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How does the hospital make a safe and stable elective surgery plan during COVID-19 pandemic?

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ABSTRACT

During the COVID-19 period, randomly arrived patients flooded into the hospital, which caused staffing beds to be occupied. Then, elective surgeries could not be carried out timely. It not only affects the health of patients but also affects hospital income. The key to the above problem is how to deal with uncertainty, which is one of the most difficult problems faced in the field of optimization. Specifically, surgery duration, length of stay, the arrival time of emergency patients, and whether they are infected with the SARS-CoV-2 virus are uncertain. Therefore, we propose a bed configuration to ensure that elective patients are not affected by non-elective patients such as COVID-19 patients. More importantly, we propose a planning model based on robust optimization and fuzzy set theory, which for the first time consider different categories of uncertainty in the same healthcare system. Given that the problem is more complex than the classical surgical scheduling problem, which is NP-hard in most cases, we propose a hybrid algorithm (GA-VNS-H) based on genetic algorithm, variable neighborhood search, and heuristics for problem traits. Specifically, the heuristic for operating room allocation is used to improve the efficiency, the genetic algorithm and variable neighborhood can improve the global and local search capabilities, respectively, and the adaptive mechanism can reduce the algorithm solution time. Experiments show that the algorithm has better calculation efficiency and solution accuracy. In addition, the elective surgery planning model under the new bed configuration model can effectively cope with the uncertain environment of COVID-19.

1. Introduction

During the COVID-19 period, a large number of patients flooded into hospitals, and limited resources (especially staffing beds) were occupied (Muthuswamy 2021). Elective surgery cannot be performed normally. For instance, many hospitals are therefore forced to postpone or even cancel elective surgery (Naderi et al. 2021). Therefore, the elective patients had to wait for a long time. Among them, some patients may be dissatisfied due to waiting, some face deterioration, and some, unfortunately, die (Campbell 2021; Norris et al. 2022; Sen-Crowe et al. 2021). On the other hand, the cancellation of elective surgery will result in a substantial decrease in hospital income because it is the main part of hospital income (Best et al. 2020). Although increasing bed capacity can alleviate the shortage of hospital beds, it will directly increase the financial burden of the hospital, especially after the decrease in income due to the reduction of elective surgery (Best, et al. 2015). Therefore, some hospitals try to restart elective surgery, but they face some challenges. For example, hospital beds are occupied by COVID-19 patients without available beds for elective patients. In addition, the uncertainty of the arrival of emergency patients will affect the planning of elective surgery. What’s more serious is that emergency patients cannot be sure whether they are infected with SARS-CoV-2, which may cause infection in elective patients once they are admitted to the hospital.

We conducted data analysis and interviews with several hospitals in China and the United States and discovered two scientific problems behind the above-mentioned actual problems: First, the traditional bed configuration is difficult to adapt to the COVID-19 epidemic. For example, mixing COVID-19 patients with elective patients is not a wise choice. In addition, the COVID-19 epidemic has exacerbated the uncertainty, such as the arrival time and the number of emergency patients, the surgery duration, and whether emergency patients are infected with the virus SARS-CoV-2 cannot be known in advance. The new challenges that the COVID-19 brings to conventional surgery scheduling:1) Historical data cannot predict new trends, such as COVID-

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19 extending hospital stays of surgical patients (Norris et al. 2022). 2) Inpatient beds and ICU beds occupied by COVID-19 patients are uncertain (René Bekker 2022), resulting in uncertain inpatient beds and ICU beds available for elective surgery patients. 3) The bottleneck resources of elective surgery scheduling became inpatient beds and ICU beds instead of operating rooms (Martin 2021). 4) The environment inside and outside the hospital is highly uncertain, which leads to the schedule being adjusted frequently.

One of the traditional bed configurations is that each medical specialty has self-owned wards, such as surgical wards and cardiology wards, as shown in Fig. 1. One of its advantages is it can match patients’ specific medical needs (e.g., dedicated staff and equipment). But in this setting, it often occurs that some beds in one specialty are scarce, while that in others are underutilized (Dai and Shi 2019). Therefore, Izady and Israa (2021) proposed clustered overflow configuration (Izady and Israa 2021), as shown in Fig. 1. Scheduling in this configuration has more flexibility to assign the patient but fails to cope with the uncertainty of emergency arriving. In this setting, planning elective and non-elective together may lead to unexpected results that the elective patient would be postponed or canceled due to the emergency. In addition, during the epidemic, the uncertainty of emergency patients will also bring the risk of infection to the elective patients. To this end, we propose a new bed configuration, named buffered clustered configuration, as shown in Fig. 1. In this bed configuration, the admission route of non-elective patients (including walk-in patients and emergency patients) has changed. Specifically, they cannot directly enter the general ward, but can only enter the buffered ward and clustered wards. Through buffer ward, non-elective patients can be isolated and tested for COVID-19. In addition, clustered wards reduce the impact of non-elective patient arrival uncertainty on elective surgery. We need to explain why elective patients do not need buffered wards. Because compared with emergency patients, elective patients have enough time to determine whether they are infected with SARS-CoV-2, and surgery can be postponed if they are not sure. However, non-elective patients are in urgent condition and must receive timely treatment before determining whether they are infected with SARS-CoV-2, and the hospital cannot

![Patient flow under different bed configurations (An example with two Specialties)](image-url)
are two effective methods to deal with insufficient data. One of their hospital stays for some elective operations, and the operation process arriving each day is difficult to be estimated by the surgeon. Therefore, physical condition. However, the number of non-elective patients can exist at the same time. For example, the elective surgery duration is objective information, such as parameter support, while the latter is becomes more complicated. Robust optimization and fuzzy optimization (2021) showed that long-term waiting leads to prolonged postoperative historically difficult to reflect new trends. For example, Norris et al. (2021) showed that long-term waiting leads to prolonged postoperative hospital stays for some elective operations, and the operation process becomes more complicated. Robust optimization and fuzzy optimization are two effective methods to deal with insufficient data. One of their difference lies in the source of decision-making information. The former is objective information, such as parameter support, while the latter is subjective information, such as surgeon estimates. Existing research usually assumes that the decision information in the same planning system is either objective or subjective. In practice, these two situations can exist at the same time. For example, the elective surgery duration can be estimated by the attending surgeon based on the patient’s physical condition. However, the number of non-elective patients arriving each day is difficult to be estimated by the surgeon. Therefore, this paper divides the uncertain parameters of surgical planning into two types, called objective parameters and subjective parameters. Specifically, the patient’s surgery duration and the length of stay are objective parameters. The arrival of emergency patients is a subjective parameter influenced by external factors. As far as we know, in surgical planning, almost no research considers these two information representations in the same decision-making environment.

In order to solve the shortage of hospital beds and the uncertainty in the process of elective surgery planning, we propose a new bed-configuration to ensure that elective patients are not affected by non-elective patients such as COVID-19 patients. In addition, we propose a fuzzy-robust model based on robust optimization and fuzzy set theory to deal with the uncertainty. At last, to solve the model, a hybrid algorithm based on genetic algorithm and variable neighborhood search is further proposed. Experiments show that the algorithm has better calculation efficiency and solution accuracy. In addition, the elective surgery planning model under the new bed configuration model can effectively cope with the uncertain environment of COVID-19.

The main contributions of this study can be summarized as follows: 1). We establish a planning model and proposes a hybrid heuristic algorithm to ensure that the hospital can safely perform surgery during the epidemic. 2). We propose and verifies that in the same system, considering the differences of uncertainty, such as robustness and ambiguity, can improve the system’s ability to deal with uncertainty. 3). We propose and verifies that uncertainty can be effectively dealt with through reasonable resource allocation when traditional uncertainty handling strategies cannot be carried out.

The remainder of this paper is organized as follows. Following the literature review in Section 2, the deterministic counterpart of our elective surgery planning problem is presented in Section 3. We developed a fuzzy-robust model in Section 4 and solve it in Section 5. Computational experiments are provided in Section 6. We conclude our research in Section 7 with discussions and remarks.

2. Related literature

Elective surgery requires a lot of resources. The two most important are the upstream resources represented by the operating room and the downstream resources represented by the hospital bed. Most scholars regard the operating room as a scarce resource (Bandi and Gupta 2020; Ferrand 2014; Lovejoy and Li 2002), while some studies regard downstream wards as scarce resources (Best, et al. 2015; Taramasco et al. 2019; Zychlinski et al. 2020). There are two common ways to deal with resource shortages. One is at the operational level, where patients are scheduled to make full use of resources (Gul et al. 2015; Naderi et al. 2021; Vancroonenburg et al. 2016), and the other is at the strategy level, where reasonable allocate resources to achieve resource balance (Best, et al. 2015; Izady and Israa 2021; Pinker and Tezcan 2013). This paper focuses on the problem of resource shortages both upstream and downstream by two methods as previously mentioned.

The operating room (OR) is an expensive resource, and its utilization not only affects the cost of the hospital but also the income. Khaniyev et al. (2020) regard OR idle time and overtime as the goal to use the existing operating room resources as much as possible while avoiding additional Occupied. This is consistent with one of our optimization goals. In practice, congestion of downstream resources will make it difficult for patients to enter the hospital for treatment and reduce the utilization rate of the operating room. Therefore, some studies consider the utilization of downstream resources. For example, Zychlinski et al. (2020) believe that the shortage of hospital beds in the downstream Geriatric Institutions will lead to congestion, causing upstream patients to be unable to receive treatment in time. Fügener et al. (2014) expanded the scope of surgical scheduling to downstream resources, such as the Intensive Care Unit and general wards that patients need after discharge. Moosavi and Ebrahimnejad (2018) regard bed exceeding capacity as an optimization goal. Similarly, we consider the utilization of downstream hospital bed resources as an optimization goal. In contrast, we not only consider elective patients but also non-elective patients (including emergency patients, walk-in patients, and COVID-19 patients).

From the perspective of resource configuration, there are significant differences in bed utilization between different specialties. (Dai and Shi 2019) proposed an overflow configuration. Specifically, if one patient has no available bed in his (her) specialty ward, overflow configuration allows the patient to be planned to one bed in another specialty ward. Under this configuration, the hospital can make full use of the idle beds of all medical specialties without increasing production capacity. However, it also brings some drawbacks. Inevitably, there are also some drawbacks. For example, due to the significant differences in nurse skills and nursing equipment in different medical specialties, overflow configuration will bring certain health risks to overflow patients (patients planned to other medical specialties wards). Therefore, (Izady and Israa 2021) proposed clustered overflow configuration, which can ensure the full use of resources and reduce health risks. The above bed configuration does not reflect the difference between elective and non-elective patients. In the case of sufficient bed resources, it has excellent applicability. However, when there is a shortage of hospital beds, its effect will be greatly reduced, because there is competition and conflict between non-elective patients and elective patients in the use of hospital beds. Specifically, non-elective patients usually have a higher priority and will preempt the beds that have been allocated to patients for elective surgery. For this reason, we proposed a buffered clustered configuration. Similar to clustered overflow configuration, we use clustered ward, the difference is that we reset the admission process of non-elective patients. In addition, we add a buffer ward to observe and detect potential COVID-19 patients.

In addition to the problem of resource shortage, uncertainty is also a challenge facing patient scheduling (Hallah and Visintin 2019; Zhang et al. 2020). The uncertainty comes from many aspects, including the uncertainty of the arrival of emergency patients, the uncertainty of surgery duration and the length of hospitalization, etc. It is difficult to predict the arrival of emergency patients from historical data because of its complication and the fact that sometimes data are not available, such as in the early stage of COVID-19. Therefore, some research and practice provide dedicated operating rooms and hospital beds for emergency operations (Bovim et al. 2020; Ferrand 2014; Li...
et al. 2017). This method is practical because the emergency requires timely surgical treatment. In addition, it can also reduce the interference of the uncertainty of emergency patients on elective surgery planning. However, during COVID-19, the shortage of downstream beds forced us to re-evaluate this approach. Specifically, the uncertainty of the arrival of emergency patients results in that the beds reserved for emergency patients may not be used in time. On the other hand, the beds reserved for elective patients may be occupied by emergency patients when there are not enough beds reserved for emergency patients, resulting in the cancellation of the planned elective surgery. Therefore, we reset the admission route for non-elective patients to reduce their interference with elective dates.

When formulating surgery planning, the planning manager knows nothing about the actual surgery duration and length of stay. Some studies assume that historical data is sufficient or the distribution is known, and use stochastic optimization to obtain optimal scheduling (Bovim et al. 2020; Eun et al. 2019). In practice, data is not always available or sufficient. Given the lack of surgery duration data, (Moosavi and Ebrahimnejad 2020) proposed a robust scheduling model. Similarly, (Wang, et al. 2019) built a distributionally robust optimization model to minimize operating room opening costs and expected overtime. Of course, sometimes even though the data is not sufficient, it can also provide a small amount of information, such as the mean, support, and moments. Therefore, (Mak et al. 2015) proposed a data-driven robust scheduling model. When historical data is not available, surgeon experience is also available decision-making information. This information, usually inferred by the surgeon based on the patient’s physical condition, can fully describe the patient. In this paper, we refer to the information from historical data as objective information and information from the surgeon’s evaluation as subjective information. Methodology for different surgery procedures and information can be seen in Table 1.

As far as we know, very few studies consider subjective information as decision-making information in surgical planning. In addition, most studies assume that the decision information is the same in the same planning system. Our research makes full use of all available decision-making information (including subjective and objective information) to improve the effectiveness of surgical planning. The feature of the fuzzy model is that it doesn’t rely on historical data(Zhao et al. 2020), while the robust model needs a small amount of data. Both models are suitable for the environment with insufficient data. The difference is that fuzzy models require expert experience while robust models rely on a small amount of data. In addition, fuzzy sets have contributed to enhancing the robustness and applicability of scheduling(José et al. 2015). At last, by modeling parameters in scheduling problems as fuzzy numbers, fuzzy scheduling can help incorporate flexibility into scheduling algorithms (Guiffrida and Nagi 1998).

3. The scheduling model under buffered clustered configuration

Although elective surgery is not as urgent as emergency surgery, it does not mean that it can be postponed indefinitely, because postponement may lead to deterioration of the patient’s condition and emotional dissatisfaction. Therefore, waiting time is an important optimization goal (Kiani et al. 2022). In addition, given that there are

| Table 1 Methodology for different surgery procedures and information. |
|-------------------------------------------------|
| The uncertainties | Decision information | Methodology |
|---------------------|----------------------|-------------|
| Surgery duration    | Distribution         | Stochastic programming, |
| Length of stay      | Partially-known characteristics of the uncertainty distribution (e.g., mean and covariance) | Robust optimization (our study), Distributionally robust optimization |
| Expert experience   | Fuzzy optimization (our study) |

| Table 2 Notation for models. |
|-------------------------------|
| Indices | |
| $i$ | Patients index; $i = 1, 2, 3, \ldots, N$, where $N$ indicates the number of the elective surgeries on the waiting list. |
| $s$ | Surgeons index; $s = 1, 2, 3, \ldots, S$, where $S$ indicates the number of surgeon teams (one surgeon team usually including the attending surgeon, OR nurse, and the anesthesiologist, etc.). |
| $j$ | OR index; $j = 1, 2, 3, \ldots, J$, where $J$ indicates the number of OR. |
| $d$ | Surgery date index; $d = 1, 2, 3, \ldots, D$, where $D$ indicates the number of days in current planning horizon. |
| $e$ | Date index of discharge from ward; $e = 1, 2, 3, \ldots, D + Q$, where $Q$ is the maximum length of stay in ward. |
| $v$ | Bed type index; $v = 1, 2, \ldots, V, V'$, where $V$ is the number of medical specialties, and $V' = V + 1$ is the index of clustered bed. |
| $\alpha$ | Objective function weights to minimize priority for all planned patients. |
| $\beta$ | Objective function weights to minimize patient waiting time. |
| $\gamma$ | Objective function weights to minimize extra beds and idle beds. |
| $\chi$ | Objective function weights to minimize OR overtime and idle time. |
| $\eta$ | Objective function weights to minimize changes for re-planning surgery day. |

| Parameters | |
|------------|-----------------|
| $\mathbf{H}^s$ | Index set of surgery date; $\mathbf{H}^s = \{1, 2, 3, \ldots, D\}$. |
| $\mathbf{H}^d$ | Index set of discharge date; $\mathbf{H}^d = \{1, 2, 3, \ldots, D + Q\}$. |
| $\mathbf{I}^d$ | Number of available inpatient beds at the beginning of current planning horizon. |
| $\mathbf{A}^d$ | Objective function weights to minimize priority for all planned patients. |
| $\mathbf{B}^d$ | Objective function weights to minimize patient waiting time. |
| $\mathbf{C}^d$ | Objective function weights to minimize extra beds and idle beds. |
| $\mathbf{D}^d$ | Objective function weights to minimize OR overtime and idle time. |

| Decision Variables | |
|--------------------|----------------|
| $X_{i,v}$ | Binary variable; $X_{i,v} = 1$, if patient $i$ is assigned to OR $v$, on day $d$ and his/her bed type is $v'$; otherwise $X_{i,v} = 0$. |
| $N_{i,v}$ | Binary variable; $N_{i,v} = 1$, if patient $i$ is discharged from ward on day $e$, and his/her bed type is $v'$; otherwise $N_{i,v} = 0$. |
| $E_{i,v}$ | Priority weight of patient $i$ planned in general ward. |
| $E_{i,v}$ | Priority weight of patient $i$ planned in clustered ward. |
| $E_{idjv}$ | Number of extra beds and idle beds of type $v$. |
| $PD_i$ | The sum of surgery date changes in the re-planning compared to the initial plan. |
| $EW_i$ | Total waiting days of patient $i$. |
| $EO_{O,i}$ | Total OR overtime and idle time of OR $i$, on day $d$. |
differences in the diseases, it is necessary to prioritize the planning of high-priority patients (Min and Yih 2010a). The hospital hopes to make full use of the operating room and hospital beds while avoiding overload. Therefore, one of the goals is to reduce OR overtime and idle time, while reducing idle beds and extra beds needed. Extra beds are temporary beds that are added to cope with the number of patients exceeding capacity. Given that the hospital faces an uncertain environment, timely adjustment is needed to improve adaptability. Therefore, one of the optimization goals is to minimize changes to the initial planning. Under normal circumstances, the hospital needs to decide the type of inpatient ward for each patient. But under buffered clustered configuration, the operating room. But under buffered clustered configuration, the operating room. But under buffered clustered configuration, the operating room. But under buffered clustered configuration, the operating room.

To present the formulation of our problem, we first introduce the following notations in Table 2:

With these notations, we can formulate our planning problem with cost minimizing objective as follows:

\[
\min \alpha \sum_{i=1}^{N} (EP_i - EP_i') + \beta \sum_{i=1}^{N} EW_i + \gamma \sum_{i=1}^{N} \sum_{d=1}^{D} \sum_{j=1}^{J} EO_{idj} + \eta \sum_{i=1}^{N} PD_i, \forall i, \forall v, \forall j.
\]

(1)

The first part is priority for all planned patients, and second part is patient waiting time. The third is extra beds and idle beds, and the fourth part is OR overtime and idle time. At last, it is the surgery day changes in the re-planning compared to the initial plan.

subject to:

\[
EP_i' = P_i \sum_{d=1}^{D} \sum_{j=1}^{J} X_{idj}, \forall i.
\]

(2)

\[
EP_i'' = P_i \sum_{d=1}^{D} \sum_{j=1}^{J} X_{idj'}, \forall i.
\]

(3)

Equation (2) is the priority weight assigned to non-clustered ward patients, while equation (3) is the priority assigned to clustered ward patients. These two equations are to schedule high-priority patients to a non-clustered ward as much as possible to ensure that the arrival of non-elective patients will not cause these elective surgeries to be canceled or postponed. For example, if the priority value of patient P1 is 1, and the priority value of P2 is 3, then P2 will be prioritized to a non-clustered ward (the larger the priority value, the higher the priority of the patient).

\[
PD_i \geq N_i' \sum_{d=1}^{D} \sum_{j=1}^{J} H_{idj} - U_i, \forall i.
\]

(4)

Constraint (4) represents the number of changes in the patient’s surgery date between the re-planning and the initial plan.

\[
EO_{idj} \geq \sum_{i=1}^{N} \sum_{j'=1}^{J'} X_{idj'}, \forall d, j.
\]

(5)

\[
\sum_{i=1}^{N} \sum_{j=1}^{J} X_{idj}L_{idj} - T_d, \forall d, j, \leq M_d, \forall j, d.
\]

(6)

Constraint (5) represents OR overtime and idle time. If the total operation time in one OR is greater than its actual normal open time, this means that OR and surgeon have to work overtime, resulting in overtime costs. On the contrary, it will lead to the idleness of OR. In addition, the OR overtime cannot exceed the upper bound as it may affect the next day’s operation and lead to surgeon and nurse fatigue.

\[
EW_i \geq \sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} H_{idj} X_{idj} - \sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} W_{idj}, \forall i.
\]

(7)

\[
EW_i \geq \left( 1 - \sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} X_{idj} \right) (W_i^p + D_i), \forall i.
\]

(8)

Constraints (7)-(8) indicate the waiting time for each elective patient. Specifically, constraint (7) represents the waiting time of patients planned in the current planning period, which is equal to the waiting time before the current planning period plus that in the current planning period. Constraint (7) is the waiting time of unplanned patients in the current planning period, which is equal to the waiting time before the current planning period plus the planning horizon.

\[
\sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} X_{idj}L_{idj} - \sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} H_{idj}, \forall i, \forall v.
\]

(9)

\[
\sum_{d=1}^{D} \sum_{i=1}^{N} N_i \leq 1, \forall i.
\]

(10)

Equation (9)-(10) is the discharge date of each patient, which is equal to the operation date plus the expected length of stay. On this basis, the patient’s expected discharge date is expressed as a 0–1 variable, as it contributes to calculating the number of patients discharged in each day.

\[
\forall d, v \neq V, \forall i.
\]

(11)

\[
\sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} X_{idj} - \sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} N_i v - B_i - \sum_{d=1}^{D} \sum_{j=1}^{J} R_{idj}, \forall d, \forall v \neq V.
\]

(12)

\[
\sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} X_{idj} - \sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} N_i v - B_i - \sum_{d=1}^{D} \sum_{j=1}^{J} R_{idj} \leq M_d, \forall d, \forall v \neq V, \forall i.
\]

(13)

\[
\sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} X_{idj} - \sum_{d=1}^{D} \sum_{j=1}^{J} \sum_{i=1}^{I} N_i v - B_i - \sum_{d=1}^{D} \sum_{j=1}^{J} R_{idj} \leq M_d, \forall d, \forall v \neq V, \forall i.
\]

(14)

Equation (11)-(14) represents idle and extra beds of each bed type. The former means that the beds are more than the actual demand, while the latter is the opposite. Note that clustered wards and non-clustered wards have different patient sources, so we have to count them separately. Specifically, Equation (11) is the idle and extra beds in the non-clustered ward that is occupied by elective patients. The available beds include the initially available beds and the new beds released by discharge patients in the current planned period. Equation (12) is the idle and extra beds in the clustered ward. The patients in this ward include elective patients, walk-in patients, and emergency patients. Equation (13)-(14) means that the excess of each type of hospital bed
cannot exceed the upper bound.
\[
\sum_{d=1}^{D} \sum_{j=1}^{J} X_{adj} \leq B_{v}^{v'}, \forall i, v.
\]  

(15)  

Constraint (15) indicates that the bed allocation needs to meet the need of the patient. Specifically, each patient can only be planned in the ward of her/his own specialty or clustered ward. For example,

\[
B_{v}^{v'} = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 \\ \end{bmatrix}
\]

\(B_{v}^{v'}\) is the matrix, where 1 means that the patient can be planned in this type of ward, and 0 means not. The matrix includes four patients, two specialties, and one clustered ward. As can be seen from \(B_{v}^{v'}\), each patient can be planned in the clustered ward.

\[
\sum_{i} \sum_{j} \sum_{v} X_{adj} \leq \sum_{i} Y_{v} v_{v'}, \forall i, d.
\]  

(16)  

Constraint (16) indicates that the patient’s operation date needs to meet the surgeon’s availability.

\[
\sum_{v'} \sum_{j} \sum_{i} \sum_{v} X_{adj} Y_{v} v_{v'} \beta_{v} \in K_{d}, \forall i, v', \forall d.
\]  

(17)  

Constraint (17) means that the surgeon’s daily working hours cannot exceed the upper bound.

Minimizing
\[
\sum_{i} \sum_{v} \left( \frac{EF_{i} - EP_{i}}{P_{v}^{\text{MAX}}} \right) + \beta \sum_{v} \frac{\sum_{i} \sum_{d} \sum_{j} \sum_{v} X_{adj}}{P_{v}^{\text{MAX}}} + \chi \sum_{d} \sum_{v} \sum_{i} \sum_{j} \sum_{v} X_{adj} \mu_{v} v_{v'} - \sum_{v} \sum_{i} \sum_{d} \sum_{j} \sum_{v} X_{adj} \mu_{v} v_{v'} - B_{v}^{v'}
\]

(26)  

\[
\sum_{d} \sum_{v} \sum_{i} \sum_{j} X_{adj} = 1, \forall i.
\]  

(18)  

\[
\sum_{d} \sum_{v} \sum_{i} \sum_{j} X_{adj} \leq 1, \forall i.
\]  

(19)  

Constraint (18) means that the patient must accept surgery before the latest surgery date. Constraint (19) means that the patient is planned at most once in the current planning horizon.

4. The fuzzy-robust model

4.1. The uncertainty of model

In determining the model, we initially assume that some parameters are known. This assumption is too strong as the existing uncertainty. Specifically, surgery duration, LOS, whether patients need to be hospitalized after surgery, and the number of non-elective patients are all uncertain. Note that the non-inpatient (surgical patients who do not need to be hospitalized after the operation) may need to occupy a hospital bed after surgery due to the patient’s condition deterioration. Therefore, it is necessary to evaluate whether the patient needs to be hospitalized after the operation. Fuzzy sets based on expert experience can describe this uncertainty well. Surgeons give an estimate based on the patient’s condition, expressed as a fuzzy set,

\[
\bar{Z} = \{ (p_{1}, \mu_{1}), (p_{2}, \mu_{2}), ..., (p_{i}, \mu_{i}), ..., (p_{k}, \mu_{k}) \},
\]

where \(\mu_{i}\) is the membership degree of the patient \(p_{i}\) belonging to inpatient set \(\bar{Z}\), and \(\mu_{i} \in [0, 1]\).

Surgery duration, \(L_{S}^{v}\), and LOS, \(L_{W}^{v}\), are expressed as fuzzy numbers \(\tilde{L}_{S} = (L_{S1}^{v}, L_{S2}^{v}, L_{S3}^{v})\) and \(\tilde{L}_{W} = (L_{W1}^{v}, L_{W2}^{v}, L_{W3}^{v})\). Fuzzy numbers are derived from expert estimates and express these vague estimates as a specific value. Therefore, constraints (5), (6), (9) and (17) is reformulated as (20)-(23).

\[
EO_{d} \geq \sum_{i} \sum_{v} X_{adj} \tilde{L}_{S}^{v} - T_{d}, \forall d, j.
\]  

(20)  

\[
\sum_{i} \sum_{v} X_{adj} \tilde{L}_{S}^{v} - T_{d} \in M^{v}, \forall j, d.
\]  

(21)  

\[
\sum_{i} \sum_{v} X_{adj} \tilde{L}_{W}^{v} - T_{d} \in M^{v}, \forall j, d.
\]  

(22)  

\[
\sum_{i} \sum_{v} X_{adj} Y_{v} \tilde{L}_{W}^{v} - T_{d} \in M^{v}, \forall j, d.
\]  

(23)  

A key advantage of the planning model under the buffered clustered configuration is that it can reduce the impact of the uncertainty of non-elective patients on elective patients. In addition, the daily arrival number of non-elective patients under the buffered clustered configuration is difficult to obtain through expert evaluation. Therefore, we express it as a robust parameter \(\tilde{C}_{d}\). Therefore, the model is re-expressed as:

\[
\sum_{d} \sum_{v} \sum_{i} \sum_{j} X_{adj} = 1, \forall i.
\]  

(26)  

Since the mathematical programming model with fuzzy number parameters and robust parameter is difficult to solve directly, we need to transform it. In Section 4.2 and 4.3, we respectively transformed the fuzzy parameters and robust parameters to obtain an easy-to-handle linear programming model.

4.2. Treating fuzzy parameters

For the objective function, we use equations (27) to convert fuzzy numbers into crisp(non-fuzzy) numbers according to Jiménez et al. (2007).

\[
EV(\tilde{c}) = \frac{E_{1} + E_{2}}{2}
\]  

(27)  

\[
\bar{c} = (c^{1}, c^{2}, c^{3})E_{1}^{*} - \frac{1}{2}(c^{1} + c^{2})E_{2}^{*} - \frac{1}{2}(c^{2} + c^{3})
\]

For constraints, according to Liou and Wang (1992), we know that
for any two triangular fuzzy numbers \(\tilde{A}_i\) and \(\tilde{A}_j\), if \(V_{\alpha}(\tilde{A}_i) > V_{\alpha}(\tilde{A}_j)\), then \(\tilde{A}_i > \tilde{A}_j\), where \(V_{\alpha}(\tilde{A}) = [(1 - \alpha)A^1 + A^2 + \alpha A^3]/2\), and \(\alpha\) represent the feasibility of the solution in a fuzzy environment. Therefore, some constraints with fuzzy numbers can be transformed into crisp (non-fuzzy) constraints. Therefore, constraints (20)-(23) can be transformed into,

\[
EO_{\alpha}^{s}
= \frac{1}{2} \sum_{j=1}^{N} \sum_{i=1}^{V'} \sum_{d=1}^{D} X_{dvi}[(1-\alpha) \bar{L}_{ij}^1 + L_{ij}^2 + \alpha L_{ij}^3] - T_{dj} \quad \forall d, j
\]

(28)

\[
= \frac{1}{2} \sum_{j=1}^{N} \sum_{i=1}^{V'} \sum_{d=1}^{D} X_{dvi}[(1-\alpha) \bar{L}_{ij}^1 + L_{ij}^2 + \alpha L_{ij}^3] - T_{dj} \quad \forall i, \forall d
\]

(29)

Fig. 2. Framework of GA-VNS-H.

Cut set can be used to transfer the fuzzy set to crisp set. Specifically, let \(A = \tilde{F}\) denote the \(\lambda\)-cut set of \(\tilde{F}\), where \(\lambda\)-cut set of a fuzzy number \(\tilde{F}\) is defined as \(F_\lambda = \{x \in \Omega | \mu_{\tilde{F}}(x) \geq \lambda\}\). Fuzzy set \(\tilde{Z}\) can be transferred as a crisp set \(\Lambda = Z_\lambda\), where \(Z_\lambda\) is \(\lambda\)-cut set of \(\tilde{Z}\). About fuzzy related theories, readers can refer to Bellman and Zadeh (1970).

1. Surgery date assignment and bed assignment are randomly generated.
2. The heuristic algorithm OR_assignment is used to schedule the ORs according to the surgery date in step 1.
3. The surgery date assignment and bed assignment are crossed over and mutated, and the ORs assignment are produced by OR_assignment.
4. Repeat step 2.
5. The AVNS is applied to the surgery date assignment and bed assignment, and the ORs assignment are produced by OR_assignment.
4.3. Treating robust parameters

The above-mentioned model with fuzzy parameters assumes that the surgery duration and LOS can be estimated by surgeons as they know patient’s condition. However, it is difficult to estimate the daily arrival number of non-elective patients as no information can be obtain about these patients. Therefore, we established a robust model. There are many studies on robust models, and scholars have proposed different types of models. Considering the requirements for computation time and model complexity, we choose a robust model proposed by Mulvey et al. (1995). It is characterized by low complexity and easy application in practice and has been used in various fields.

Mulvey et al. described robustness as the robustness of the model and the robustness of the solution (Mulvey et al. 1995). The former emphasizes solutions that are less sensitive to modification, and the latter emphasizes solutions that minimize constraint violations. This method can better balance both robustness.

Specifically, consider the following model,

\[ \min \ Z = c^T x + d^T y \]

s.t.

\[ Ax = b, \]
\[ Bx + Cy = e, \]

\[ x, y \geq 0. \]

which can be transformed into an equivalent model,

\[ \min \ Z = \sigma(x, y_1, ..., y_p) + \sigma(z_1, ..., z_q) \]

s.t.

\[ Ax = b, \]
\[ Bx + Cy = e, \]

\[ x, y_1, y_2, ..., y_p, z_1, ..., z_q \geq 0. \]

Therefore, (24)-(26) can be transformed into the following:

\[
\begin{align*}
&\left[ a \sum_{d=1}^{D} \left( \frac{E^{d}_{\delta} - E^{d}_{\gamma}}{\delta_{\max}} \right) + b \sum_{d=1}^{D} \sum_{i=1}^{I} \frac{E^{d}_{\beta^{i}}}{\beta_{\max}^{i}} + r \sum_{d=1}^{D} \sum_{i=1}^{I} \frac{E^{d}_{\theta^{i}}}{\theta_{\max}^{i}} + x \sum_{d=1}^{D} \sum_{i=1}^{I} \frac{E^{d}_{\phi^{i}}}{\phi_{\max}^{i}} + \gamma \sum_{d=1}^{D} \sum_{i=1}^{I} \frac{P^{d}_{\Delta^{i}}}{P^{\max}_{\Delta^{i}}} \right] \\
&\quad \quad + WR \sum_{d=1}^{D} \sum_{l=1}^{L} P^{d}_{\Delta^{l}_{d}} - \sum_{d=1}^{D} \sum_{l=1}^{L} P^{d}_{\Delta^{l}_{d}} + SR \sum_{d=1}^{D} \sum_{l=1}^{L} P^{d}_{\gamma},
\end{align*}
\]

subject to:

\[
\begin{align*}
&\Delta^{d}_{l} \geq \sum_{d=1}^{D} \sum_{i=1}^{I} \lambda^{d}_{i} X_{d i}^{l} - \sum_{d=1}^{D} \sum_{i=1}^{I} N_{\omega^{d}}^{i} - B^{d}_{l}, \\
&- \sum_{d=1}^{D} R_{d}^{l} + \sum_{d=1}^{D} C_{d}^{l} + \sum_{d=1}^{D} F_{d}^{l}, \quad \forall d, l,
\end{align*}
\]

5. Algorithm

The proposed problem is NP-hard, because it is an extension of the NP-hard problem considered in (Vijayakumar et al. 2013). In addition, uncertainty causes additional complexity. Commercial software packages cannot solve real-life problems in a reasonable time. We propose a heuristic rule called OR-heuristic and combine it with the variable neighborhood search (VNS) and genetic algorithm (GA) to obtain a hybrid algorithm which we call the ‘GA-VNS-H’ algorithm. GA algorithm has excellent global search performance. In most cases, its solution efficiency is high (at least, a satisfactory solution can be obtained in a limited time), but sometimes there are disadvantages such as low solution accuracy and unstable solution. Therefore, some studies combine GA with some heuristic and meta-heuristic algorithms to increase its local searchability. This paper proposes a heuristic algorithm and an
adaptive VNS (AVNS), then combines these two algorithms with GA.

5.1. Framework of GA-VNS-H

Compared with the traditional GA algorithm, GA-VNS-H adds AVNS and a heuristic algorithm. But it is not a simple stack of functions, we have optimized it overall as shown in Fig. 2. Specifically, first, we design a certain initialization strategy based on the characteristics of the model to improve the quality of the initial solution. Secondly, GA and VNS are modified into adaptive iteration to reduce the invalid search of the algorithm. Finally, the heuristic algorithm is integrated into GA-VNS-H to improve search efficiency. In population initialization, GA-VNS-H uses a heuristic rule to generate as many feasible solutions as possible. Specifically, for each patient, if the random number is less than 0.5, the patient will be assigned to his (her) medical specialty ward, otherwise, he (she) will be assigned to the clustered ward (i.e., bed type is V).

5.2. Avns

Compared with the classic VNS, AVNS redesign the neighborhood operator and search mechanism. The design of the neighborhood operator needs to adapt to the model. For this reason, we design the neighborhood operator for each subpart of the chromosome. In addition, the classic VNS usually restarts the search process from the first neighborhood after finding a better neighborhood solution. The main disadvantage of this search process is that even if a better solution is obtained in the current neighboring area, it will still go to the first search area (K. Wang et al. 2021). Therefore, compared with other neighborhoods, the first neighborhood is more likely to be used. Once the search effect of the first neighborhood is not good, it will lead to a waste of computing power and reduce the efficiency of the algorithm. In addition, the search time of the VNS algorithm is relatively long. Once there are many neighborhoods, the search time will increase significantly. Therefore, we propose an improved adaptive search mechanism.

We set a separate neighborhood operator for each substring of the chromosome. This means that if there are four operators, then for one chromosome, at least $3^*4 = 12$ iterations are required to complete the search for all genes of the chromosome. The reason for this is that different segments of the chromosome represent different decision variables, which are subject to different constraints. This setting helps each local search to be more refined. In addition, it also helps to make full use of heuristic algorithms (Section 5.3). The specific neighborhood operators are as follows:

1) Swap operator: randomly select two points in the chromosome and swap the positions of the genes at the two points.
2) Replace operator: randomly select a gene that already exists in the chromosome to replace another gene.
3) Cover operator: according to the value range of the gene, a gene is randomly generated to replace the existing gene. This operation is similar to the mutation operation in the genetic algorithm.
4) Flip operator: flip some of the gene fragments in the chromosome.

AVNS is a local search strategy of GA-VNS-H. If there are too many neighborhood operators, it will significantly increase the search time of the algorithm. To this end, we designed a search mechanism based on rewards and consumption. The basic principle is that each neighborhood operator has an initial energy value, and each application of the neighborhood operator consumes one unit of energy value. When all the neighborhood operator run out of the energy value, the search ends. If the neighborhood operator gets a better solution in a certain iteration, it will get a certain amount of energy as a reward. The next neighborhood selection is based on the existing energy value of each operator. Specifically, it uses the Roulette Wheel Selection mechanism of the classic GA algorithm.

5.3. Heuristic algorithm for operating room allocation

As we all know, heuristics can make full use of the nature of the model to improve efficiency. For this reason, we propose a heuristic for operating room allocation based on algorithm proposed by Wang et al. (2022). Operating room allocation can be understood as a classic set partition problem. There are some heuristic algorithms for this kind of problem such as greedy algorithm. However, the solving efficiency of these algorithms for proposed model is low, so the following heuristic

![Running times of uncertain models.](image-url)
6. Computational Experiments

In this section, we describe the experimental settings and results. In Section 6.1, we describe the model-related parameter settings and explain the method of constructing our experimental data set. We conducted a preliminary verification of the experimental setup and discussed it with practitioners in a Chinese hospital (a hospital in Liaoning Province). In Section 6.2, we demonstrated the performance of the proposed algorithm and its components. Section 6.3 reports the performance of the fuzzy-robust model (FR) and Section 6.4 is the performance of buffered clustered configuration.

Our algorithm is programmed in Python, and executed on a 3.7 GHz Intel Core i7 CPU computer with 16 GB memory. We use solver CPLEX within the Python `docplex` package for the MIP model. CPLEX parameters are set to 7200 s by default (Akbarzadeh et al. 2019).

### 6.1. Experimental design

Table 3 summarizes the remaining model parameters. We try to find a compromise between the interests of different stakeholders and set the objective function weights according to the priority of the hospitals visited in real life like (Akbarzadeh et al. 2019). For example, $\alpha = 1$, $\beta = 5$, $\gamma = 1$, $\chi = 1$, $\eta = 1$. Other parameter settings are shown in Table 3.

Table 3 numerically adopts the surgery duration data configuration proposed by Min and Yih (2010) and LOS data from hospital. Specifically, surgical patients included 9 groups, namely ENT, OB/GYN, ORTHO, NEURO, GEN, OPHTH, VASCULAR, CARDIAC, and UROLOGY. Specific data statistics are shown in Appendix A.

### 6.2. Evaluation of GA-VNS-H

The relative percentage deviation (RPD), as a common performance indicator (K. Wang et al. 2021), was used to evaluate the optimization effect of the algorithm. We use average RPD (ARPD) as a performance evaluation index. Its formula is given as follows:

$$\text{ARPD} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{R_i - R_{\text{best}}}{R_{\text{best}}} \right| \times 100$$

where $n$ is the number of runs, $R_{\text{best}}$ is the best objective function value obtained by CPLEX, and $R_i$ denotes the objective function value obtained by a specific algorithm.

As we all know, there are many excellent heuristic algorithms, such as particle swarm algorithm, bat algorithm, genetic algorithm, gray wolf algorithm, and so on. After our initial experiment, we select the algorithm with better performance as our comparison algorithm. To analyze the effects of the strategies included in the algorithm, we conducted the following comparative experiments:

- **DE**: This is a standard differential evolution algorithm (Storn and Price 1997).
- **HPSO**: This is a hybrid particle swarm algorithm (Niu et al. 2008), to solve the job-shedding scheduling problem. Considering the similarity between surgery scheduling and job shop scheduling, we applied it to our problem for comparison.
- **FDE**: This is a fuzzy self-tuning differential evolution algorithm (Tsafarakis et al. 2020). Fuzzy logic is used to adjust parameters automatically to reduce human intervention.
- **GA-I**: Standard genetic algorithm (Bonabeau et al. 1999) with proposed population our initialization strategy.
- **GA-VNS**: Standard genetic algorithm with proposed AVNS.
- **GA-H**: Standard genetic algorithm with proposed heuristic algorithm OR assignment.
- **GA-VNS-H**: proposed algorithm with all policy.

As shown in Table 4, in small-scale test instances, each algorithm can find the optimal solution such as test instance 1. However, as the scale of the problem increases, the accuracy of DE, HPSO, and FDE has dropped considerably. From the perspective of the algorithm running time, as shown in Table 5, these algorithms are also longer, which showed that the DE, HPSO, and FDE cannot effectively solve the proposed model. In comparison, GA-VNS-H is significantly better than other algorithms in terms of accuracy and computation time. To further highlight the role of the internal components of the algorithm, we have compared the various sub-strategies proposed in this article. The results prove that each component can effectively improve the efficiency of the GA-VNS-H. Note that GA-VNS is sometimes better than GA-VNS-H because the latter adds heuristic OR assignment for operating room arrangements. When the operating room in the test instance is relatively idle, the effect of the heuristic will reduce.
6.3. Performance of fuzzy-robust model (FR)

To evaluate the model, we selected two classic models for comparison. They are the Deterministic model (DM) and the Completely robust model (CR) proposed by (Mulvey et al. 1995). In DM, the values of uncertain parameters are randomly selected in the support set. In CR, the support of uncertain parameters can be directly applied to the model. In FR, surgery duration and LOS are fuzzy numbers, and the number of non-elective patients is the parameter support.

As shown in Table 6, ob, cons, and fr respectively represent the objective value of feasible solutions, the number of violations of constraints in infeasible solutions, and the proportion of feasible solutions in the simulation environment. The solution of the model may be infeasible in the actual environment because of the uncertainty of the actual environment. DM has the largest number of constraint violations, which indicates that its ability to adapt to the environment is weak. Especially when resources are in short supply, the proportion of feasible solutions of DM in the simulation environment is very low. Therefore, although its objective function value of the feasible solution is the smallest, it is infeasible with high probability in the actual environment. We also found that both CR and FR have high robustness because the number of violations is very small. Furthermore, FR is superior to CM in both the robustness of the model and the robustness of the solution. Note that the average proportion of feasible solutions of FR in the simulation environment has reached 95.1%, indicating that its environmental adaptability is outstanding. In addition, as shown in Fig. 3, the CM generates long running times. In comparison, the FR has less computation time.

6.4. Performance of buffered clustered configuration

To evaluate the impact of different resource configuration strategies, we respectively compared traditional configuration, clustered overflow configuration, and buffered clustered configuration. Given that most COVID-19 patients can be identified within 24 h through the blood routine, two nuclear acid tests, chest CT and epidemiological survey, etc., so most patients stay in the buffered ward is one day. Only a small number of patients require long-term stay and observation in Buffered Ward. As shown in Table 6, WT represents the waiting time, and PR represents the priority of the planned patient. PRD represents the change of the operation date in the re-planning. BED_O represents the excess of the hospital bed.

As shown in Table 7, compared to traditional configuration, clustered overflow configuration and buffered configuration have lower WT, which shows that clustered wards contribute to arranging more patient admission in time to reduce waiting time. It also indirectly shows that clustered wards help to make full use of the bed because they can balance the use of resources in different specialties. The PR of buffered clustered configuration and clustered overflow configuration is larger, which shows that they can allocate high-priority patients to obtain surgery. In addition, the PRD of buffered configuration is smallest than others, which proves the buffered configuration can reduce the interference of the non-elective patient’s random arrival to the elective patient. Of course, we also see that the BO of the buffered configuration is higher than that of the traditional configuration. This shows that although we can reduce the patient’s infection risk and the interference of elective surgery through the buffered configuration, the cost is that the bed is exceeded. Fortunately, this excess is not great.

In the above experiment, we assume that most patients stay in the buffered ward within 24 h, which may not completely eliminate the risk. In practical applications, the risk can be reduced by extending the patient’s stay in the buffered ward.

7. Discussion and concluding remarks

In order to solve the shortage of hospital beds and the uncertainty in the process of elective surgery planning, we propose a new bed configuration to ensure that elective patients are not affected by non-elective patients. In addition, we propose a fuzzy-robust model based on robust optimization and fuzzy set theory to deal with the uncertainty. At last, to solve the model, a hybrid algorithm based on genetic algorithm and variable neighborhood search is further proposed. Experiments show that the algorithm has better calculation efficiency and solution accuracy. In addition, the elective surgery planning model under the new bed configuration model can effectively cope with the uncertain environment. Most hospitals postponed or canceled scheduled surgeries because of the potential risk brought by COVID-19 patients. We are providing a method of bed allocation and patient management to help safely perform elective surgery. It can help protect patients present in the hospital and reduce the waiting times for surgery out of the hospital. Of course, it also helps to ensure the income of the hospital.

In addition, we get some management insights:
1) Under the condition of insufficient data, considering the uncertainty in the surgical planning system as a non-single uncertainty may improve the effect of planning.
2) Under the condition of insufficient medical data, a surgeon’s experience is also a piece of very useful decision-making information.
3) If the surgical planning and bed configuration match, the adaptability of the model can be improved.

There are still shortcomings in the article. Specifically, in the simulation experiment, we did not conduct further research on the impact of potential COVID-19 patients on elective patients from the perspective of infectious disease transmission model. Therefore, in future research, we will explore this issue.

CRediT authorship contribution statement

Zongli Dai: Investigation, Methodology, Formal analysis, Visualization, Writing – original draft. Jian-Jun Wang: Conceptualization, Methodology, Funding acquisition, Supervision, Writing – review & editing. Jim (Junning) Shi: Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Tables A1 and A2.
Table A1
The structure of test problem.

| Surgical group | Surgery duration (minute) | LOS (day) | Observations |
|----------------|---------------------------|-----------|--------------|
| ENT            | 74                        | 3         | 788          |
| ORGYN          | 86                        | 2         | 342          |
| ORTHO          | 107                       | 1         | 859          |
| NEURO          | 160                       | 2         | 186          |
| GEN            | 93                        | 3         | 817          |
| OPHTH          | 38                        | 4         | 110          |
| VASCULAR       | 120                       | 5         | 303          |
| CARDIAC        | 240                       | 2         | 90           |
| UROLOGY        | 64                        | 6         | 1           |

Table A2
The settings of test problem.

| N   | J   | J0  |
|-----|-----|-----|
| 10  | 2   | (5.5,6) |
| 2   | 2   | (5.5,6) |
| 3   | 2   | (5.5,6) |
| 4   | 2   | (5.5,6) |
| 5   | 2   | (5.5,6) |
| 6   | 2   | (5.5,6) |
| 7   | 2   | (10,10,10) |
| 8   | 2   | (10,10,10) |
| 9   | 2   | (10,10,10) |
| 10  | 2   | (10,10,10) |

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Z. Dai et al.