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## Chapter

# Application of Operations Research to Healthcare

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## Abstract

Operations research (OR) is significantly important to healthcare. OR techniques can make efficient use of medical resources to enhance patients, providers and agencies' satisfaction. Given limited medical resources and high demand from patients, the primary goal of OR is to use optimization models to quantify the problem and apply mathematical algorithms to obtain a close-to-optimal solution. For example, OR has been widely used to scheduling problems by minimizing the number of nurses or maximizing demand coverage, while keeping service regulations satisfied. In this chapter, we first give a brief introduction of optimization models, followed by the application of OR to healthcare problems such as nurse scheduling, home healthcare delivery and transportation services for patients.

**Keywords:** operations research, mixed integer linear programming, mathematical models, healthcare optimization, nurse scheduling, home healthcare delivery, transportation service

## 1. Introduction

Operations research (OR) plays a critical role in healthcare of both rich and poor countries, especially when the medical resources are limited and the patient demand is high. OR techniques could be applied to optimize the use of medical resources, significantly improve service quality and reduce operations cost. For example, techniques such as mixed integer linear programming (MILP) algorithms, heuristics and data analytics could be used to design nurse schedules, patient-provider assignment and transportation routes. The past experience has shown that it is possible to obtain high-quality solutions to the most difficult planning and scheduling problems by applying mathematical modeling and advanced decomposition techniques in conjunction with intelligent heuristics.

The general idea of OR application to healthcare is to make decisions by mathematical optimization models. Examples of mathematical formulation on a nurse scheduling problem and a routing problem will be presented in Sections 2 and 3, respectively. Before making decisions, we must have several components that pass on to the optimization model our requirements. Components include:

### 1. Objective function

The objective function is the goal we wish to achieve. It can be the minimization of “cost” (such as the number of hired nurses, overtime hours, or patients’ travel distance), or the maximization of “profit” (such as hospital revenue, patient demand coverage, or satisfaction level). Some problems require a multi-objective function. For example, hospitals aim to achieve maximum patient demand coverage with a minimum number of nurses.

### 2. Constraints

Constraints are the rules and regulations we must obey. For example, nurses cannot work 20 hours a day, even though the violation of this rule can cover more patient demand with fewer nurses. Constraints that cannot be violated are considered “hard.” In addition to hard constraints, there are “soft” constraints that can be violated with a penalty cost added to the objective function. For instance, nurses are not encouraged to work more than 40 hours per week, but overtime is allowed if all the demands must be covered. If a nurse works overtime for an hour, then the one-hour penalty cost is added to the objective function. That means all demand is covered at the cost of overtime.

### 3. Decision variables

Decision variables indicate what we are supposed to decide. For example, in a home healthcare delivery problem, we need to decide on nurse-patient assignment, nurses’ travel routes, and service start time at each patient’s location.

### 4. Parameters

Parameters are given as constants. For instance, when designing nurses’ travel routes, we know the distance between every two locations. In real-life problems, however, some parameters are uncertain, such as patient demand and travel time, which may vary during different periods of the day. In such cases, robust optimization will be involved to address uncertainty.

In practical cases, a mathematical optimization model usually contains thousands, even tens and thousands of decision variables, making it extremely time-consuming for commercial solvers (such as CPLEX or Gurobi) to get a good solution within a reasonable amount of time. In reality, a lot of health institutes are reluctant to purchase the license of commercial solvers due to the high price. Therefore, mathematical algorithms (optimization-based heuristics or metaheuristics) are developed to solve large-scale problems. Optimization-based algorithms usually require solutions to mathematical models, but instead of solving the large-scale problem directly, the problem can be decomposed or transferred to smaller and easier problems. Common optimization-based algorithms include but are not limited to Lagrangian Relaxation, Column Generation, Benders Decomposition, Cutting Plane Algorithm and so forth. Metaheuristics do not rely on the type of the problem, but it must keep all the hard constraints satisfied while searching for a close-to-optimal solution. Metaheuristics include but are not limited to Genetic Algorithm, Greedy Algorithm, Tabu Search, Ant Colony Algorithm, Simulated Annealing, and Memetic Algorithm. Even though optimization-based algorithms and metaheuristics can find good feasible solutions within a limited amount of time, they are both at the cost of optimality. The quality of

solutions obtained from the algorithm significantly depends on the algorithm parameters, such as time limit and the number of iterations for each step.

The remainder of this chapter displays several examples of OR application to healthcare, such as nurse scheduling, home healthcare delivery, and transportation services for patients.

## 2 Nurse scheduling

Nurse scheduling is a critical branch of OR application to healthcare. Nurses are of vital essence in hospital and clinic operations, generally accounting for more than 50% of the budget [1]. The efficient use of nursing resources can directly impact a healthcare system's financial well-being. This is true for both public and private facilities, and especially true for those that serve economically disadvantaged areas [2].

### 2.1 Problem description

In a nurse scheduling problem, the goal is to assign nurses to different shifts over a one-or-several-week planning horizon. A shift usually lasts 6–12 hours with a fixed start and end time. For example, the start and end time of the morning, evening, and night shifts are [7 am, 3 pm], [3 pm, 11 pm], [11 pm, 7 am], respectively. The union of all shifts covers the entire planning horizon.

The stakeholders in a nurse scheduling problem include nurses and patients. On the side of patients, the demand should be covered as much as possible. That means a sufficient number of nurses should be assigned to each shift, so that patients can receive necessary medical treatment. Also, nurses' skill qualification is of vital significance. For example, a nurse for a blood test cannot be assigned to help a patient with her physical therapy.

On the side of nurses, the laws and regulations are mostly on hours of service. For example, for each nurse, there is an upper and lower limit on the number of working hours and working days per week, the number of consecutive working days and days off, the number of consecutive working hours, the number of overtime hours per week, the number of shifts per day, and the number of weekend shifts. In addition, each nurse must rest for at least 8 hours between any two shifts assigned to her.

Furthermore, some clinics and hospitals allow nurses to report on their preference for days and shifts before the schedule is decided. For example, if a nurse reports her preferred working day is Sep. 28, and she will not be available on Oct. 1, then a "profit" will be added to the objective function if a shift is assigned on Sep. 28, and a "cost" will be incurred if she is scheduled to work on Oct. 1. Other factors contributing to nurses' satisfaction level include shift transition, work-day transition, and equity. The shift transition happens if a nurse is assigned different shifts on two consecutive days (e.g., morning shift on day 1 and evening shift on day 2). Shift transition makes it harder for nurses to keep a regular life schedule. Work-day transition involves two cases: (i) 1-0-1 schedule: work on day 1, rest on day 2, work on day 3; and (ii) 0-1-0 schedule: rest on day 1, work on day 2, rest on day 3. Neither 1-0-1 nor 0-1-0 schedule is beneficial as they add an interruption to nurses' work or rest. Equity means the number of overtime hours, 1-0-1 schedules, 0-1-0 schedules, or any other preference violations should be evenly spread among nurses. For example, it is not ideal to assign nurse A 20-hour overtime, while asking nurse B not to work overtime at all.

2.2 Mathematical optimization model

The requirements for nurses and patients can be either “soft” or “hard” constraints, depending on the hospital or legal regulations. In this subsection, a mathematical formulation for the nurse scheduling problem (Model 1) is presented. For simplicity, we assume the planning horizon is 1 week. The objective function is to minimize the number of uncovered demand hours, 1-0-1 violations, 0-1-0 violations, and violation differences among nurses. The hard constraints include the upper and lower limits on the number of working hours for each nurse in a week. Each nurse can work at most one shift per day.

Sets and indices

$a$	index for 1-0-1 or 0-1-0 schedule violation $a$
$d$	index for day $d$
$h$	index for hour $h$
$i$	index for nurse $i$
$t$	index for shift $t$
$D$	set of days in the planning horizon
$H$	set of hours on each day
$LD_n$	last $n$ days of the planning horizon being scheduled
$N$	set of nurses
$T$	set of shifts

Parameters

$\alpha$	weight for an uncovered demand, assuming weight for 1-0-1 and 0-1-0 violation is 1
$D_{dh}$	demand (the number of nurses required) in hour $h$ on day $d$
$F_{ht}$	1 if shift $t$ covers hour $h$ , 0 otherwise
$\overline{H}_i, H_i$	the upper and lower limits of the number of working hours for each nurse during the planning horizon
$h_t$	the length of shift $t$ , which is the difference between start and end time of shift $t$
$r_a$	penalty for $a$ violations, $a = 1, 2, \dots, V_{\max}$
$V_{\max}$	maximum number of preference violations allowed for each nurse

Decision variables

$P_{id}$	(accounting) 1 if nurse $i$ has a 0-1-0 pattern schedule starting on day $d$ , 0 otherwise
$Q_{id}$	(accounting) 1 if nurse $i$ has a 1-0-1 pattern schedule starting on day $d$ , 0 otherwise
$U_{dh}$	uncovered demand on day $d$ in hour $h$
$V_{ia}$	(binary) 1 if nurse $i$ has $a$ violations, 0 otherwise
$X_{idt}$	(binary) 1 if nurse $i$ is assigned to shift $t$ on day $d$ , 0 otherwise

## Model 1

$$\text{Minimize } \alpha \sum_{d \in D} \sum_{h \in H} U_{dh} + \sum_{i \in N} \sum_{a=1}^{V_{\max}} r_a V_{ia} \quad (1a)$$

subject to

### 1. Demand constraints

$$U_{dh} \geq D_{dh} - \sum_{i \in N} \sum_{t \in T} F_{ht} X_{idt} \quad \forall h \in H, d \in D \quad (1b)$$

### 2. Upper and lower limits on the number of working hours for each nurse in the planning horizon

$$\sum_{d \in D} \sum_{t \in T} h_t X_{idt} \leq \bar{H}_i \quad \forall i \in N \quad (1c)$$

$$\sum_{d \in D} \sum_{t \in T} h_t X_{idt} \geq \underline{H}_i \quad \forall i \in N \quad (1d)$$

### 3. At most one shift per day for each nurse

$$\sum_{t \in T} X_{idt} \leq 1 \quad \forall i \in N, d \in D \quad (1e)$$

### 4. Definition of 0-1-0 and 1-0-1 violations

$$\sum_{t \in T} X_{idt} + \left(1 - \sum_{t \in T} X_{i,d+1,t}\right) + \sum_{t \in T} X_{i,d+2,t} + P_{id} \geq 1 \quad \forall d \in D \setminus LD_2, i \in N \quad (1f)$$

$$\left(1 - \sum_{t \in T} X_{idt}\right) + \sum_{t \in T} X_{i,d+1,t} + \left(1 - \sum_{t \in T} X_{i,d+2,t}\right) + Q_{id} \geq 1 \quad \forall d \in D \setminus LD_2, i \in N \quad (1g)$$

### 5. Violation computation

$$\sum_{d \in D} (P_{id} + Q_{id}) = \sum_{a=1}^{V_{\max}} a V_{ia} \quad \forall i \in N \quad (1h)$$

### 6. Variables definition

$$X_{idt}, P_{id}, Q_{id}, V_{ia} \in \{0, 1\} \quad \forall i \in N, d \in D, t \in T, 0 \leq a \leq V_{\max} \quad (1i)$$

$$0 \leq U_{dh} \leq D_{dh} \quad \forall d \in D, h \in H \quad (1j)$$



Objective function (1a) consists of two terms. The first term is the weighted demand uncovered, that is, sum of the number of nurses required but not supplied in each hour every day. If the hospital requires 10 nurses on Monday between 8:00 am and 9:00 am, but only 7 nurses are assigned to this hour, then we have uncovered a demand of 3, that is,  $U_{\text{Mon},8} = 3$ . Instead of adding 3 directly to the objective function, we add  $3\alpha$  to quantify the significance of demand coverage. The weight for an uncovered demand ( $\alpha$ ) is usually larger than 1 because we give demand coverage a higher priority. The second term is the penalty for 1-0-1 and 0-1-0 violations. Binary variable  $V_{ia} = 1$  if nurse  $i$  has a 1-0-1 and 0-1-0 violations throughout the planning horizon. Note that  $r_a$  is usually a constant exponential of  $a$ . For example, if nurse  $i$  has 3 1-0-1 and 0-1-0 violations, then a penalty cost of  $e^3$  will be added to the objective function. We use a constant exponential of  $a$  because we would like to improve equity among nurses, that is, not to assign one particular nurse a large number of violations, while giving other nurses few violations.

Constraints (1b) define the number of uncovered demands in each hour every day. On the right-hand side of (1b),  $D_{dh}$  is the number of nurses required in hour  $h$  on day  $d$ . The term  $\sum_{i \in N} \sum_{t \in T} F_{ht} X_{idt}$  indicates the number of nurses scheduled to work in hour  $h$  on day  $d$ . We use " $\geq$ " instead of " $=$ " in this set of constraints due to the following reasons:

1. If  $D_{dh} - \sum_{i \in N} \sum_{t \in T} F_{ht} X_{idt} \geq 0$ , then there is no over-coverage in hour  $h$  on day  $d$ . Even though constraints (1b) require the variable  $U_{dh}$  to be greater than or equal to  $D_{dh} - \sum_{i \in N} \sum_{t \in T} F_{ht} X_{idt}$ , the objective function automatically makes  $U_{dh} = D_{dh} - \sum_{i \in N} \sum_{t \in T} F_{ht} X_{idt}$  due to its nature of minimization.
2. If  $D_{dh} - \sum_{i \in N} \sum_{t \in T} F_{ht} X_{idt} < 0$ , then there is over-coverage in hour  $h$  on day  $d$ . Since variable  $U_{dh}$  is defined to be nonnegative,  $U_{dh} = 0$ .

Constraints (1c) and (1d) force each nurse to work between  $\underline{H}_i$  and  $\bar{H}_i$  hours in the planning horizon. Constraints (1e) require a nurse should work at most one shift per day. Constraints (1f) and (1g) indicate whether nurse  $i$  has a 0-1-0 or 1-0-1 violation starting on day  $d$ . Take constraints (1f) for example, if nurse  $i$  rests on day  $d$  (i.e.,  $\sum_{t \in T} X_{idt} = 0$ ), works on day  $d + 1$  (i.e.,  $\sum_{t \in T} X_{i,d+1,t} = 1$ ) and rests on day  $d + 2$  (i.e.,  $\sum_{t \in T} X_{i,d+2,t} = 0$ ), then to make constraint (1f) satisfied, binary variable  $P_{id}$  must equal 1, indicating nurse  $i$  has a 0-1-0 violation starting on day  $d$ . Constraints (1h) calculate the total number of 0-1-0 and 1-0-1 violations. Constraints (1i) and (1j) give variables definitions.

### 3 Home healthcare delivery

Home healthcare (HHC) delivery plays an important role in medical service, especially for patients with chronic illnesses and ambulatory disabilities. Instead of requiring patients to travel to hospital for medical treatment, hospitals schedule qualified nurses to provide service for patients at their place of residence. The quality of the weekly and daily schedules assigned to the nurses can impact the level of service patients receive, as well as nurse productivity and job satisfaction. Efficient patient-nurse scheduling and routing can significantly reduce the cost and improve the service quality of HHC.

### **3.1 Problem description**

In a home healthcare scheduling and routing (HHCSR) problem, nurses are scheduled to provide medical treatment for patients who reside in different locations of a city. On each day of the planning horizon, a nurse starts from home (or a depot), visits patients that are assigned to her, and returns home. Decision variables include (i) nurse-patient assignment, that is, which nurse should be assigned to visit each patient; (ii) the travel route of each nurse (i.e., visit sequence of patients for each nurse); and (iii) nurses' arrival time at patients' home. The objective of an HHCSR problem includes but is not limited to the minimization of nurses' travel distance and the maximization of patients' satisfaction level. Details of each stakeholder will be discussed in the remainder of this subsection.

#### *3.1.1 Patients*

Before the agency (clinic or hospital) designs nurses' assignments and routes, patients request visits with specific service dates, time windows, and skill requirements. Nurses' schedules and routes are designed based on the information from patients. In addition to meeting the requirements on time and skill qualification, the agency should try to keep the continuity of care (CoC) for patients with multiple visits in the planning horizon by assigning the same nurse to a patient. CoC has the benefit of maintaining treatment consistency as the nurse becomes more familiar with the patient's physical condition and treatment details.

#### *3.1.2 Nurses*

To ensure the nurses can provide high-quality service for patients, the daily workload of each nurse is limited to a specified range. The workload can be associated with the number of working hours, the number of patients serviced, and the type of medical treatment offered by the nurse. In addition, nurses usually have agreements with the agency on the start and end time of each day. However, in some cases, nurses are allowed to work overtime to complete more requested visits. Moreover, the differences in workload among nurses with the same skill level should be minimized to achieve the objective of equity. Finally, to provide a healthy working environment, a lunch break is taken into account.

The requirements from patients and nurses can be either "hard" or "soft" constraints in the optimization problem, depending on the agreement among patients, nurses, and the agency. If a constraint is relaxed as a "soft" constraint and is violated in a schedule, then we should add a penalty cost to the objective function.

The above paragraphs describe the basic version of a HHCSR problem. In practice, the problem can be extended and involve more stakeholders. For example, in some cases, on each day of the planning horizon, nurses start from pharmacies, visit patients to drop off medicine, provide medical treatment, and collect biological samples (such as blood or tissue). After visiting all the scheduled patients, nurses deliver all collected biological samples to laboratories for tests [3]. In such cases, besides decisions in the basic version of a HHCSR problem, patient-pharmacy assignment and pharmacy-laboratory assignment should be made. Furthermore, vehicle capacity must be considered due to the transportation of medicine and biological samples.



3.2 Mathematical optimization model

In this subsection, we assume the nurse-patient assignment is completed by clustering based on the geographical locations of patients. Model 2 decides the sequence of requested visits assigned to nurse  $w$  on day  $d$ , as well as the service start time of each visit. The objective is to minimize the travel time, the number of hours a visit is completed outside of the patient’s time window, and the number of hours nurse  $w$  works overtime. Model 2 makes use of following notation.

Sets and indices

$i$	index for requested visit
$I_{dw}$	set of all requested visits to be completed by nurse $w$ on day $d$

Parameters

$\alpha$	penalty weight of travel time in the objective function
$h_{dw}^s, h_{dw}^e$	start and end time of nurse $w$ ’s shift on day $d$
$h_i^s, h_i^e$	start and end time of the time window for requested visit $i$
$t_i$	service time for visit $i$ ; amount of time nurse $w$ spends on visit $i$ excluding travel time
$\tau_{ii'}$	travel time from the location of requested visit $i$ to that of $i'$

Decision variables

$T_{diw}$	(continuous) time when nurse $w$ begins treatment for visit $i$ on day $d$
$X_{dii'w}$	(binary) 1 if visit $i'$ is scheduled immediately after visit $i$ for nurse $w$ on day $d$ , 0 otherwise
$Y_{diw}^{VS}, Y_{diw}^{VE}$	(continuous) length of time window violation for an early or late arrival of nurse $w$ for visit $i$ on day $d$
$Y_{diw}^{WS}, Y_{diw}^{WE}$	(continuous) number of hours outside of the start or end time of a shift for nurse $w$ on visit $i$ on day $d$

Model 2 (for fixed nurse  $w$  on day  $d$ )

Minimize

$$\alpha \sum_{i \in I_{dw}} \sum_{i' \in I_{dw}} \tau_{ii'} X_{dii'w} + \sum_{i \in I_{dw}} (Y_{diw}^{VS} + Y_{diw}^{VE} + Y_{diw}^{WS} + Y_{diw}^{WE})$$

(2a)

subject to.  
Each visit has a predecessor and successor on a route

$$\sum_{i' \in I_{dw}} X_{dii'w} = 1$$

$\forall i \in I_{dw}$

(2b)

$$\sum_{i \in I_{dw}} X_{dii'w} = 1$$

$\forall i' \in I_{dw}$

(2c)

Violation of patient time windows

$$Y_{diw}^{VS} \geq h_i^s - T_{diw} \quad \forall i \in I_{dw} \quad (2d)$$

$$Y_{diw}^{VE} \geq T_{diw} + t_i - h_i^e \quad \forall i \in I_{dw} \quad (2e)$$

Violation of shift start and end times

$$Y_{diw}^{WS} \geq h_{dw}^s - T_{diw} \quad \forall i \in I_{dw} \quad (2f)$$

$$Y_{diw}^{WE} \geq T_{diw} + t_i - h_{dw}^e \quad \forall i \in I_{dw} \quad (2g)$$

Subtour elimination constraints

$$T_{diw} + (\tau_{ii'} + t_i) - M(1 - X_{dii'w}) \leq T_{di'w} \quad \forall i \neq i' \in I_{dw} \quad (2h)$$

Variables definitions

$$X_{dii'w} \in \{0, 1\} \quad \forall i \neq i' \in I_{dw} \quad (2i)$$

$$Y_{diw}^{VS}, Y_{diw}^{VE}, Y_{diw}^{WS}, Y_{diw}^{WE} \geq 0 \quad \forall i \in I_{dw} \quad (2j)$$

$$T_{diw} \geq 0 \quad \forall i \in I_{dw} \quad (2k)$$

Objective function (2a) contains two terms. The first term minimizes the travel time. The second term minimizes four components. The first two components represent the length of time window violation for an early or late arrival of nurse  $w$  for visit  $i$  on day  $d$ . The third and fourth components are the number of hours outside of the start or end time of a shift for nurse  $w$  on day  $d$ .

Constraints (2b) and (2c) ensure that each requested visit has exactly one predecessor and successor on a route, assuming there is a dummy origin and destination. This makes the route a closed loop. Constraints (2d) and (2e) calculate the number of hours a visit is completed outside of its time window. Constraints (2f) and (2g) compute the number of hours nurse  $w$  works overtime. Constraints (2h) prevent the model from creating subtours among the requested visit locations. Constraints (2i)–(2k) define the variables range.

## 4 Transportation services for patients

Transportation services for nonemergency medical appointments are of vital importance, especially to financially disadvantaged patients. In urban communities, a lot of poor patients cannot afford a car, and thus they have to rely on public transportation to keep medical appointments. However, public transportation is insufficient and inconvenient for people with ambulatory issues. As a result, clinics experience high cancelation/no-show rates. Moreover, many patients do not have the means to pick up their medicine after appointments, which makes their situation even worse. Good transportation services can significantly help patients to keep appointments and save operations costs of the clinic [4].

Unlike the problem described in Sections 2 and 3, offering transportation services for patients can hardly be integrated into one single optimization model but involves multiple problems such as the prediction of no-show rate, the decision on

transportation mode, and the assignment of transportation services. The remainder of this subsection introduces details of each problem.

#### **4.1 Prediction of no-show probability**

When designing transportation services for patients with nonemergency medical appointments, we first need to investigate the impact of transportation barriers on no-show, and predict the no-show probability assuming the transportation service is not available. This can be achieved by collecting patients' historical data, such as home address, transportation difficulty level, transportation mode, ambulatory issue, and travel time, whether they have chronic diseases, and whether they kept their appointments. Then, statistical analysis can be conducted to predict the no-show probability based on those factors, and verify whether the transportation barrier significantly impacts the no-show probability. Logistic regression models can be applied to predict the probability. This step shows whether providing transportation services is necessary, and recognizes the group of patients that need transportation services [5, 6].

#### **4.2 Decision on transportation mode**

Unlike regular urban transportation, transportation services for patients must be uniquely designed due to patients' weak physical conditions. Therefore, the transportation mode should meet the following requirements. First, the transportation mode should allow patients to either sit or stand. For example, it is improper to offer free bicycles to patients. Second, some patients have ambulatory issues, so the transportation mode must have enough capacity to hold wheelchairs. Third, some clinics or hospitals do not have bus stations nearby, so the transportation service should give patients a ride to their destination. Finally, the transportation mode should allow patients to receive service without long waiting, especially in areas of severe weather. Based on the above requirements, taxis and shuttle buses with short intervals are common transportation services provided for patients.

#### **4.3 Vehicle routing-based optimization problem**

The vehicle routing-based optimization problem is a crucial branch of transportation services if shuttle buses are offered. In a regular vehicle routing problem, vehicles depart from a depot, visit several locations and return to the depot. In a medical situation for patients, each vehicle starts from the clinic, visits several stops to pick up and drop off patients, and goes back to the clinic. In this optimization problem, we need to decide the number of vehicles, the route of each vehicle, and the vehicle's arrival time at each stop. With a rough estimation of the number of patients at each bus stop, we should also take vehicle capacity into consideration. Moreover, the shuttle interval and travel time must be restricted to an upper bound for the sake of patients' health conditions. The objective can be minimization of vehicles' fixed cost, travel cost, patients' waiting, or travel time. Examples of vehicle routing problem models can be found in Luo et al. [7] and Guo et al. [4].

### **5 Summary**

Operations research has been widely applied to healthcare by maximizing the benefits of all stakeholders with a limited amount of medical resources. In addition to

nurse scheduling, home healthcare delivery, and transportation services for patients, other problems such as operating room and surgeon assignment, inventory management of medical material, and healthcare project prioritization can also be addressed by mathematical models and algorithms.


Besides knowledge and skills in healthcare management, mathematics, and computer, expertise in other fields plays a crucial role in OR application. For example, topology and network theories are of vital importance in transportation design, and inventory techniques can significantly improve the order and storage decisions of medical material. The OR application to healthcare is a combination of mathematics, computer skills, medical knowledge, and a variety of interdisciplinary expertise.

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