 1.

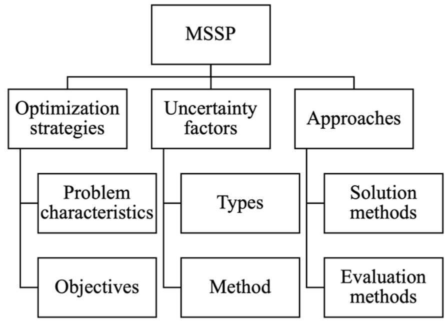


**FIGURE 2. Topic areas of the MSSP that are discussed in this review.**

Seven databases were chosen for the search: Scopus, WoS, Dimensions.ai, SpringerLink, ACM Digital Library, IEEE Xplore, and Google Scholar. The search phrases used are "master surgery schedule" and "tactical surgical scheduling". The Boolean operators "AND" and "OR" are used in the search string entered for the databases to ensure accurate results. After retrieving papers from the search results, the screening process starts with removing the duplicates, yielding 513 unique papers out of the 686 initially compiled. Next, the titles of the papers were evaluated to determine whether they relate to surgical scheduling, returning 188 papers. The relevancy of papers is then identified by comparing the information obtained from the abstract and keywords to the selection criteria, which resulted in 65 papers. Finally, the primary studies were obtained by further screening on the relevance of the issues related to the research questions. The final set of papers comprises 29 papers. The screening results are represented in Fig. 3. A summary of the contribution, limitations, and applicability of the findings of the primary studies can be found in Table 2.

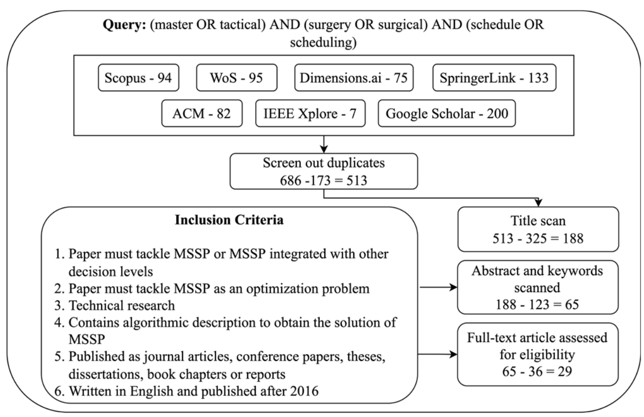


**FIGURE 3. Number of articles from each database after each screening process.**

Based on Tables 1 and 2, we identified several studies that incorporate similar approaches. For example, two papers implemented the rolling horizon approach [49], [50]. The rolling horizon approach by Spratt and Kozan [50] is on the operational level, whereas Oliveira *et al.* [49]

**TABLE 1.** Summary of MSSP studies published between 2000 and 2015.

| Author | Summary |
|---|---|
| [27] | Two-level metaheuristic for joint operating room planning and patient scheduling problem. |
| [28] | Modelled patients' pathways using a Business Process Modelling Notation (BRMN 2.0). |
| [29] | Evolutionary algorithm for the bicriteria optimization problem. |
| [30] | Heuristic algorithm for the operational surgical case scheduling. |
| [31] | Decomposition approach to the MSSP and Surgical Case Assignment Problem (SCAP). |
| [32] | Comparison of efficiency, balancing, and robustness in MSSP. |
| [33] | A non-linear stochastic programming model for the MSSP. |
| [34] | Exact distributions calculation of patients in the intensive care unit and ward from a given master schedule. |
| [35] | Simulation model for the efficacy of two methods in improving operating room utilization from the operational level. |
| [36] | Row and column generation approach for the cyclic and robust scheduling problems. |
| [37] | Analysed performance of four surgery categorization approaches using simulation and a newsvendor model. |
| [38] | A combined three-level mathematical model to minimize bed shortage due to stochastic length of stay. |
| [39] | Analysed the trade-off between static and dynamic master schedules that adapt according to changes in the waiting list by proposing mathematical models. |
| [40] | A multi-objective model that integrates tactical and elective case scheduling. |
| [41] | Pareto frontier for the multi-objective tactical scheduling model with Genetic Algorithms. |
| [42] | A mathematical model for the combined MSSP and SCAP was solved using a heuristic algorithm. |
| [17] | Mixed-integer programming with the objectives of levelling bed occupancy and minimizing operating room sharing and schedule changes. |
| [43] | Dynamic programming algorithm to mixed-integer linear programming for surgery sequencing problem. |
| [19] | Integrated stochastic length of stay in the mathematical model. |
| [44] | 0-1 linear programming model to solve the combined MSSP and SCAP. |
| [45] | Integrated nurse and operating room scheduling concrete model solved using column generation methods. |
| [46] | Comparison of the master surgery scheduling open scheduling approach in a Belgian hospital. |
| [16] | A model that considers demand and capacity constraints for minimizing bed shortages. |
| [47] | Two optimization models for strategic and tactical decisions and a simulation model to analyse the different surgery sequencing approaches. |
| [48] | Improvement of heuristic for an integer-programming model to allocate operating room time to surgical specialities. |

are on the tactical level. Spratt and Kozan [50] measured the deviation of individual patients from the original four-week plan generated. In contrast, Oliveira *et al.* [49] were concerned with the weekly and monthly changes to the master plan. Besides, several papers implement the optimization-simulation approach [14], [32], [47], [49]. Cappanera *et al.* [32] and Oliveira *et al.* [49] used simulation to incorporate uncertainty. In contrast, Testi *et al.* [47] used simulation to analyse different sequences of surgeries in operational-level scheduling. Bovim *et al.* [14] used the simulation model to obtain feedback for the optimization model, which is more beneficial in optimizing the MSSP.

On the other hand, Agnetis *et al.* [31] used a decomposition approach rather than an integrated approach to solve the combined MSSP and Surgical Case Assignment Problem. Spratt and Kozan [25] later implemented the opposite, using an integrated instead of the decomposition approach. Apart from that, schedule robustness to uncertainty was achieved in different methods. Three papers have implemented robust optimization where extreme values of the stochastic variables are considered [24], [51], [52]. Spratt and Kozan [50] achieved robustness against stochastic surgery duration and emergency arrivals using the rolling horizon approach. Kheiri *et al.* [53] attained robustness by extending their optimization model to be scenario-based. Other similarities and differences in the optimization components of the MSSP for the primary studies are discussed in Sections IV-VII.

## IV. OPTIMIZATION STRATEGIES FOR MSSP

This section discusses the optimization strategies (problem characteristics and goals) that encompass RQ2.

### A. PROBLEM CHARACTERISTICS

Each hospital has different requirements for the master plan. Three characteristics of the master plan are discussed: the types of surgery group, planning horizon length, and schedule cyclicity.

#### 1) TYPES OF SURGERY GROUP

A surgery group is a cluster of patients grouped based on their similar characteristics [54]. We identified that the most common type of surgery group is the medical specialities associated with the surgeries, used in 19 papers [14], [25], [49], [50], [51], [52], [53], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64]. In contrast, other researchers assigned surgeons, which enabled them to consider surgeons' availability and preferences [50], [65], [66], [67], [68], [69], [70], [71]. Meanwhile, Schneider *et al.* [54] and Abedini *et al.* [18] schedule clustered surgery groups according to their length of stay (LoS) and surgery duration. Kumar *et al.* [72] applied classification and regression tree analysis on Intensive Care Unit (ICU) LoS data to classify their patients. Dellaert and Jeunet [73] categorizes patients based on consumption of resources, including OT hours, ICU nursing hours, ICU beds, and Medium Care Unit beds. Fig. 4 illustrates the frequency distribution of surgery group types used by the primary studies.

**TABLE 2. Summary of the contribution, limitations and applicability of the primary studies.**

| Author | Contribution | Applicability of the Findings/Results | Limitations |
|---|---|---|---|
| [60] | Multi-objective programming model using the $\varepsilon$-constraint, balances surgeons' workload and surgeries prioritization. | Balance the surgeons' workload. | Not considered uncertainty, downstream resources, trade-off, bed availability, and length of stay. |
| [62] | Developed mixed-integer programming (MIP) model, two dynamic programming-based heuristics (DPH1 & DPH2) and an iterated local search algorithm (ILS). | MIP find an excellent solution with high computational time. The DPHs and ILS find high-quality solutions in a short time. | |
| [56] | Hierarchical multi-objective optimization model, multi-neighbourhood local search-based matheuristic and generated new data instances. | Workload balancing solutions > patient priority maximization solutions. | |
| [18] | An integer programming model that minimizes blocking between two consecutive stages of surgery. | A model can be generalized into two consecutive stages. | |
| [55] | Hybridized Bees Algorithm (BA) and Simulated Annealing (SA). | The Hybrid BA-SA shows promising results. | |
| [71] | Proposed a hybrid Grey Wolf Optimizer (GWO) with Variable Neighbourhood Search (VNS). | High solution quality and convergence speed. | |
| [52] | A two-stage approach to generate a plan then find a patient mix, stochastic using robust optimization (RO) and worst-case criterion. | OT utilization and robustness parameters affect the master plan. | |
| [64] | Lexicographical goal programming approach, robust estimation to reduce outliers. | The integer linear programming model outperforms the current master plan. | |
| [24] | Novel complete opening policy, incorporate stochasticity using RO, a two-stage heuristic algorithm. | Outperforms CPLEX solver in deterministic and stochastic conditions. | Limited data set and computational experiments. |
| [73] | Explore VNS's capability of solving the MSSP. | VNS outperforms CPLEX, simple and appealing for users. | |
| [57] | An artificial neural network to forecast emergency demand and stochastic surgery duration using fuzzy chance-constraint programming. | Forecast surgery demand. | |
| [69] | Create patterns, schedule using a MIP model and address ward restrictions probabilistically. | Reduced the risk of exceeding wards, flexibility and longer planning horizon required. | |
| [63] | A mathematical model with a novel combination of three objectives. | Increasing surgeon workload can increase the surgeries assignment. | |
| [49] | Dynamic master plans for a long planning horizon, optimization-simulation approach, and stochastic surgery demand. | The flexible approach balances waiting lists but causes variability in the schedule. | |
| [61] | Applying Genetic Algorithm (GA) to the MSSP. | GA has been proven to be capable of solving the MSSP. | |
| [58] | Multi-objective optimization, lexicographic and weighted goal programming model. | Objective weights affect schedule performance, and lexicographical and weighted approaches produce similar master plans. | Not considered emergencies or uncertainties. |
| [50] | Robust MIP formulation, rolling horizon, constructive heuristic and hyper-heuristic algorithms. | Patients rescheduled and solved complex problems with low computational effort. | Not considered elective patients to non-elective blocks shift for high urgent cases. |
| [65] | A hierarchical approach to solving MSSP, Hybrid VNS–GA and Late Acceptance Hill Climbing. | The proposed method performs competitively to models from the literature. | Emergency patients were omitted, and intensive care unit (ICU) beds were not considered. |
| [66] | Stochastic weighted goal programming model, SA to obtain the solution. | Improved memory usage and computational time compared to Xpress solver. | Assumptions in bed availability, surgeons are equally competent, and patients are interchangeable. |
| [14] | Optimization-simulation approach - simulation evaluates the master plan and relays feedback. | Removes dependency on historical data. | Difficulty in choosing the initial schedule. |
| [53] | Partitioned graph colouring-based optimization model and scenario-based optimization model to improve robustness. | Scenario-based optimization model ensures the solution's robustness. | Increases complexity. |
| [59] | Proposed an improved GA to overcome the convergence problem. | Better than the actual master plan of a hospital. | Assumptions on OT and surgeries uncertainties. |

**TABLE 2.** *(Continued.)* **Summary of the contribution, limitations and applicability of the primary studies.**

| Author | Contribution | Applicability of the Findings/Results | Limitations |
|---|---|---|---|
| [54] | Clusters surgeries based on surgery duration and LoS, single-step mixed-integer linear programming (MILP) and SA. | Applying SA after MILP improved the objective value. | Aggregated surgery group clusters. |
| [72] | Sequential MIP model, stochastic LoS incorporated using scenario realizations. | A robust master plan without large LoS scenario realizations. | Optimal master plans for patients who need an ICU bed. |
| [67] | Proposed the first scenario-based formulation for the MSSP, sample average approximation scheme. | The scenario-based model proposed is flexible and can be extended easily. | Multinomial probability distribution assumption without error. |
| [51] | Stochastic surgery duration and emergency arrivals using RO method. | RO approach is less sensitive to the input parameters than the stochastic recourse programming model. | The trade-off between the variability and feasibility of the objective function is not considered. |
| [68] | MIP model incorporates ward bed availability, different OT types, surgeon availability and preferences and equipment availability. | Solve the MSSP in a reasonable time. | Not considered uncertainty or week-to-week case-mix variation. |
| [25] | Use an integrated approach rather than decomposition, hybridized SA with reduced VNS (RVNS). | Outperformed benchmark metaheuristics and solved complex problems. | The model cannot schedule surgeries for a duration greater than 10 hours. |
| [70] | A two-stage approach focuses on bed usage, finding the master plan, and then adjusting bed position in wards. | Has a low computation time, and the model can be extended. | Require human intervention for the solution. |

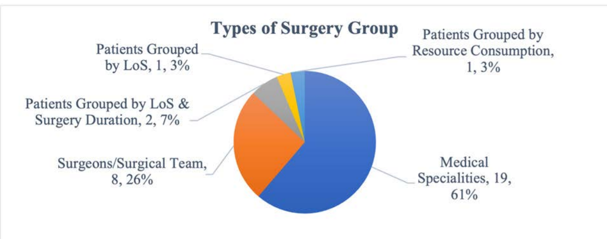


**FIGURE 4.** Surgery groups used by each primary studies.

### 2) PLANNING HORIZON LENGTH

Hospital planners decide the planning horizon, which is the range of dates the master plan should cover. It could span as short as three days or as long as several years. Most papers (13 papers) implement a horizon length of seven to 27 days [14], [18], [25], [51], [52], [54], [55], [60], [61], [64], [69], [70], [71] followed by 28 to 90 days (four papers) [50], [65], [66], [73]. Two papers have a horizon length of more than 365 days [49], [63]. The other settings are less common, with only one paper each for one to six days [59] and 91 to 365 days [57]. Fig. 5 represents the frequency distribution of the planning horizon length used in the primary studies.

### 3) SCHEDULE CYCLICITY

The cyclicity of a schedule refers to the recurrent use of the master plan. A master plan can either be cyclic or non-cyclic. For example, a cyclic schedule has a weekly timetable that repeats throughout the year in a one-year planning horizon, whereas a non-cyclic schedule has different plans each week. All but two studies included in this review produced a cyclic schedule [49], [63]. Oliveira *et al.* [63] measured the changes in the master plan as monthly and weekly stability in their non-cyclic master plan. Table 3 shows the problem characteristics exhibited by each primary study.

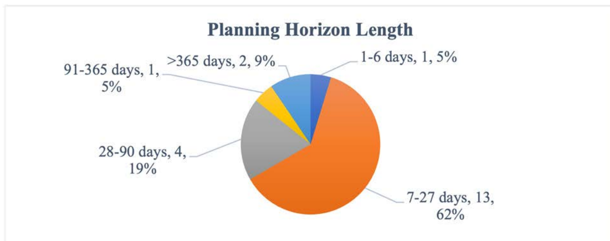


**FIGURE 5.** Planning horizon length covered by the master plan in the primary studies.

## *B. OBJECTIVE FUNCTION*

We extracted the objective function of each mathematical model from the papers selected. The objectives were classified into eight categories: throughput, waiting measure, patient scoring, OT utilization, emergency capacity, costs, schedule assignment, and upstream and downstream resources. Most studies (13 papers) focus on downstream resources such as ward and ICU beds. Some authors tried to minimize variation in bed usage instead of maximizing bed utilization [24], [54]. This method can show the optimal number of beds to be made available, which the hospital can subsequently implement. Next, OT utilization, including overtime and idleness, was used in 10 papers. Throughput, which refers to the number of surgeries the hospital serves, was incorporated in eight papers. Cancellations and postponements are included in this category as they affect throughput.

Schedule assignment objectives are featured in five papers. This category includes objectives that are related to the

**TABLE 3. Problem characteristics of the primary studies.**

| Schedule Cyclicity | Surgery Group | Planning Horizon Length | References |
|---|---|---|---|
| Cyclic | Resource consumption | Variable | [73] |
| | LoS and surgery duration | 14 & 28 days | [18, 54] |
| | LoS | Five weeks | [72] |
| | Medical specialities | Less than one week | [25, 59] |
| | | One week | [14, 51-53, 55, 56, 60, 61, 64] |
| | | Variable | [24, 58, 62] |
| | | 6-12 months | [57] |
| | Surgeons | Less than one week | [69-71] |
| | | 28 days | [66] |
| | | 4 & 6 weeks | [50, 65] |
| | | Variable | [67, 68] |
| Non-cyclic | Medical specialities | One year | [49, 63] |

assignment of the master plan, such as staff preference and assignment variation. Next, the waiting measure, utilized in four papers, is defined as the measure of time and cost of waiting for surgeries to be done. Waiting time is often measured in days, whereas the waiting cost is measured by its impact on the patient's satisfaction and health condition [24], [51], [55]. Waiting time is influenced by the patient's age, comorbidity, ethnicity, physical status, financial status, health insurance, hospital type, and the number of medical personnel [74], [75], [76]. Meanwhile, patient scoring incorporates one or more factors related to the patient into a single value, as was done in four of the primary study. Then, four studies incorporate cost objectives, including overtime costs or loss and profit from scheduling the surgeries. Finally, the emergency capacity objective aims to minimize the reserved capacity so that more elective surgeries can be carried out. Only Spratt and Kozan [50] used this objective in a separate model to reserve emergency capacity before constructing a master plan. Fig. 6 shows the frequency distribution of studies for each objective type, whereas Table 4 shows the detailed definitions of objectives and the studies incorporating them.

Mathematical models may have single or multiple objectives. In a single-objective optimization, only one specific criterion is optimized. This form of optimization is simple as it does not require additional steps to aggregate multiple evaluation metrics. Papers with a single-objective optimization model (11 papers or 38%) are [18], [25], [49], [50], [52], [53], [57], [62], [67], [69], and [70]. Multi-objective optimization

**TABLE 4. Classification of objectives used in the primary studies.**

| Types | Objective Function | References |
|---|---|---|
| Throughput | Minimize unmet demand | [61] |
| | Maximize the number of surgeries | [14, 25, 50, 69] |
| | Maximize service level (surgeries performed before waiting time target) | [65] |
| | Maximize weighted throughput | [72] |
| | Minimize penalty for too few surgeries | [65] |
| | Minimize cancellation | [14, 72] |
| | Minimize surgical postponement | [51] |
| Waiting Measure | Minimize waiting time | [51, 55] |
| | Minimize waiting cost | [24] |
| | Minimize the anticipated number of patients waiting for service | [58] |
| Patient Score | Maximize scheduled patients' score | [52, 56, 60] |
| | Minimize clinical deterioration | [62] |
| OT Utilization | Minimize the difference between OT time allocated and demand/target value (match demand) | [49, 61, 63] |
| | Minimize overtime | [24, 73] |
| | Minimize idleness and underutilization | [24, 57, 58, 64, 65, 73] |
| | Maximize utilization | [54, 72] |
| Emergency Capacity | Minimize the number of operating room times reserved for emergency surgeries | [50] |
| Costs | Minimize total hospitalization cost | [71] |
| | Minimize machine cost | [65] |
| | Minimize overtime cost | [59, 71] |
| | Minimize loss due to utilization disruption | [51] |
| | Maximize profit | [59] |
| Schedule Assignment | Maximize closeness of strategic allocation and MSSP allocation | [64] |
| | Balance workload | [60] |
| | Maximize staff preference | [63, 68] |
| | Minimize frequency of surgeon assigned to low preference score | [68] |
| | Minimize workday variation | [65] |
| | Maximize the frequency of surgeons assigned to the same slot each week | [68] |
| | Minimize frequency of surgeons assigned to consecutive slots in the same theatre and day | [68] |
| | Minimize frequency of surgeons assigned to consecutive slots in a different theatre on the same day | [68] |
| Upstream and Downstream Resources | Maximize bed utilization | [56] |
| | Minimize the difference between the number of beds available and used | [18, 68] |
| | Minimize the maximum number of patients | [58, 65, 66] |
| | Minimize the number of unused beds | [53, 70] |
| | Minimize expected bed shortage | [67] |
| | Minimize variation in bed usage | [54, 58, 66] |
| | Minimize deviation from a target value | [24, 63] |
| | Minimize the number of patients in the wrong ward | [14] |

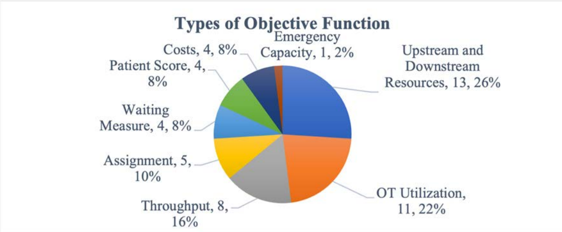


**FIGURE 6.** Frequency distribution of objective types (one paper can have more than one type).

incorporates several objectives simultaneously. Most primary studies use the multi-objective approach (18 papers or 62%) [14], [24], [51], [54], [55], [56], [58], [59], [60], [61], [63], [64], [65], [66], [68], [71], [72], [73]. There are various methods for implementing multi-objective optimization such as hierarchical approach [65], weighted sum [68], goal programming [58], Epsilon-constraint method [60], and LP-metric method [51].

## V. TYPES AND APPROACHES OF UNCERTAINTY SCHEDULING FACTORS IN MSSP

Basic MSSP modelling uses deterministic variables, whereas the stochastic approach considers uncertainties, discussed in this section to answer RQ3. We identified five types of uncertainties which are bed availability [52], [53], [67], emergency arrivals [14], [24], [50], [51], patients' LoS [14], [24], [65], [66], [67], [72], number of patients per surgeon [67], and surgery duration [14], [24], [25], [50], [51], [52], [57], [65], [66], [69]. Several papers consider multiple uncertainties. Fig. 7 shows the papers' distribution incorporating each of the uncertainties stated.

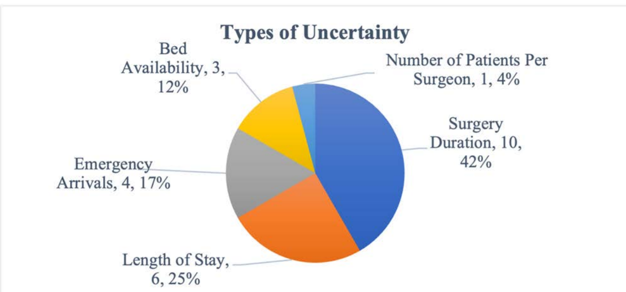


**FIGURE 7.** Types and frequency of uncertainty incorporated by primary studies.

The approaches for dealing with uncertainty are stochastic programming, robust optimization, and fuzzy programming. Stochastic programming substitutes uncertain parameters with a known probability distribution to find the optimal solutions [77]. Schneider *et al.* [54] could not utilize 3-parameter lognormal distribution due to the failure to obtain an exact result for the distribution. Spratt and Kozan [25] used a lognormal approximation due to insufficient recent historical data and problems in different reporting systems at their hospital. Bovim *et al.* [14] and Spratt and Kozan [50] are other papers using stochastic programming.

Robust optimization (RO) involves transforming a deterministic model into a robust model, as was done by Moosavi and Ebrahimnejad [24], Makboul *et al.* [52], and Lalmazloumian [51]. Moosavi and Ebrahimnejad [24] argued that the robust optimization approach is better than stochastic programming. They argued that RO is better at ensuring feasibility and better when data availability is limited. Another method to handle uncertainty is fuzzy programming which uses fuzzy sets to express uncertain parameters [78]. Fuzzy sets are characterized as a collection of elements with a range of membership levels [79]. Ghasemkhani *et al.* [57] adopted the fuzzy method by Jiménez *et al.* [80], in which they use expected intervals and expected values of fuzzy numbers for uncertain surgery duration.

## VI. SOLUTION AND EVALUATION APPROACHES TO DEAL WITH MSSP

RQ4 aims to review the approaches used to address the optimization model and the methodologies used to assess the performance of the proposed solution.

### A. SOLUTION METHODS

Two main approaches in obtaining the solution of MSSP optimization models are exact and heuristic methods. Exact methods were chosen by 16 papers (55%) [14], [18], [49], [51], [52], [53], [57], [58], [60], [63], [64], [67], [68], [69], [70], [72], whereas heuristics were implemented in 13 papers (45%) [24], [25], [50], [54], [55], [56], [59], [61], [62], [65], [66], [71], [73].

Exact methods always return a single optimal solution. This approach is suitable for small problem instances where the computation is feasible. Mixed-integer programming models, including mixed-integer linear programs, are often solved by a commercial solver. Many papers use IBM ILOG CPLEX to solve their models [51], [52], [58], [60], [63], [67], [70]. Other commercial solvers that were utilized are FICO® Xpress Optimization [14], [66], [68], GAMS software [18], [57], [64], Gurobi [69], and COIN Cbc [53]. Kumar *et al.* [72] did not mention the name of their solver. Two papers also used CPLEX besides implementing a heuristic approach [54], [59].

In the heuristic approach, the solution presented is an approximation of a problem's optimal solution. However, heuristics can balance the solution quality and the computational effort required [5]. Table 5 summarizes the heuristic approaches implemented by the primary studies.

There are two basic types of heuristics, which are constructive and perturbative. Basic heuristics are specific to a problem. Hence, some researchers prefer to use it for more complex problems [24], [53], [62]. Meanwhile, metaheuristics are an extension of basic heuristics designed to be interchangeable with different problems. In metaheuristics, the algorithm provides a general outline for searching. It has been

**TABLE 5. The heuristic approach implemented by the primary studies.**

| Heuristic Approach | References |
|---|---|
| A two-stage perturbative heuristic algorithm | [24] |
| Dynamic programming-based heuristics and iterated local search algorithm | [62] |
| Simulated Annealing | [54, 66] |
| Genetic Algorithm | [61] |
| Nondominated Sorting Genetic Algorithm II (NSGA-II) | [59] |
| Variable Neighbourhood Search | [73] |
| Hybrid Bees Algorithm - Simulated Annealing | [55] |
| Hybrid Simulated Annealing - Variable Neighbourhood Search | [25] |
| Hybrid Variable Neighbourhood Search - Genetic Algorithm | [65] |
| Hybrid Grey Wolf Optimizer - Variable Neighbourhood Search | [71] |
| Hyper Simulated Annealing – Tabu Search | [50] |
| Multi-neighbourhood local search-based matheuristic | [56] |

applied in nine papers [25], [54], [55], [59], [61], [65], [66], [71], [73], where four of them hybridized metaheuristics to improve their performance [25], [55], [65], [71]. On the other hand, hyper-heuristics can be defined as ''heuristics to choose heuristics'' [81]. In hyper-heuristics, a set of heuristics acts as the search space [82]. Only one study implemented hyper-heuristic [50]. Finally, matheuristics are the hybrid between metaheuristics and mathematical programming techniques [83], [84]. It uses metaheuristics as the primary strategy to obtain high-quality solutions, which are then improved with exact methods by solving subproblems [85]. Only one paper used this technique [56].

### B. EVALUATION METHODS

Nineteen papers applied benchmarking where the proposed methods are compared to the state-of-the-art methods [14], [18], [24], [25], [50], [54], [55], [56], [57], [59], [61], [62], [65], [67], [70], [71], [73]. Other methods of evaluation, such as sensitivity analysis [24], [50], [58], [60], [64], [66], [68], [70], robustness analysis [18], [24], [49], [52], [56], Pareto Frontier analysis [18], [24], [49], [52], [56], and model variant analysis [54], can gain an insight into the proposed methods. Simulations were conducted in five primary studies [14], [18], [53], [66], [72]. Fig. 8 shows the distribution of papers implementing each evaluation method in their studies.

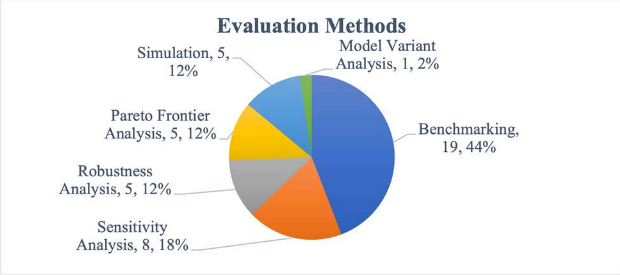


**FIGURE 8. Frequency distribution of evaluation methods implemented by primary studies.**

#### 1) BENCHMARKING

Benchmarking can be classified into three main types. Firstly, the proposed MSSP model can be benchmarked against another model, either to models from previous literature [18], [65] or to different versions of proposed models [70]. Secondly, several studies chose to benchmark their solution methods against other methods. Solutions from commercial solvers were used as benchmarks in several studies. Others benchmark their proposed solution methods to benchmark algorithms. Table 6 shows the proposed and benchmark algorithms from the primary studies papers. In addition, Moosavi and Ebrahimnejad [24] evaluated the approaches under certain and uncertain conditions. Dellaert and Jeunet [73] tested two settings of the initial solution, i.e., random initialization and CPLEX solution. Meanwhile, Schneider *et al.* [54] explored the potential of Simulated Annealing in improving the solution obtained from commercial solvers. Thirdly, the generated schedule can be compared against the schedule in use at the hospital under study [24], [54], [59].

#### 2) SENSITIVITY ANALYSIS

Sensitivity analysis can assess how far the problem instance can change before the optimal solution changes. For example, Spratt and Kozan [50] investigated the effects of planning horizon length and maximum total iteration on the mean total number of scheduled patients.

#### 3) ROBUSTNESS ANALYSIS

Robustness refers to the capability to adapt to changes in variables [53]. Makboul *et al.* [52] compared their two versions of mathematical models, i.e., deterministic and robust formulations. Results show that the deterministic model performed better than the robust formulation regarding computational time and utilization rate. However, the expected surgery duration will likely deviate and cause overtime. Hence, robust optimization provides a buffer for these uncertainties by planning a lower utilization rate. Moosavi and Ebrahimnejad [24] determined the price of robustness defined as the impact of robustness on the objective function. The authors claimed that the robust optimization strategy pays a nominal price of robustness to considerably improve solution and model robustness. Oliveira *et al.* [49] analysed the robustness of their solutions against overtime. They concluded that planning surgeries to 80% of actual length could bring the overtime rate close to zero.

#### 4) MODEL VARIATION ANALYSIS

Schneider *et al.* [54] explored variants of the proposed model to demonstrate its potential. A total of four variants with minor modifications were discussed in the paper.

**TABLE 6.** The benchmark algorithms chosen by the primary studies.

| Ref | Proposed Algorithms | Benchmark Algorithms | Results |
|---|---|---|---|
| [50] | Constructive heuristic, Hyper Simulated Annealing and Hyper Simulated Annealing -Tabu Search | Basic Simulated Annealing | Hyper Simulated Annealing is the best-performing metaheuristic |
| [56] | Matheuristic algorithms | Xpress solver-based heuristics and iterated local search algorithm | Reduction of average running time up to 16 times |
| [62] | Dynamic programming heuristic and iterated local search | Gurobi solver | Low computational times, whereas heuristics produce a high-quality solution and is easy to implement in a short time. |
| [61] | Genetic Algorithm | AIMMS solver | Equal to AIMMS but with a slightly higher runtime |
| [24] | Partial-Mixed Integer Programming algorithm and their proposed two-stage heuristic algorithm | CPLEX solver | Best average computation time with comparable objective values. Besides, CPLEX failed to solve some instances within the time limit. |
| [73] | Proposed Variable Neighbourhood Search | Classical Variable Neighbourhood Search | Better in some hard-to-solve test instances |
| [67] | Sample average approximation method | Expected value approach | Outperforms the expected value approach |
| [55] | Hybrid Bees Algorithm - Simulated Annealing | Tabu Search algorithm | Obtained better solution in terms of weekend stay bed utilization in most test instances |
| [25] | Hybrid Simulated Annealing - Reduced Variable Neighbourhood Search | Basic Simulated Annealing, adaptive Simulated Annealing, and Reduced Variable Neighbourhood Search | Outperformed the benchmark metaheuristics |
| [71] | Hybrid Grey Wolf Optimizer - Variable Neighbourhood Search | Basic Grey Wolf Optimizer, Variable Neighbourhood Search, and Particle Swarm Optimization | Best results in average cost, minimum cost, best and average Relative Percent Deviation |

### 5) PARETO FRONTIER ANALYSIS

In multi-objective optimization, Pareto optimal front is analysed to determine the best compromise between objectives based on the preference of schedule makers. Moosavi and Ebrahimnejad [24] investigated the effect of optimizing only one objective function at a time. Results show that the combined objective function performed best. Li *et al.* [58] examined the effects of different priority levels and weight preferences on the objective functions. Results showed that by varying objectives weightings, the quality of the schedule obtained also differs. However, the two approaches to defining objective weightings (weighted and lexicographical) produced identical schedules.

### 6) SIMULATION

Simulations are a valuable tool as they can emulate real-world settings to verify the effectiveness of the proposed schedules. Furthermore, the simulation output can be fed back to the optimization model, enabling it to learn and improve. Britt [66] developed a discrete event simulation to simulate a 28-day planning horizon. The results in terms of OT utilization were analysed in their study.

## VII. CHALLENGES AND RECOMMENDATIONS FOR FUTURE STUDIES IN THE MSSP

To answer RQ5, we compile the challenges highlighted in the primary studies. We identified seven challenges that we believe should be addressed. Researchers are then pointed to interesting directions to undertake in future studies. Besides, the recommendations for each component of MSSP optimization discussed in this review are based on the recent trend. This will help future researchers to produce good master plans.

### A. CHALLENGES IN THE PRIMARY STUDIES

The primary studies highlighted the challenges they faced. We highlight seven potential areas of study for resolving these issues.

#### 1) IGNORING OBJECTIVES

Consideration of a single objective may reduce the complexity of the model. However, optimizing a single objective may negatively affect other performance measures not incorporated into the model. For example, Sigurpalsson *et al.* [69] found that when their model was set to maximize patient throughput, shorter surgeries were prioritized due to other factors such as the patients' waiting time and the surgery urgency being ignored. Oliveira *et al.* [49] argue that the model loses practicability in real-world hospitals without incorporating surgeon preference and availability in the model. Future studies on MSSP optimization should consider these factors.

#### 2) PRIORITY OF OBJECTIVES

The model formulated by Su and Hu [70] produces several different solutions in some runs. The responsibility falls to the hospital manager to select which schedule to use. The authors suggested enhancing the model by utilizing hierarchical goal programming. Future works can also explore other methods for assigning priorities to multiple objectives.

#### 3) IGNORING UNCERTAINTY

Several studies did not incorporate uncertainty in their model formulation [56], [58], [62], [64], [68], [71]. Surgery duration is the most common uncertainty because it is affected by many variables. Lu *et al.* [59] highlighted that surgery duration is affected by surgeons' skill and fatigue levels and patients' physical condition. Britt [66] also argues that surgeons have different levels of competency affecting surgery duration. Therefore, future studies can explore the factors affecting surgery duration to minimize its uncertainty.

#### 4) ASSUMPTIONS IN HOSPITAL PRACTICE

Models with many assumptions do not reflect the real-world situation. For example, Almaneea and Hosny [55] assumed that the bed capacity in the recovery ward is unlimited. Furthermore, Kheiri *et al.* [53] highlighted an assumption in the LoS calculation, where patients discharged in the morning are counted as occupying the bed for the whole day. In reality, another patient can occupy the empty space. Fewer assumptions in the model will increase the accuracy of the model output, although at the cost of increased complexity. Future studies are recommended to find the balance between these factors.

#### 5) DATA AVAILABILITY

The limited availability of data is highlighted by Moosavi and Ebrahimnejad [24]. Surgery scheduling involves sensitive data of patients. Hence, the hospital's authority may be reluctant to provide data access to the public. Several authors resorted to generating random test instances [49], [62], [67], [70]. This demonstrates the problem of not using real-world instances in the evaluation. Besides, Dellaert and Jeunet [73] conducted the computational experiments using data from only one department. Future studies should use actual and diverse data instances for their evaluation.

#### 6) SIMULATION VS REAL WORLD

Real-world implementation is still an obstacle for research in the MSSP. Almost all studies do not apply their schedule in the hospitals being studied. The closest approximation to real-world implementation is using simulation or computational experiments with real-world data. Penn *et al.* [68] underlined two reasons for not testing their model on an actual hospital, which are time constraints and pressures on hospital staff. We would like to highlight the importance of real-world implementation, where possible, in future studies.

#### 7) SOFTWARE COST

The issue of software cost is highlighted by Penn *et al.* [68]. In healthcare, the utilization of technology depends on cost-effectiveness, which can influence decision makers' willingness to use it [86]. Some hospitals are reluctant to spend their revenue on running software required to generate the schedule, mainly when the schedule only provides minimal benefits. However, it has been shown that by allowing minor changes to the master plan, considerable improvements in average patients' waiting time and due date performance can be achieved [39]. Therefore, future studies should be able to convince hospital planners to invest in the software needed. Furthermore, social influence, benefits, and effort expectancy can influence hospital staff's desire to use information systems [87]. Thus, it is crucial to convince the planners of the benefits of the proposed system.

### B. RECOMMENDATIONS FOR MSSP OPTIMIZATION COMPONENTS

Besides analysing the trends, we have also identified the advantages and disadvantages of each setting of MSSP optimization components. We provide six recommendations for future researchers for each aspect based on the comparison of the settings. Firstly, clustering surgeries by their requirement of OT time and downstream beds has advantages. Due to their higher probability of deferrals, long surgeries can be assigned earlier in the week. Furthermore, assigning longer LoS surgeries earlier in the week can clear capacity for next week's operations. Since surgery duration and LoS are estimated values, machine learning approaches applied to patients' diagnosis information can be explored to improve accuracy, resulting in more accurate clusters.

A shorter planning horizon enables more accurate surgery scheduling since changes in resource availability can be considered [59]. Most papers incorporate cyclicity due to increased schedule predictability and personnel coordination [88]. However, previous studies have shown seasonality in emergency and elective demands throughout the year [89], [90]. Therefore, future works should balance schedule cyclicity and the seasonality of surgery demand.

Most papers have more than one objective since multi-objective optimization allows the consideration of various stakeholders. Future works are highly encouraged to include multi-objective optimization with objectives that can benefit the hospital and patients.

Uncertainty in LoS must be considered in models that aim to improve downstream resources performance since it affects bed occupancy levels. As for the approach, robust optimization should be considered more often. Besides, a common assumption is that every case for one surgery group has the same surgery duration and LoS. However, this is inaccurate in reality, as each medical speciality has multiple types of surgeries with different requirements. Therefore, future researchers are encouraged to segregate patients by surgery types, duration or LoS.

Computational complexity is often cited as the reason for heuristic implementation over exact methods as the problem size grows. Hyper-heuristics should be investigated further, as only one paper investigated this methodology for the MSSP in the last five years, despite being effective in other optimization problems [91], [92]. Furthermore, hyper-heuristics' advantages are their generalizability and simplicity, making them applicable to different instances or problem domains [93].

In our opinion, benchmarking is essential in evaluating solutions. Besides, we recommend that researchers conduct a robustness analysis of the master plan produced. A robust schedule is desirable as it can withstand small changes to the schedule without affecting performance.

## VIII. CONCLUSION

This paper reviewed the studies on MSSP published from 2000 to 2021, emphasizing articles between 2016 and 2021. We identified the trends in the key components of the MSSP optimization model, such as objectives, uncertainties and solution methods. We reviewed the problem characteristics, types and methods for uncertainty. Methods to handle uncertainty are identified as stochastic programming, robust optimization, and fuzzy programming. The recent trend showed that uncertainty is still a prevalent issue in MSSP. Exact and heuristic approaches are identified as the solution methods, and it is argued that heuristic methods are better due to the size and complexity of the MSSP. We summarized the evaluation by previous studies considering sensitivity and robustness analysis, uncertainty in surgery duration and LoS, which shows little attention to uncertainty in surgery demand. However, some areas of the domain remain unreviewed such as strategies to improve performance, optimization model's output implementation, effects of multiple decision levels, factors that influence objectives usage, and complexity of the MSSP.

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