ORIGINAL PAPER

INTRA-HOSPITAL PATIENT TRANSPORTATION SYSTEM PLANNING USING BI-LEVEL DECISION MODEL

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ABSTRACT. Background: The intra-hospital patient transportation is an important aspect of patient care. It is about the transfer of patients between different healthcare units in the hospital. Many tasks are required for transferring the patients from one to another unit depending on available resources and the needs of the patients, such as types of supporting equipment, transfer routes, and supporters. Limited and unprepared resources for transferring the patients, such as lack of supporting equipment and available supporters, may impact the patient treatment and service quality. Therefore, these resources should be managed effectively in order to minimize these impacts. The case study hospital located in Chiang Mai province, northern Thailand is currently encountering the problem in managing and planning the intra-hospital transportation process. Therefore, this research aimed to propose a mathematical model for planning the intra-hospital transportation system in this case study hospital.

Methods: Our research proposed a bi-level mathematical model to tackle the intra-hospital transportation planning problems. The system is represented by a deterministic model using integer linear programming. The first level of the mathematical model is for identifying the locations and setting them as transportation depots. The second level of the model is to optimize the number of resources used for intra-hospital patient transportation. The model was then validated by using two sets of instances via LINGO solver.

Results: This research proposed a bi-level mathematical model that could help to manage the intra-hospital transportation challenges in the case study hospital. Furthermore, the outcomes from the test with two instances were depots positioned at a set of feasible locations. The model was used to designate resources to each depot for the instance, such as wheelchairs, stretchers, oxygen tanks, and employees. In each case, the outcomes are dependent on varying service timings and demands.

Conclusion: This research used the deterministic mathematical model for planning the intra-hospital transportation system consisting of the location assignment and resource allocation. The model, in addition, can solve with the exact method. Consequently, we can ensure that the presented model can apply to real situations in further study.

Keywords: Intra-hospital transportation, Patient transportation, Bi-level decision model, Hospital logistics, Optimization

INTRODUCTION

The hospital is where many complicated healthcare operations are performed. It has a direct meaning that refers to the hospital we are familiar with, as well as an implied meaning that refers to all medical treatment institutions where there are roles in supporting the population's health. Hospital care is administered in both the private and public sectors and can be used as a health-care alternative for the people. To deliver the greatest service to customers, numerous challenges must be carefully considered. The logistics perspective is one of those many concerning issues. The diversity of logistic flow in the healthcare system, such as food, medicine, waste, equipment, medical test samples, and patients, has important responsibilities to play in supporting medical activities for providing service to patients. Patient transportation, especially, has a significant impact on the performance of the healthcare system. The continuous flow of healthcare services in any hospital depends on these logistic activities under their own distinct rules and complexities. Generally, we can divide hospital transportation into two categories: 1) inter-hospital, which is related to transportation from outside to the hospital, and 2) intra-hospital, which is

concerned with transportation between different services within the hospital. Intra-hospital transportation, which is the focus of this study, is a daily essential logistical activity that involves picking up and delivering patients between care units in the hospital. Transferring patients between healthcare units and service areas is the job of the transportation department in any hospital.

Intra-hospital transportation can be divided into two categories. First is the transferring of patients between departments, such as delivering a patient from an inpatient department to the medical diagnostic facility, returning a patient to the inpatient department, or transferring patients to another inpatient department. The second category of intra-hospital transportation is patient discharge, which refers to moving patients to locations unrelated to the medical treatment, such as pick-up and drop-off points. The patient transportation process starts when the medical personnel in the inpatient departments or clinics call the nearest patient transportation department when requiring transport. After someone makes a request, an employee at the transportation department requests information including the origin, destination, and type of vehicle. Next, they go with the equipment needed to pick up the patient at the requesting point then bring them to the destination. After ensuring that a patient arrives at their destination safely and is taken care of, the employee goes back to the original depot to prepare to receive the next job. Another situation is a service that is provided when a patient directly contacts the transportation department for assistance. An employee then transports the patient by the same method.

This case study hospital is a provincial hospital that provides healthcare services mainly for residents of Chiang Mai provinces, Thailand. There are complicated services for various types of patients arriving. Hence, there are a lot of transportation jobs daily that are determined by patient needs. The inpatient department is extremely busy because there are many patients awaiting admission. There are almost no empty beds in real-life situations. New patients are brought in as soon as a bed becomes available. Consequently, the speed of picking up a patient who is ready to be relocated has a high influence on the patient service system. The unavailability of patient transportation units due to issues such as taking too much time to reach a patient, lacking porters and equipment, or transport delay all lead to delayed treatment services, inconvenience, and dissatisfaction among the patients. It is critical to structure management efficiently so that the internal hospital transportation system is accessible with the least amount of difficulty. These concerns are often investigated to improve service quality.

Therefore, the objective of this study is to propose a model for planning intra-hospital transportation systems. It is in the field of internal healthcare logistics optimization. To specify the problem, we used mixed-integer programming. Appropriate models are the key to resolving the service quality issues that we are addressing. A bi-level mathematical decision model was developed to aid in making decisions in this planning problem. A numerical example was tested to validate the model via LINGO solver.

LITERATURE REVIEW

The application of Industrial Engineering (IE) tools in healthcare management studies has gotten a lot of attention for a long time. Boonmee and Kasemset [2019] surveyed the IE tools used to solve problems in the healthcare area, especially in Thailand. Operation research is one alternative approach by using a mathematical model to represent a real-life problem. One of the issues solved by this method was finding the best location to locate the facility. A location model is an underlying approach that has been applied to consideration on those. Daskin [2008] illustrates a taxonomy of those discrete location problems with the basic model formulation. The mixing of two goals into a single objective model that consisted of minimizing the number of facilities and minimizing the total distance of customers to facilities was applied to the facility location problem [Wayan Suletra et al. 2018]. A multi-level problem is another option used to solve multiple related problems within a study. There is a hierarchy of decisions in different stages in planning. Allocating depots to possible locations is considered in strategic level decisions [Fermín Cueto et al. 2021]. Application of the mixed-integer programming (MIP) model to integrating facility location problem on humanitarian

logistics aspect was presented by Boonmee and Kasemset [2020]. It can be applied in healthcare logistic terms. Furthermore, resource management in the healthcare system is another critical concern. Boonmee et al. [2021a] use a MIP model to schedule patients served in the service using mathematical models. For the logistics aspect, fleet size or vehicle planning is considered along with installing depots. The decision on optimal fleet composition for a depot supplying customer demands is a concern that is formulated and solved with MIP [Etemadi and Beasley 1983]. A bi-level decision-making concept has been mentioned in multiple level hierarchy problem-solving. Numerous management and optimization issues in the real world can be addressed by using multilevel decision-making tools. Lu et al. [2016] examined current multilevel decision-making strategies and methodically clustered techniques developments.

There are some previous studies that have attempted to solve intra-hospital transportation problems. Those studies applied many approaches that can facilitate the determinants of hospital performance. To disrupt the traditional organization, Naesens and Gelders [2009] show the advantages of developing a decentralized structure to replace the centralized patient transportation system. The simulation technique was applied by Phongthiya et al. [2021] to evaluate the intra-hospital patient transportation strategies in their case study hospital. The strategies that they proposed could help to reduce the transportation time and, accordingly, increase the number of completed jobs per staff. The mathematical model technique is also widely adopted to solve the patient transportation problem, for example, Bouabdallah et al. [2013] used the MIP to determine the stretchers service in order to minimize the moves of empty stretchers. Kuchera and Rohleder [2011] and Gopal [2016] used a computerized tool to manage and optimize the use of staff in patient transportation to reduce patient waiting times and, in turn, improve service quality and customer satisfaction. The MIP model was also used in a study by Séguin et al. [2019] to solve the problem of assigning the employees to a specific route without disrupting the current staff schedules to solve transportation problems in a large hospital. Additionally, Turan et al. [2011] applied the routing planning models for non-ambulant patient transportation.

In the model development process, model validation is an important step. Testing the method with a small-size example is recommended before putting it into practice for the real problem. It is necessary to examine the adequacy of given constraints and satisfy the problem objective. Gass [1983] has recommended a technique about model validity in the paper. Model validation with the instance is recommended before practicing the model on the real problem [Turan et al. 2011]. Experiment numerical examples are generated based on real-world circumstances to verify and validate the developed mathematical model before approaching real-world application [Kasemset et al. 2020, Boonmee et al. 2021b]. Table 1 presents the previous studies on intra-hospital transportation that applied the mathematical models. Most research works applied a single-level mixed-integer model for optimizing a single variable either staff or transporters.

Table 1: Previous studies in the scope of intra-hospital transportation

Publication	Modelling method	Focused issue
Bouabdallah et.al. [2013]	Single-level mixed-integer model	Determining the stretcher usage planning.
Kuchera and Rohlwder [2011]	Single-level mixed-integer model	Optimizing staff schedules.
Gopal [2016]	Single-level mixed-integer model	Optimizing staff schedules and simulation.
Séguin et al. [2019]	Single-level mixed-integer model	Assigning specific employees to routes.
Turan et al. [2011]	Weighted sum approach model	Evaluating the optimal number of assigned porters.

As mentioned above, we proposed the bi-level formulation that includes more intra-hospital components (i.e., staff, supporting equipment, transporters, routes, and depots). Our formulation is different from those in other existing studies because our solution can cover the most required components in intra-hospital transportation. Other hospitals that provide intra-hospital transportation similar to the case study of this research can apply the formulation of this study.

PROBLEM DESCRIPTION

It is important to understand the current hospital situation before making decisions. The hospital needs to restructure its current operation due to the high volume of requests and inadequate response time. The concept is to distribute the internal patient transportation service points over the hospital's area to facilitate the requests comprehensively with the shortest access time. The considered locations, which are possible to become transportation service points, are empty areas or old transportation points in the hospital. The service departments which request transportation, known as demand nodes, can be a clinical point, different inpatient department, or discharge point. For discharge points, it is not only discharging a patient but can also be for admission. We assume those points are the same as the requesting department in this study. Furthermore, each transportation service point, or depot, needs the resources to serve patients' transportation requests adequately. The patient transportation process in this study operates with wheelchairs, stretchers, portable oxygen tanks, and employees—referred to as porters.

In practice, we divide the problem model into two levels of decisions because of the convenience of the management: structure-level and operation-level. The transportation depot determination is a structure-level decision because it should not be updated frequently to avoid personnel confusion. Quick recognition of personnel at depot locations influences in-hospital operation convenience. It is therefore an independent decision. For fast and convenient patient transportation, the hospital can have more than one service point. Operation-level decisions aim to allocate resources effectively to each depot to achieve high-quality service and patient satisfaction. To ensure that resources are used as efficiently as possible, the resources in each depot can trade-off independently when having a re-decision on the patient demand change. Modifications at this level can be made simply without affecting the operations of other departments since there is no significant impact on the overall system if the number of resources increases or decreases.

MATHEMATICAL MODEL

In the bi-level mathematical model formulation, we assume that the first level is a long-term decision to choose the optimized transportation depots for the patient transport from a list of possible depots. The second level is a short-term decision. It is about allocating the patient transportation resources to each depot obtained from the first level; they must be sufficient to meet the patient's requirements. Deterministic mixed-integer programming is used to represent the problem.

Transport Depots

The first level is to find suitable locations to install a transportation service depot that is able to offer service covering the maximal transportation requirements of patient service departments. At this level, we are interested in identifying the minimum number of depots that can provide the conditions that must cover the patients' demands. Therefore, the discrete location problem approach is applied in solving this level. We looked for various locations in the hospital areas which had the potential to become a transportation depot. Then, we chose the best locations considering the constraints. In the model, we are interested in customer satisfaction, so it is necessary to consider the restricted time to reach a patient. In the real situation, the service points are not only located on the same level of ground but also on the different floors which can be accessed by elevators. Thus, we did not use distance to restrict the model.

Sets:

I Sets of patient service departments (demand nodes)

J Sets of possible locations

Parameters:

d_i Patient transportation requests at node $i \in I$

t_{ij} Travel time between possible location $j \in J$ and node $i \in I$

t_{max} Maximum acceptable travel time to a patient

l Minimum number of required depots

Decision Variables:

$$x_j = \begin{cases} 1, \text{ if depot located at possible location } j \in J \\ 0, \text{ otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1, \text{ if demand node } i \in I \text{ is assigned to depot located at } j \in J \\ 0, \text{ otherwise} \end{cases}$$

Objective:

$$minimize \sum_{j \in J} Mx_j + \sum_{j \in J} \sum_{i \in I} d_i t_{ij} y_{ij} \tag{1}$$

Subject to:

$$\sum_{j \in J} y_{ij} = 1 \quad , \forall i \in I \tag{2}$$

$$y_{ij} - x_j \leq 0 \quad , \forall i \in I, j \in J \tag{3}$$

$$t_{ij} y_{ij} - t_{max} \leq 0 \quad , \forall i \in I, j \in J \tag{4}$$

$$l - \sum_{j \in J} x_j \leq 0 \tag{5}$$

$$x_j, y_{ij} \in \{0,1\} \quad , \forall i \in I, j \in J \tag{6}$$

The objective function uses the sum of two terms. The first term is to minimize the number of depots located at the possible locations. M is a large number used to prioritize the first term. The second term is to minimize the total demand-weights time. Equation (2) ensures the patient transportation requirement from each service department is assigned to only one depot. Equation (3) assumes that the service required department is assigned to only an open depot. Equation (4) ensures the travel time to the assigned department cannot exceed the maximum acceptable travel time determined by the hospital service quality policy. The restrictions ensure that patients do not have to wait for too long. Equation (5) is the lower bound of the number of depots determined by the hospital's requirements. Lastly, Equation (6) specifies the decision variables to be binary integers. In this study, the depot setting cost is the same everywhere in the hospital, so it is insignificant to consider in the model.

Resources Allocation

After obtaining the optimal depot at the first level, the next decision is allocating resources to each depot to ensure that the hospital can provide services available to satisfy overall demand. This level considers the optimal number of resources of each category for each depot. The hospital has two types of vehicles: wheelchairs and stretchers. The employee will choose the type of equipment, depending on the ability to self-support of patients. In very severe cases, it is necessary to use an oxygen tank to help the patient. The portable oxygen tank has to be installed on a stretcher. Hence in this study, we group an oxygen tank and the required installing stretcher into one vehicle type. Because of patient safety regulations, it is assumed that each trip can only carry one patient. Furthermore, each trip must begin and end at the same station. This study introduces a model providing the minimum number of allocated resources.

Sets:

D Sets of depots from previous level decisions $D \subseteq J$

K Sets of transportation requests for each depot

V Sets of vehicle types

Parameters:

d_{kj}^v The request $k \in K$ with vehicle type $v \in V$ of depot $j \in D$

c^v Acquisition cost of each vehicle type $v \in V$

q Daily wage of an employee

q^o Overtime wage of an employee per minute

L_j Minimum number of employees at depot $j \in D$

A Length of work period a day in minutes

t_{kj} Average travel time of request $k \in K$ of depot $j \in D$

t_v Average service time of vehicle type $v \in V$

Average travel time, t_{kj}, begins when an employee walks with equipment from depot $j \in D$ to requesting department $i \in I$ following the request $k \in K$, leads the patient to the destination, then ends when the employee returning to the original depot. Each request $k \in K$ is travelling from $i \in I$ to each destination.

According to the assignment supporting demand node i by the depot j in the first level, they must start from the depot j for travelling k implicitly. Average service time, t_v, is time to service a patient in transportation processes except for the time required for oxygen tank set up time or waiting time for the patient to lay down on a stretcher.

Decision Variables:

n_j^v The number of vehicle types $v \in V$ are assigned to depot $j \in D$

e_j Employees are assigned to depot $j \in D$

h_j Overtime at depot $j \in D$

Objective:

$$minimize \sum_{v \in V} \sum_{j \in D} c^v n_j^v + \sum_{j \in D} q e_j + \sum_{j \in D} q^o h_j \tag{7}$$

Subject to:

$$\sum_{k \in K} d_{kj}^v (t_{kj} + t_v) - w_j A \leq 0 \quad , \forall j \in D, v \in V \tag{8}$$

$$\sum_{k \in K} \sum_{v \in V} d_{kj}^v (t_{kj} + t_v) - e_j A \leq h_j \quad , \forall j \in D \tag{9}$$

$$e_j - L_j \geq 0 \quad , \forall j \in D \tag{10}$$

$$n_j^v, e_j \in \mathbb{Z}, h_j \in \mathbb{R}^+ \quad , \forall j \in D, v \in V \tag{11}$$

With three terms, the goal function is to minimize the total operation cost. The total acquisition cost of each vehicle type is the first term. The second is the expense of recruiting an employee. The third term is the total overtime cost if there is a workload longer than the length of the work shift. Equation (8) determines the number of each vehicle type assigned to each depot to ensure it can support the sum of demands at each department under work time. It is a calculation of the goal number of resources based on possible round trips. Equation (9) ensures the demand can be met with the number of assigned employees. However, overtime is allowed. Equation (10) is the lower bound number of employees. Equation (11) forces the decision variables to be integers and positive numbers.

MODEL VALIDATION

This section explains how our model was validated. After we constructed the model and were satisfied, the next stage was to test the model's suitability for the physical system it represents. The model assumption, structure, parameters, and restrictions that are assigned in the model must undergo consistency testing to be able to ensure that the optimal solution can be found. The model testing was done by the LINGO solver. The two instances which were used to validate the model were generated. The size of the problem and the boundary instance used for testing are shown in Table 2.

Table 2: Testing instances

Situations	$|I|$	$|J|$	d_{kj}	d_{kj}^w	d_{kj}^s	d_{kj}^o	t_{ij}	t_{kj}	$|K_j|$
I	6	20	[6,28]	[0,10]	[0,7]	[0,3]	[7,15]	[13,33]	15
II	10	30	[10,40]	[0,13]	[0,8]	[0,2]	[3,16]	[7,39]	20

Results

All parameters were assigned a value to validate the model by using small numerical problem examples. The result of the first level selects located depot in 5 from 6 possible locations. In the first circumstance, one of the possible locations was not chosen to become the depot. For the second situation with changing demand and time, there is selecting located depot in 4 from 10 possible locations. According to a solution, those depots can cover demand in all demand nodes with those depots. The result of

model testing using example data illustrate (e.g., see Tab.3). The obtained solution from the LINGO solver is a global optimal solution.

Table 3: Testing results

Situations	Depot (j)	Wheelchairs	Stretchers	Oxygen tanks	Employees	Overtime
	1	4	4+1	1	12	0
	2	3	2+1	1	6	0
I	3	1	1+1	1	3	0
	5	1	1+1	1	2	0
	6	1	1+1	1	2	0
	3	3	3+1	1	8	0
II	4	5	3+1	1	11	0
	6	6	4+1	1	13	0
	9	4	2+1	1	8	0

Both levels of the model were able to operate to discover solutions based on the assumptions and limitations that have been established. The solutions show the number of resources required by each depot to serve patients in each situation efficiently. In practice, the number of stretchers not only comes from the stretchers variable but also must include the number of oxygen tanks variable because of the previous determination of grouping two pieces of equipment into one variable. The solutions were examined with the assumption and constraints. It was concluded that our models can represent the problems and be used to find optimal solutions.

CONCLUSION AND RECOMMENDATIONS

In the healthcare logistics aspect, this study considers a location and resource allocation problem. There is the application of a bi-level deterministic mathematical model to represent the problem of the actual scenario and obtain optimal operation planning. The first level is to optimize the number of internal transportation depots in as many locations as possible. The second level is the assignment of the number of each type of resource to each determined depot. The LINGO solver was used to find the optimal solutions for both levels. The aim of choosing this basic model is to make it easy to apply in a variety of situations conveniently. However, the demand and service time is not close to real-life situations. Future research based on this area should extend the model to represent the problem of uncertain demand and travel time using the stochastic model. Emergency patients should be

given the first priority to service. Thus, the order of urgency should be considered. The solutions may use other techniques that are efficient to implement in larger or more complex problems.

In hospitals, especially in some developing countries like Thailand, it is difficult to predict the number of patients because the patients can go to the hospitals anytime without appointments. This unpredictable situation leads to complications in providing healthcare services to the patients because there was an unbalance between the supply side that is limited (i.e., resources for intra-hospital transportations) and the demand side that are unplanned (i.e., number of patients). Therefore, it is crucial to find ways to manage and utilize the limited resources in order to service those unplanned number of patients. The mathematical model is thus often used for planning, managing, and optimizing the use of those resources. As discussed in this paper, our research has proposed the bi-level mathematical models that include as many as components/variables that should be considered to manage the intra-hospital patient transfer effectively – which is different from the existing studies that consider only one or two specific variables, as discussed in the literature review section.

Although our mathematical models could present many components/variables that need to be considered in order to manage the intra-hospital transfer process, we suggest that future studies that aim to apply or adapt our models or develop a new mathematical model based on our logic for the hospitals in other contexts, such as different sizes, wards, specialization, ownership,

or even in different countries, should consider the components/variables that are related or have the impact on their intra-hospital transfer process.

ACKNOWLEDGEMENTS

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