[Computers & Industrial Engineering 96 \(2016\) 192–200](http://dx.doi.org/10.1016/j.cie.2016.02.023)

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

An application of stochastic programming method for nurse scheduling problem in real word hospital

Mohsen Bagheri ^a, Ali Gholinejad Devin ^{a,}*, Azra Izanloo ^{b,}*

^aDepartment of Industrial Engineering, Sadjad University of Technology, Mashhad, Iran ^b Research and Education Department, Razavi Hospital, Mashhad, Iran

article info

Article history: Received 30 January 2015 Received in revised form 1 February 2016 Accepted 24 February 2016 Available online 14 March 2016

Keywords: Nurse scheduling Uncertainty Stochastic programming Sample average approximation Recourse action

ABSTRACT

Given its complexity and relevance in healthcare, the well-known Nurse Scheduling Problem (NSP) has been the subject of several researches and different approaches have been used for its solution. The importance of this problem comes from its critical role in healthcare processes as NSP assigns nurses to daily shifts while respecting both the preferences of the nurses and the objectives of hospital. Most models in NSP literature have dealt with this problem in a deterministic environment, while in the real-world applications of NSP, the vagueness of information about management objectives and nurse preferences are sources of uncertainties that need to be managed so as to provide a qualified schedule. In this study, we propose a stochastic optimization model for the Department of Heart Surgery in Razavi Hospital, which accounts for uncertainties in the demand and stay period of patients over time. Sample Average Approximation (SAA) method is used to obtain an optimal schedule for minimizing the regular and overtime assignment costs, with the numerical experiments demonstrating the convergence of statistical bounds and moderate sample size for a given numerical experiment. The results confirm the validity of the model.

2016 Elsevier Ltd. All rights reserved.

1. Introduction

The NSP is a well-known combinatorial optimization problem that has encouraged many researchers to develop exact and (meta-) heuristic approaches to obtain a qualified solution. The NSP involves constructing a schedule for nursing staff and assigning nurses to different shifts based on individual and system preferences within the framework of government regulations.

Given its various constraints, objectives and many possible combinations, NSP is a complex problem. In the NSP, the nurse manager creates a schedule based on nurse preferences and/or scheduling requirements. Here, the problem is finding a schedule that both supports the preferences of nurses and satisfies the individual and system preferences as well as government regulations.

Since there are a plethora of constraints and many possible solutions for NSP, different approaches such as optimization, artificial intelligence and heuristic and meta-heuristic approaches have been used to solve it. In the following, an overview of literature is presented.

* Corresponding authors.

In the early 1970s, [Warner \(1976\)](#page--1-0) presented a multiple-choice programming in which each nurse described a group of variables each of which serving as a possible schedule for that nurse in the planning horizon. [Millar and Kiragu \(1998\)](#page--1-0) provided a mathematical model for minimizing nurse assignment costs in both cyclic and non-cyclic types for NSP.

[Venkataraman and Brusco \(1996\)](#page--1-0) presented a mixed-integer liner programming for evaluating nurse preference and management regulations. [Ozkarahan \(1989\)](#page--1-0) proposed a flexible decision support system that sought to satisfy the preferences of both hospitals and nurses. [Jaumard Semet, and Vovor \(1998\)](#page--1-0) proposed a generic binary linear programming model for NSP with the aim of minimizing salary costs and maximizing both nurse preferences and team balance so as to satisfy the demand coverage constraints. [Klinz, Pferschy, and Schauer \(2007\)](#page--1-0) proposed two mathematical models to minimize the total number of work shifts. [Bard and](#page--1-0) [Purnomo \(2005\)](#page--1-0) offered an integer programming model for nurse assignment for both regular and pool nurses under different conditions to satisfy the demands stipulated in the planning horizon.

[Hattori, Ito, Ozono, and Shintani \(2005\)](#page--1-0) presented a nurse scheduling system based of Constraint Satisfaction Problem (CSP) with different levels of importance and subject to dynamic change. [Parr and Thompson \(2007\)](#page--1-0) used Sawing and Noising with simulated annealing in NSP to ensure the sufficiency of nurse demands

E-mail addresses: M_Bagheri@sadjad.ac.ir (M. Bagheri), Al.Gh130@sadjad.ac.ir (A. Gholinejad Devin), A.izanloo@yahoo.com (A. Izanloo).

in each shift. [Punnakitikashem, Rosenberger, and Buckley Behan](#page--1-0) [\(2008\)](#page--1-0) proposed a stochastic integer programming model for NSP to minimize the workload penalty on nurses and satisfy the expected demands in the planning horizon. [Fan et al. \(2013\)](#page--1-0) used binary integer linear programming to maximize nurse preferences and hospital regulations. [Li and Aickelin \(2004\)](#page--1-0) used the Bayesian optimization and classifier systems for NSP to minimize the total preference cost of nurses in the planning horizon.

[Topaloglu and Selim \(2007\)](#page--1-0) used a fuzzy goal programming model for NSP to measure uncertainty in an objective evaluation of hospital regulations and nurse preferences. [Topaloglu and](#page--1-0) [Selim \(2010\)](#page--1-0) proposed a multi-objective integer programming for NSP to both produce an equitable schedule for nurses and satisfy hospital management objectives. [Maenhout and Vanhoucke](#page--1-0) [\(2007\)](#page--1-0) presented a novel electromagnetism meta-heuristic technique for the NSP to minimize the total pattern penalty costs in the planning horizon. [Landa-silva and Le \(2008\)](#page--1-0) used a multiobjective approach to cope with real-world uncertainties in NSP. To do so, they used an evolutionary algorithm to achieve highquality non-dominated schedules.

[Tsai and Li \(2009\)](#page--1-0) presented a two-stage mathematical modeling approach for the NSP with respect to hospital management requirements, government regulations, and nurse preferences. [Ohki, Uneme, and Kawano \(2010\)](#page--1-0) used a new approach using cooperative genetic algorithm (CGA) to solve NSP. [Zhang, Hao, and](#page--1-0) [Huang \(2011\)](#page--1-0) proposed a hybrid Swarm-based optimization algorithm in hospital environments that incorporated genetic algorithm and variable neighborhood search to address highlyconstrained NSP with respect to hospital management requirements.

In [Table 1,](#page--1-0) a brief classification of models in literature is presented.

In the real-world applications of NSP, the vagueness surrounding the target values of management and nurse preferences are a source of uncertainties that need to be addressed to provide a high-quality schedule. For this purpose, the basic parameters such as the demand and patient-stay period are stochastic in nature and the distribution of these parameters is determined from historical data.

The rest of this article is organized as follows: in Section 2, the proposed optimization model for NSP is presented and the structure of the model is investigated. In Section [3](#page--1-0), the solution approach is introduced with a detailed description of SAA method. Numerical experiments are presented in Section [4](#page--1-0). Finally, concluding remarks are made in Section [5.](#page--1-0)

2. The model for nurse scheduling problem

In the following, the indices, parameters, variables and our mathematical model describes Stochastic Nurse Scheduling Problem (SNSP) (see [Table 2\)](#page--1-0).

MIN
$$
z = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} p_j x_{ijt} + \sum_{\xi \in B} \sum_{j=1}^{J} \sum_{t=1}^{T} \phi(\xi) O_j V_{jt}^{\xi}
$$

St :

$$
x_{i1t} = 1 \t i = 1, 2, t \in T_A \t (1)
$$

$$
x_{i2t} + x_{i3t} \leq 1 \qquad \forall i = 3, ..., I, t = 1, 2, ..., T
$$
 (2)

$$
x_{i3t} + x_{ij(t+1)} \leq 1 \qquad \forall i = 3, \ldots, I, \ t = 1, 2, \ldots, T, \ j = 1, \ldots, J \qquad (3)
$$

$$
\sum_{j=1}^2 \sum_{t=1}^T x_{ijt} + 2 \sum_{t=1}^T x_{i3t} \geqslant 26 \qquad i=1,2,\ldots, I \qquad \qquad (4)
$$

$$
Q_{jt}^{\xi} = Q - \sum_{w=1}^{j-1} \sum_{k=1}^{(Z_{j-w})^{\xi}} (p_{w,k,j-w})^{\xi} \qquad t = 1, 2, ..., T, j = 1, ..., J,
$$

$$
\xi = 1, 2, ..., B
$$
 (5)

$$
Z_{jt}^{\xi} \le Q_{jt}^{\xi} + (1 - h_{jt}^{\xi})M \qquad t = 1, 2, ..., T, j = 1, ..., J,\n\xi = 1, 2, ..., B
$$
\n(6)

$$
Z_{jt}^{\xi} > Q_{jt}^{\xi} - (1 - d_{jt}^{\xi})M \qquad t = 1, 2, ..., T, j = 1, ..., J, \xi = 1, 2, ..., B
$$
\n(7)

$$
d_{jt}^{\xi} + h_{jt}^{\xi} = 1 \qquad t = 1, 2, \dots, T, \ j = 1, \dots, J, \ \xi = 1, 2, \dots, B \tag{8}
$$

$$
A_{jt}^{\xi} = Z_{jt}^{\xi} h_{jt}^{\xi} + Q_{jt}^{\xi} d_{jt}^{\xi} \qquad t = 1, 2, ..., T, \ j = 1, ..., J, \ \xi = 1, 2, ..., B
$$
\n(9)

$$
T_{jt}^{\xi} = A_{jt}^{\xi} + \sum_{w=1}^{j-1} \sum_{k=1}^{(Z_{j-w})^{\xi}} (p_{w,k,j-w})^{\xi} \qquad t = 1, 2, ..., T, j = 1, ..., J,
$$

$$
\xi = 1, 2, ..., B
$$
 (10)

$$
R_{jt}^{\xi} = \beta^{-1} T_{jt}^{\xi} \qquad t = 1, 2, ..., T, \ j = 1, ..., J, \ \xi = 1, 2, ..., B \qquad (11)
$$

$$
R_{jt}^{\xi} > \sum_{i=1}^{I} x_{ijt} - (1 - f_{jt}^{\xi})M \qquad t = 1, 2, ..., T, \ j = 1, ..., J,
$$

$$
\xi = 1, 2, ..., B
$$
 (12)

$$
R_{jt}^{\xi} \leq \sum_{i=1}^{I} x_{ijt} + Mf_{jt}^{\xi} \qquad t = 1, 2, ..., T, \ j = 1, ..., J, \ \xi = 1, 2, ..., B
$$
\n(13)

$$
V_{jt}^{\xi} = \left(R_{jt}^{\xi} - \sum_{i=1}^{I} x_{ijt}\right) f_{jt}^{\xi} \qquad t = 1, 2, ..., T, j = 1, ..., J, \xi = 1, 2, ..., B
$$
\n(14)

$$
f_j^{\xi}, d_j^{\xi}, h_j^{\xi} \in (0, 1), M \text{ is a big number } j = 1, ..., J, \xi = 1, 2, ..., B
$$
\n(15)

The main objective of the model is to minimize the regular and overtime assignment costs. Let $\phi(\xi)$ be the corresponding probability of scenario $\xi = 1, 2, 3, \ldots, B$ and $\sum_{\xi \in B} \phi(\xi) = 1$. (1) Ensures that nurse 1 and 2 are assigned to shift one in allowed dates. According to hospital regulations, nurses 1 and 2 (head nurses) should be assigned to shift one (morning shift) in working days. In this hospital, no one is allowed to work on two consecutive afternoon and night shifts. (2) Applies this constraint. If a nurse is assigned to a night shift, he/she is not allowed to work in the following days. (3) Considers this limitation. (4) Shows that every nurse should work at least 26 shifts, knowing that shift 3 (night shift) has a double work load compared to shifts 1 and 2 (morning and afternoon shifts). (5) Shows how empty beds in shift j at date t can be calculated from total beds available and the number of patients that are present in shift *j* in date t . (6–9) calculate the number of accepted patients in shift j in date t considering the remaining capacity. (10) Shows the total number of patients present in shift *j* in date t . (11– 14) computes additional nurses in shift j in date t . For this purpose, if the number of available nurses is less than required, the number of overtime nurses will be a positive value, as calculated by (14).

In this research Z_{jt} and N_{kjt} are assumed to be uniformly (discretely) distributed: $Z_{jt} \sim DU[a, b]$ and $N_{kjt} \sim DU[c, d]$ for $k = 1, 2, 3, \ldots, Z_{it}, t = 1, 2, \ldots, T, j = 1, \ldots, 3.$

Download English Version:

<https://daneshyari.com/en/article/1133177>

Download Persian Version:

<https://daneshyari.com/article/1133177>

[Daneshyari.com](https://daneshyari.com)