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A Two-Stage Stochastic Optimization Model Of Hospital Nursing Staff Management Problem

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***Abstract*— For inpatient hospital care, capacity management system requires information on beds and nursing staff capacity. This paper presents a capacity model under uncertainty that gives insight into required nursing staff capacity and opportunities to improve capacity utilization on a ward level. A capacity model is developed to calculate required nursing staff capacity. The uncertainty turns up on the availability schedule of staff and the number of patient.**

***Index Terms*—Capacity management, nursing-staff management, stochastic modeling.**

I. INTRODUCTION

Nowadays, for modern society, particularly who live in big city, such as, Medan city, the capital of North Sumatera province, Indonesia, the need to get health service is increasing from time to time. Obviously, one of the the main cause of this rise lies in the ageing populations who are putting heavy demands for health care. Eventhough the number of hospitals are getting more and more, still there are more and more people who seek health care from neighbour contries, such as, Malaysia and Sinagpore. Undoubtedly, the urgent need to tackle this situation is to improve health service performance in hospitals.

All operations related to the health service performance in hospitals are limited in terms of capacity. Therefore, in order to fulfill the patients' demand for health care, the hospitals management should have a planning and controlling the capacity of the operations [1-3].

In hospitals, capacity planning is concerned with making sure of balancing the quality of health care delivered with the cost of providing that care. Such planning involves predicting the quantity and particular attributes of resources required to deliver health care service at specified levels of cost and quality. The most fundamental measure of hospital capacity planning is the number of inpatient beds accordingly the number of doctors and the number of nurses. Hospital bed capacity decisions have traditionally been made based on target occupancy levels. Certain units in the hospital, such as, intensive care units (ICUs) are often run at much higher utilization levels because of their high costs.

For inpatient care facilities for most hospitals in Medan, this requires information on bed capacity and nursing staff capacity, on a daily as well as annual basis. Quantitative models can be used to calculate capacity needs for different planning purposes and for short, medium and long term planning issues. Although several useful models are described in the international literature [4-6] many of them are difficult to apply in practice because they require a great deal of data and clerical work [4].

To be able to apply capacity management in practice, models must fulfill different functions: "annual staff planning," "roster scheduling support," and "daily assignment of nurses to wards [7-8]." In addition, "strategic decisions" are sometimes mentioned as a separate planning level [6, 9, 10]. Models based on mathematical optimization techniques from operations research are generally focused on short-term scheduling [11, 12]. Models that do integrate different planning horizons (daily, periodical (1–2 months), and annual) are for example described by Abernathy *et al.* [9] and Wright *et al.* [12]. These models contain connected models for periodical staff planning and daily scheduling. However, models incorporating operational planning issues with tactical and strategic decisions or operational scheduling support with annual staff planning were not found in the literature.

In general, capacity models are aimed at calculating the number of nurses needed, whereas capacity management models should ideally also give insight into opportunities for improving capacity usage.

In reality there are uncertainty factor could turn up in the problem, such as, the availability schedule of staff and the number of patient. This paper addresses the capacity problems which have uncertainty parameters. The proposed model explicitly permits the incorporation of uncertain parameters. Most of the references concerning optimization problems in the presence of uncertainty come under the heading of stochastic programming. Two-stage stochastic programs with recourse typify a particularly important class of models. In such models, the objective function commonly corresponds to the minimization of expected costs or to the maximization of expected benefits (linear or nonlinear), although it can also refer to the expected value of the absolute or quadratic deviations of certain specific goals or the variance of the second-stage recourse function.

II. FRAMEWORK OF TWO-STAGE RECOURSE MODEL

In the following, the framework of two-stage stochastic integer programming model is briefly described. For detail, the reader is referred to van der Vlerk and Haneveld [13]. The

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stochastic integer linear programming model is expressed as follows:

$$\min\ c_x^T x + \sum_{s=1}^{S} \pi_s (q^T y^s) \quad (1)$$

$$\text{s.t.}\quad Ax = b \quad (2)$$

$$T^s x + W y^s = h^s \qquad s = 1,..,S \quad (3)$$

$$x, y^s \geq 0 \text{ and integer} \qquad s = 1,...,S \quad (4)$$

Equations (2) represent the first-stage model and (3) represent the second-stage model. x is the vector of first-stage decision variables which is scenario-independent. The optimal value of x is not conditional on the realization of the uncertain parameters. c_x is the vector of cost coefficient at the first-stage. A is the first-stage coefficient matrix and b is the corresponding right-hand-side vector. y is the vector of second-stage (recourse) decision variables. q is the vector of cost (recourse) coefficient matrix and h^s is the corresponding right-hand-side vector and T^s is the matrix that ties the two stages together where $s \in \Omega$ represents scenarios in future and π_s is the probability that scenario s occurs. In the second-stage model, the random constraint defined in (3), $h^s - T^s x$, is the goal constraint: violations of this are allowed, but the associated penalty cost, $q^T y$, will influence the choice of x. $q^T y$ is the recourse penalty cost or second-stage value function and $\sum_{s=1}^{S} \pi_s (q^T y^s)$ denotes the expected value of recourse penalty cost (second-stage value function).

III. DETERMINISTIC MODEL

First we formulate a deterministic model for the capacity nursing staff management problem.

We define notations to be used in the model

Decision variables

- DA_{ij} : Initial number of type j doctors in department i
- SA_{ij} : Initial number of type j nurses in department i
- SBA_{ij} : Initial number of type j nurse-aids in depertment i
- D_{ij} : Type j doctors added in department i
- S_{ij} : Type j nurses added to department i
- SB_{ij} : Type j nurse-aids added to department i
- TPA_i : Initial number of private beds in department i
- TUA_i : Initial number of common beds in department i
- TP_i : Number of private beds added to department i
- TU_i : Number of common beds added to department i
- TBP_i : Number of private beds used as common beds in department i

Parameters

- bd_{ij} : The cost of j type doctors in department i
- bs_{ij} : The cost of j type nurses in department i
- bsa_{ij} : The cost of j type nurse - aids in department i
- bt_i : The cost of operating private beds in department i
- bo_i : The cost of operating common beds in department i
- bw_i : Waiting cost for private beds in department i
- bwu_i : Waiting cost for common beds in department i
- α_{ij} : Percentage of type j doctors needed to department i
- β_{ij} : Percentage of type j nurses needed to department i
- γ_{ij} : Percentage of type j nurse-aids needed to department i
- δ_i : Percentage of private beds used as common beds in department i
- μ_i : Maximum beds can be added to department i
- ρ_i : Maximum fund available for department i

A. Objective Function

The objective of this problem is to minimize total operating cost which can expressed as

$$\begin{aligned}\text{Minimize} &\sum_{i=1}^{n}\sum_{j=1}^{m} bd_{ij}(DA_{ij}+D_{ij}) + \sum_{i=1}^{n}\sum_{j=1}^{m} bs_{ij}(SA_{ij}+S_{ij}) \\ &+ \sum_{i=1}^{n}\sum_{j=1}^{m} bsa_{ij}(SBA_{ij}+SB_{ij}) + \sum_{i=1}^{n} bt_i(TPA_i + TP_i - TBP_i) \\ &+ \sum_{i=1}^{n} bo_i(TUA_i + TU_i) + \sum_{i=1}^{n} bw_i(TPA_i + TP_i) \\ &+ \sum_{i=1}^{n} bwu_i(TUA_i + TU_i) \end{aligned} \quad (5)$$

B. Constraints:

$$\alpha_{ij}(TP_i + TU_i) \leq D_{ij}; i = 1,2,...,n; j = 1,2,...m \quad (6)$$

$$\beta_{ij}(TP_i + TU_i) \leq S_{ij}; i = 1,2,...n; j = 1,2,...,m \quad (7)$$

$$\gamma_{ij}(TP_i + TU_i) \leq SB_{ij}; i = 1,2,...n; j = 1,2,...m \quad (8)$$

$$\delta_{ij}(TU_i + TUA_i) \leq TBP_i; i = 1,2,...,n; j = 1,2,...,m \quad (9)$$

$$TP_i + TU_i \leq \mu_i; i = 1,2,...n \quad (10)$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} bd_{ij} D_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m} bs_{ij} S_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m} bsa_{ij} SB_{ij} + \sum_{i=1}^{n} bt_i TP_i + \sum_{i=1}^{n} bo_i TU_i \leq \rho_i; i = 1,2,...,n \quad (11)$$

$$DA_{ij}, S_{ij}, SB_{ij}, TBP_i, TP_i, TU_i \geq 0 \quad \text{and integer} \quad (12)$$

Constraint (6) expresses the percentage for adding beds cannot be greater that the number of each type of doctors added for each department. The same thing happens for nurses and nurse-aids needed for each type and department, expressed in constraints (7) and (8). Constraint (9) represents the number of private beds that can be used as common bed in each depertment. The number of beds that can be added for each department has an upper bound μ_i, expressed in (10) Budget available for each department is presented in (11).

The model is in the form of integer programming problem.

IV. STOCHASTIC PROGRAMMING MODEL

We add another notations.

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π_s : probability that scenario s will occur, with $s \in K$
K : set of scenario

In real situation the hospital management is not sure whether he/she should add some resources, in order the hospital can perform well. Therefore, the objective function is to minimize the overall costs together with the expectation costs for adding resources, such as, doctors, nurses, and beds. It is assumed that randon vector ω has finite support with probability $\pi_1, \ldots, \pi_s$. Therefore the uncertainties can be represented with scenario.

Minimize

$$\sum_{i=1}^{n}\sum_{j=1}^{m} bd_{ij}\, DA_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m} bs_{ij} SA_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{m} bsa_{ij} SBA_{ij} + \sum_{i=1}^{n} bt_i (TPA_i - TBP_i) + \sum_{i=1}^{n} bwu_i TUA_i + \sum_{i=1}^{n} bo_i TUA_i + \sum_{i=1}^{n} bw_i TPA_i + \sum_{s\in K}\pi_s \sum_{i=1}^{n}\sum_{j=1}^{m} bd_{ij} D_{ij} + \sum_{s\in K}\pi_s \sum_{i=1}^{n}\sum_{j=1}^{m} bs_{ij} S_{ij} + \sum_{s\in K}\pi_s \sum_{i=1}^{n}\sum_{j=1}^{m} bsa_{ij} SB_{ij} + \sum_{s\in K}\pi_s \sum_{i=1}^{n} bt_i TP_i + \sum_{s\in K}\pi_s \sum_{i=1}^{n} bwu_i TU_i + \sum_{s\in K}\pi_s \sum_{i=1}^{n} bo_i TU_i + \sum_{s\in K}\pi_s \sum_{i=1}^{n} bw_i TP_i \quad (13)$$

The constraints consist the anticipation if the uncertainties occur.

$$\alpha_{ij}(TP_i^s + TU_i^s) \le D_{ij}^s; i = 1,\ldots,n; j = 1,\ldots,m; s \in K \quad (14)$$

$$\beta_{ij}(TP_i^s + TU_i^s) \le S_{ij}^s; i = 1,\ldots,n; j = 1,\ldots,m; s \in K \quad (15)$$

$$\gamma_{ij}(TP_i^s + TU_i^s) \le SB_{ij}^s; i = 1,\ldots,n; j = 1,\ldots,m; s \in S \quad (16)$$

$$\delta_{ij}(TU_i^s + TUA_i^s) \le TBP_{ij}^s; i = 1,\ldots,n; j = 1,\ldots,m; s \in S \quad (17)$$

$$TP_i^s + TU_i^s \le \mu \quad ; i = 1,2,\ldots,n; s \in K \quad (18)$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} bd_{ij} D_{ij}^s + \sum_{i=1}^{n}\sum_{j=1}^{m} bs_{ij} S_{ij}^s + \sum_{i=1}^{n}\sum_{j=1}^{m} bsa_{ij} SB_{ij}^s + \sum_{i=1}^{n} bt_i TP_i^s + \sum_{i=1}^{n} bo_i TU_i^s \le \rho_i; i = 1,\ldots,n; s \in K \quad (19)$$

$$DA_{ij}, D_{ij}^s, S_{ij}^s\, SB_{ij}^s, TBP_{ij}^s\, TP_{ij}^s, TU_{ij}^s, TU, A_{ij}^s \ge 0 \text{ and integer } \forall i,j,s \quad (20)$$

The model is in deterministic form. This is a large scale integer programming problem which depend on the number of scenario generated.

V. FEASIBLE NEIGHBORHOOD HEURISTICS SEARCH

While a straightforward brand-and-bound approach could be adopted to solve the problem Eqs (13) – (20), for many classes of large-scale problems such a procedure would be prohibitively expensive in terms of total computing time. We have adopted the approach of examining a reduced problem in which most of the integer variables are held constant and only a small subset allowed varying in discrete steps.

This may be implemented within the structure of a program by marking all integer variables at their bounds at the continuous solution as nonbasic and solving a reduced problem with these maintained as nonbasic.

The procedurecan be summarized as follows:

Step 1 : Solve the problem ignoring integrality requirements.

Step 2 : Obtain a (sub-optimal) integer feasible solution, using heuristic rounding of the continuous solution.

Step 3 : Divide the set *I* of integer variables into the set I_1 at their bounds that were nonbasic at the continuous solution and the set I_2, $I = I_1 + I_2$.

Step 4 : Perform a search on the objective function, maintaining the variables in I_1 nonbasic and allowing only discrete changes in the values of the variables in I_2.

Step 5 : At the solution obtained in step 4, examine the reduced costs of the variables in I_1. If any should be released from their bounds, add them to set I_2 and repeat from step 4, otherwise terminate.

The above summary provides a framework for the development of specific strategies for particular classes of problems. For example, the heuristic rounding in step 2 can be adapted to suit the nature of the constraints, and step 5 may involve adding just one variable at a time to the set I_2.

At a practical level, implementation of the procedure requires the choice of some level of tolerance on the bounds on the variables and also their integer infeasibility. The search in step 4 is affected by such considerations, as a discrete step in a super basic integer variable may only occur if all of the basic integers remain within the specified tolerance of integer feasibility.

In general, unless the structure of the constraints maintains integer feasibility in the integer basic variables for discrete changes in the superbasic, the integers in the set I_2 must be made superbasic. This can always be achieved since it is assumed that a full set of slack variables is included in the problem.

VI. Conclusion

This paper presents a capacity nursing-staff management model under uncertainty. The result model would be a large scale integer problem, which depend on the number scenarios. We propose a feasible neigfhbourhood integer search for solving the integer model.

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