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Artificial Bee Colony Algorithm for Solving Fuzzy Multi-Objective Bed Allocation Model

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Abstract

With the improvement of the medical services frameworks rivalry, hospitals face more and more challenges. In the interim, allotment of resource has a crucial influence on performing competitive benefits in a hospitals. To choose the suitable beds number is one of the most essential tasks in hospital administration. Anyway, in true condition, bed allotment choice is a multiple-side problem with weakness and haphazardness of the information available. It is so sophisticated. Therefore, the research about bed allotment difficulty is comparatively rare under considering multiple departments, nursing hours, and stochastic information about arrival and service of patients. In this paper, we improve a fuzzy multi-objective bed allotment pattern for defeating doubtfulness and various sections. Fuzzy objectives, and weights are at the same time used to assist the administrators to choose the appropriate beds about various departments. The suggested pattern uses Artificial Bee Colony (ABC), which is so efficient algorithm. The research portrays a use of the pattern in a public hospital in Iraq. The outcome has shown presented an appropriate system for bed allotment and ideal usage.

Keywords

Bed Allocation Problem; Fuzzy Logic; Artificial Bee Colony; Multi-Objective Optimization.

1. Introduction

Busy hospital systems continually provide new challenges to their managers and decision-makers because of high demands for service, high costs, limited budget and healthcare resources. Therefore, decision-makers are continuously studying productivity and competence of present hospital systems and must be able to evaluate the outcomes of any changes they make to these systems [1]. Hospitals today are encountered with several pressures as raising equipment prices, a lack of qualified healthcare specialists and restricted hospital facilities [2].

Generally, bed allocation problem involves the fixed number of beds assigned to the different medical and surgical specialties in a hospital. A proper bed allocation is important for cost-efficiency or productiveness of hospitals. Few beds appointed to a specialty may lead the customer to face units with unsuitable equipment and insufficient staff training. This would cause lower quality of care. Also, many beds increase cost by the lack of usage of resources [1].

Some studies concentrate on the bed allocation problem across various sections, medical specialties, or patients' type in a hospital. To save time and get the cost in an easy way [3], develop a mathematical model used in inventing admission policy for different types of patients [1]. Provide access to beds reallocations of services from time to time to reduce the expected increase. Their requirement predicting system utilizes an M/G/∞ model of queuing for rounding up total number of patient dynamics for every labor. The study accentuates the importance of predictions must create the foundation for analysis and receive conjecture by models of queuing for the aim of procedural plainness.

[4] Regarding the difficulty of allotting a beds number to various medical and surgical specialties in a hospital, taking into consideration that the making a timetable of medical routines changes above a week and that the requirement for various medical labors reveals quality of being seasonal. To make good decisions concerning the size of each unit, a period sequence pattern is improved by using continual census information. Correspondingly, to decide the frequency distribution connected with a hospital care units census [5−7], present an analytic access dependent upon an adjusted form of the Holt-Winters multiplicative quality of being seasonal predicting pattern.

Small number of studies, anyway, regard the difficulty of bed allocation as a problem with many objectives [8,9]. Present by a logical computer-imitation pattern that: there isn't controlling answer to the difficulty of bed-allocation, so showing the type of the difficulty which has many objectives [10−13]. Describe a GP pattern to examine the act of a Medical Assessment Unit (MAU) and look for answers for allotment of bed to patients with least possible postponement. It is hard to examine the systems act for best work flow because of the deterministic nature of the model built. Hence [14,15], present a simulation model which consider the factors in length of stay, number of beds, nurses and doctors in the MAU. Afterwards a GP model is applied to perform exchanging analysis, using the results from the imitation model. To help lowering postponements and increase the movement of patients, the hourly allotment plans of resources can be spread out within the MAU.

Recently, the bed allocation problem (BAP) has got expanding considerations. Types of mathematical models for BAP were created in the literature, including the benefits of queuing hypothesis are very common. In Refs. [2,16] the model of *M/PH/n* queues was recommended, where *M* symbolizes patient reaching under the influence of Poisson distribution (Markov arrivals), *PH* marks patient periods of stay (*LoS*) under the influence of period-type distribution, and *n* is the number of beds.

Lack in the number of beds or incorrect bed distribution can increase waiting times, patients' being in the wrong place and not trusting bed management [16,17]. Planning beds in an accurate way is important to satisfy patients' needs, arrange departments and develop the provided service as to quality and amount.

This paper presents the using of Artificial Bee Colony (ABC) which is an effective one in some public hospitals in Iraq to choose the suitable bed numbers and bed allocation taking into consideration number of departments, entire quantity of beds in the

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hospital, arrival times, service times and nursing hours.

This research introduces a fuzzy determination which is has many objectives and helping pattern dependent upon theory of queuing for allotment of beds in a general hospital. An assumption is that beds number influences the act of a section in the sense of (1) the approval chance when a recent patient reaches and (2) the work hours of nursing.

The objective of this research is to choose the suitable bed numbers and bed allocation which is a necessary task in hospital administration by using Artificial Bee Colony (ABC) especially in the general hospitals in Iraq to raise patient's permission ratio, nursing hours and service level.

The paper is organized as follows: Section (2) present a brief revision of fuzzy set theory and artificial bee colony. Section (3) present the proposed fuzzy model of bed allocation problem. The artificial bee colony to solve FMOBAP has been proffered in Section (4). On Section (5), the results and debate are added. Section (6) demonstrate the differences between fuzzy and non-fuzzy solutions. The inference of this study has been given in Section (7).

2. Fuzzy set theory and artificial bee colony algorithm

2.1. Fuzzy set theory

Fuzzy set theory (FST), initially recommended by Zadeh [18], is one of the best devices to manage the inaccuracy or ambiguity. Under many conditions, brittle data are insufficient to represent real world circumstances, because human opinions are usually ambiguous and cannot be guessed by an accurate numeral value. To deal with ambiguity of human idea, Zadeh [18] before all else announced the fuzzy logic theory, which was directed to the sensibleness of doubtfulness caused by imprecision or ambiguity. Hence a great contribution of FST (fuzzy set theory) is its skill or ability for symbolizing ambiguity.

The fundamental definitions and notations below will be used in every part of this paper.

Definition 1. Let X be a universe of discussion; A is a fuzzy subset of X if, for all $x \in X$, there is a number $\mu_A \in [0, 1]$ appointed to stand for the membership of x to A, and it is called the membership function of A.

Definition 2. When the (crisp) set of elements belong to the fuzzy set A, the degree of its membership function goes beyond the level α: $A_\alpha = [x \in X \mid \mu_A \geq \alpha]$.

Definition 3. $(x) = (f_1,\ldots,f_m)$ are the objective functions and $G(x)$ are the system constraints. $f_i^*(x)$, $i = 1 \ldots$, is the optimal goal value to the objective.

Definition 4. (fuzzy decision). A fuzzy decision is defined in a parallelism to non-fuzzy conditions "as the choice of activities which at the same time fulfill objective functions and restrictions." In fuzzy set theory the intersection of sets usually matches to the logical "and "The "decision" in a fuzzy environment can therefore be observed as the intersection of fuzzy restrictions and fuzzy objective functions [19]. The objectives and restrictions are normally not equally important and have different weights in the multi objective fuzzy decision [20]. In many cases, the decision-maker cannot exactly determine his relative weights. Therefore, the weights are supposed to be fuzzy numbers with either triangular or trapezoidal membership functions.

2.2. Artificial bee colony

The artificial bee colony (ABC) algorithm, which is a multitude based on collecting of information maximum production algorithm, was presented in (2007) by Karaboga for numerical duty maximum production by imitating the forging behavior of bee colonies [21]. The head steps of ABC algorithm can be depicted as explained below.

- Initialization.
- Repeat.
- Occupied bee phase: appoint the occupied bees on the origins of food in the memory.
- Observer bee phase: appoint the observer bees on the origins of food in the memory.
- Seeker bee phase: dispatch the seeker bees to the investigation area for finding out recent food conditions.
- Up to the time which (requirements are fulfilled).

In the artificial bee colony algorithm, the colony comprises of three sorts of honey bees: occupied bees, observer bees and seeker bees. One part of the colony is occupied bees, and the other part is observer bees. The occupied bees examine the nourishment origin and produce the data of the nourishment origin to the observer bees. The observer bees select a nourishment origin to take advantage of dependent upon the information received from the occupied bees. The seeker bee that belongs to the occupied bees which nourishment origin are rejected discovers a new nourishment origin accidently. The place of a nourishment origin is a reasonable answer to the maximum production difficulty. Symbolize the nourishment origin number as *SN*, the location of the *i*th nourishment origin as x_i for each $i = 1, \ldots, SN$, which is a *D* dimensional vector [14,22].

In the ABC algorithm, the *i*th fitness value *i fit* for a reduction difficulty is specified as [23]:

$$f_i t_i = \begin{cases} \dfrac{1}{1+f_i} & if \quad f_i \geq 0 \\ 1 + abc(f_i) & if \quad f_i < 0 \end{cases} \tag{1}$$

Where f_i is the cost value of the *i*th solution. The possibility that food origin being chosen by an observer bee is given by:

$$p_i = \frac{f_i t_i}{\sum_{i=1}^{SN} f_i t_i} \tag{2}$$

An applicant answer from the previous one can be created as:

$$v_{ij} = x_{ij} + \Phi_{ij}\left(x_{ij} - x_{kj}\right) \tag{3}$$

where $k \in \{1, 2, \ldots, SN\}$, $k \neq i$ $\cdots$and $j \in \{1, 2, \ldots, D\}$ are accidentally chosen points out, $\Phi_{ij} \in [-1, 1]$ is a without variation distributed accidental number. The applicant answer is contrasted by the previous one, and the superior answer must be kept [14]. In case of rejected nourishment origin is x_i, the seeker bee takes advantage a recent nourishment origin depending on:

$$x_{ij} = x_{min,j} + rand(0,1)\left(x_{max,j} - x_{min,j}\right) \tag{4}$$

where $x_{max,\mathrm{j}}$ and $x_{min,\mathrm{j}}$ are the higher and less advanced limits of the *j*th measure of the difficulty's investigation space [23].

3. The fuzzy model of BAP

3.1. A multiobjective BAP model

In this study, the model contains two objective functions and three constraints. The sets of objectives and constraints are given below.

According to Gorunescu et al. [2], the BAP model is defined as a *M/PH/n* queue. In the hospital there are *n* beds and *D* departments. For each department *i*, $i = 1, 2, \ldots$, D. n_i is a symbol for beds number, λ_i is a symbol for the Poisson reaching ratio, and μ_i is a symbol for the average of length of stay which is estimated by the Phase-type allotment. We conclude that the average arrivals number through the period of stay is $\lambda_i \mu_i$. Therefore. In Eq. (5) the probability P_i that some appearances are wasted due to n_i beds are filled depending on Erlang's loss formula.

$$p_i = \left[\frac{(\lambda_i \mu_i)_i^{n}}{n_i!}\right] \Big/ \sum_{j=0}^{n_i} \left[\frac{(\lambda_i \mu_i)_j}{j!}\right] \tag{5}$$

where phases of the service time number is defined as *j*. Therefore, we infer the entrance ratio of patient in department *i* as.

$$Pa_i = 1 - P_i \tag{6}$$

The total nursing hours in department *i,* can be represented by Eq. (7):

$$Fn_i = ts_i \times n_i \tag{7}$$

where ts_i is nursing hours for each bed in department *i*. The pattern restriction set (8)−(10) is displayed under. The constraint (8) makes certain that the entire beds number (*N*) is equal to the amount of beds in every department. The second constraint makes certain that the entire nursing hours between H and L, where H is highest hour of nursing with most additional time and L is lowest hour of nursing with the least additional time. The ultimate constraint makes certain that there is no department without beds.

$$\sum_{i=1}^{D} n_i = N \tag{8}$$

$$L \leq \sum_{i=1}^{D} Fn_i \leq H \tag{9}$$

$$n_i > 0, \; i = 1, 2, \ldots, D \tag{10}$$

3.2. A fuzzy multiobjective BAP model

Suppose that the administrators want to arrive some ambition degree which is not explicitly defined instead of actually intending to reach the actual maximum or minimum of the objective. Objective that makes the resolution turn into fuzzy programming. The corresponding not explicit one objective model for the FMOBAP. That procedure sequence, which has been adapted depending on BAP case, is depicted as follows.

Step 1. Build the fuzzy model of BAP invention difficulty depending on the criteria and restrictions of the administrators.

Step 2. Decide the less advanced limit and higher limit of ambition degree (DM's aim) for each purpose.

Step 3. For the objective functions and fuzzy constraints, find the fellowship or total number of members.

Step 4. Express in formula the corresponding brittle model of the fuzzy optimization.

Step 5. Find the answer to the brittle example by using algorithm of ABC to find the perfect or best answer n*.Concerning the previous steps, fuzzy multi-objective bed allocation problem formula (FMOBAP) can be depicted as follows.

Step 1. If the administrators or decision makers (DM) has a fuzzy aim such as the objective function should be considerably equal to or less than some ambition degree, then the FMOBAP can be expressed in a formula as expressed in the coming section.

find $n_i^* = [n_1, n_2, n_3, \ldots, n_D]$

$$\widetilde{Pa_i} = 1 - Pa \gtrsim Pa_i^*,\ i = 1, 2, \ldots, D$$

$$\widetilde{Fn_i} = ts_i \times n_i \gtrsim Fn_i^*,\ i = 1, 2, \ldots, D$$

s.t

$$\sum_{i=1}^{D} n_i = N$$

$$L \leq \sum_{i=1}^{D} Fn_i \leq H$$

$$n_i > 0,\ i = 1, 2, 3, \ldots, D \tag{11}$$

where $\widetilde{Pa_i}$ and $\widetilde{Fn_i}$ are ambition level that a administrators want to fulfill. The symbol "$\gtrsim$" in the objective function shows fuzzy inequality which has the lingual explanation "essentially bigger than or equal".

Step 2. Suppose that (Pa_i^0, Fn_i^0) and (Pa_i^1, Fn_i^1), are the values of the objective function $(Pa_i,\ Fn_i)$ such that 0 or 1 is the degree of fellowship function, relatively. Those values can be earned by either a multi-objective solution as one objective problem or a recovery from historical data (DM's experience).

Step 3. The fellowship function for Pa_i and Fn_i are described as Eq. (12), Eq. (13) respectively, using non-increasing linear function

$$\mu Pa_i(n) = \begin{cases} 0, & \text{if } Pa(n) \geq Pa_i^1 \\ 1 - \dfrac{Pa_i^1 - Pa_i(n)}{Pa_i^1 - Pa_i^0}, & \text{if } Pa_i^0 \geq Pa(n) \geq Pa_i^1,\ i = 1, 2, \ldots, D \\ 1, & \text{if } Pa_i(n) \leq Pa_i^0 \end{cases} \tag{12}$$

$$\mu Fn_i(n) = \begin{cases} 0, & \text{if } Fn(n) \geq Fn_i^1 \\ 1 - \dfrac{Fn_i^1 - Fn_i(n)}{Fn_i^1 - Fn_i^0}, & \text{if } Fn_i^0 \geq Fn(n) \geq Fn_i^1,\ i = 1, 2, \ldots, D \\ 1, & \text{if } Fn_i(n) \leq Fn_i^0 \end{cases} \tag{13}$$

Step 4. Taking into account that the fuzzy aims and fuzzy restrictions are dealt with equivalently which suggests that all determination criteria have identical importance. The equivalent brittle one objective programming for Eq. (11) can be depicted as explained in the following:

$$max\ \lambda = \min\{\mu Pa_i(n),\ \mu Fn_i(n)\}$$

$$\mu Pa_i(n) \leq \frac{Pa_i^1 - Pa_i(n)}{Pa_i^1 - Pa_i^0}$$

$$\mu Fn_i(n) \leq \frac{Fn_i^1 - Fn_i(n)}{Fn_i^1 - Fn_i^0}$$

$$\sum_{i=1}^{D} n_i = N$$

$$L \leq \sum_{i=1}^{D} Fn_i \leq H$$

$$n_i > 0,\ i = 1,2,3,\ldots,D \tag{14}$$

Step 5. The final step is to find a solution to the equivalent brittle model by using ABC algorithm (see Section (4)).

4. Using ABC algorithm for solving FMOBAP

In this study, the BAP has two objectives, namely patient admission rate and nursing hours, to optimize. Main activities that describe our altered ABC are illustrated as follows.

4.1. Input information

For the fuzzy multi-objective bed allocation problem, the software implemented takes into consideration as much parameters as possible found in actual hospital environments:

- aspiration level for every objective function.
- number of departments *D*.
- entire quantity of beds in the hospital N.
- arrival times (λ).
- service times (μ).
- nursing hours (*ts*).
- The upper limit (*H*) and lower limit (*L*) of the nursing hours.

4.2. Encoding

For FMOBAP, only one parameter is involved which represent the number of beds n_i in each department *i*. For a BAP with *D* departments, each food source is encoded as $[n_1, \ldots, n_i, \ldots, n_D]$.

4.3. Initial population

The ABC algorithm begins the investigation by creating a population of applicant explanations. In our implementation, this population is randomly generated according to the uniform distributions. First of all, we generate a random value (*Ri*) for each department *i* from uniform distribution *U* [*0,1*]. Then calculating the number of beds in each department by using Eq. (15), Eq. (16) respectively.

$$n_i = round\left(\left[\frac{R_i}{\sum_{j=1}^{D} R_j}\right] \times N\right),\ i = 1,2,\ldots,D-1 \tag{15}$$

$$n_i = N - \sum_{j=1}^{D-1} n_j\ ,\ i = D \tag{16}$$

4.4. Chromosomes evaluation

The aim of Eq. (12) is to make most of the weighted additive of fellowship role of objectives. Assuming DM's have equal importance, the suitability function for ABC may be recorded as the following.

$$\text{functionz} = \text{f(n)}$$

$$\mu_{Pa}(n) = min\{\mu_{Pai}(n)\}$$

$$\mu_{Fn}(n) = min\{\mu_{Fni}(n)\}$$

$$g(n) = \ldots$$

$$z = min(\mu_{Pa}(n),\ \mu_{Fn}(n) + g(n)$$

end.

4.5. Search mechanism

In algorithm of ABC, the occupied bee phase stands for the investigation algorithm capability, and the observer bee phase stands for the selfish use capability of the algorithm.

In employee bee stage, each bee X_i generates a new candidate solution V_i in the neighborhood of its present position as equation below:

$$V_{ij} = round\left(X_{ij} + a_{ij}\left(X_{Kj} - X_{ij}\right)\right) \quad (17)$$

Where $i,k \in \{1,2, \ldots, SN\}$ is an accidental chosen index which is different from $j \in \{1, 2, \ldots, D\}$ is an accidental chosen index, $a_{ij} \in (0,1)$ is without variation distributed accidental number.

After all employed bees finish the investigation process; they have in common the knowledge of their food origins with the observer bees through swinging dances. An observer bee appraises the nectar information taken from all employed bees and selects a food origin with a likelihood connected to its nectar quantity. This probable choice is really a gambling choice mechanism which is depicted as Eq. (2).

The onlooker bee stage includes adding and subtracting one bed to different random locations in the source food.

If a viewpoint cannot be made better over a defined beforehand number (called limit) of cycles, then the food origin is rejected. Suppose that the rejected origin is *Xi*, and then the scout bee finds out a new food origin to be substituted using Eq. (15), Eq. (16) relatively. The function of Scout bee is to keep the difference of the population so that to hinder too fast convergence of the algorithm.

4.6. Stopping conditions

There are no universal stopping conditions accepted for ABC algorithm. In this paper, we clearly stop our algorithm after a given number of repetitions (*Ng*).

5. Results and discussions

In this section, a real life bed allocation problem is presented. For confidential reason, the name of the hospital concerned is not mentioned. The hospital has 7 departments and 202 beds. The maximum and minimum hour of nursing with overtime are 200 h and 150 h respectively. The Poisson arrival rate, the mean of length of stay and nursing hours for each bed are shown in Table 1. The parameters for ABC algorithm after many experiments were a limit parameter equal to 30; the number of iterations $N_g = 500$; the number of population is 100.

To evaluate, the FMOBAP model will be used to find a solution to the hospital problem. Firstly, the fewer and higher limit of ambition level for all purposes must be clarified. The values of Z_i^0 and Z_i^1 are shown in Table 2. It is essential to recognize that the ambition level should be logical values to keep away from unpractical solution.

Table 1
Arrival rate, the mean of LOS and nursing hours for each bed.

I	Department	λ_i	μ_i	ts_i (h)
1	General Surgery 1	18.115	10.3462	1.2
2	General Surgery 2	18.192	10.3846	1.15
3	General Surgery 3	18.538	12.156	1.25
4	Urology Surgery	19.153	9.8077	0.65
5	Fascia Surgery	4.461	2.1923	0.9
6	Orthopedics	7.961	3.5385	0.55
7	ENT	18	11.1538	0.6

Having substituted the parameter values into Eq. (14). The fuzzy multi-objective model for the BAP is acquired as explained in the coming section:

$$max\ \lambda = \min\{\mu Pa_i(n),\ \mu Fn_i(n)\}$$

$$\mu Pa_i(n) \le 1 - \frac{Pa_i^1 - Pa_i(n)}{Pa_i^1 - Pa_i^0}$$

$$\mu Fn_i(n) \le 1 - \frac{Fn_i^1 - Fn_i(n)}{Fn_i^1 - Fn_i^0}$$

$$\sum_{i=1}^{7} n_i = 202$$

$$120 \le \sum_{i=1}^{7} Fn_i \le 230$$

$$n_i > 0,\ i = 1,2,3,\ldots,7 \quad (18)$$

As the population size is set as 100, 100 solutions are generated by the ABC algorithm to find the best solution. The degree fulfillment and attainment level of aims for the optimum explanation are acquired as shown below.

$\mu Pa_1(n) = 0.66$, $\mu Pa_2(n) = 0.64$, $\mu Pa_3(n) = 0.28$.

$\mu Pa_4(n) = 0.45$, $\mu Pa_5(n) = 0.97$, $\mu Pa_6(n) = 1$, $\mu Pa_7(n) = 0.41$.

$\mu Fn_1(n) = 0.93$, $\mu Fn_2(n) = 0.87$, $\mu Fn_3(n) = 0.76$.

Table 2
The fewer and higher limit of ambition level.

i	Pa_i^0	Pa_i^1	Fn_i^0	Fn_i^1
1	43%	100%	20	50
2	41%	100%	20	50
3	42%	100%	19	50
4	43%	100%	15	30
5	67%	100%	4	20
6	72%	100%	5	20
7	40%	100%	15	30

$\mu Fn_4(n) = 0.47$, $\mu Fn_5(n) = 0.14$, $\mu Fn_6(n) = 0.14$, $\mu Fn_7(n) = 0.36$ (see Fig. 1).

We compare our solution with the earlier allotment determination of their hospital. As revealed in Table 3, n is the beds number allotted for each department, Pa is the entrance permission ratio, and Fn is the nursing hours. In addition, Fig. 2, explains the alterations in act of the patient entrance permission ratio in every department, at the same time Fig. 3, shows the alterations in act of the nursing hours in every department. The benefits of the allotment determination created by ABC are summed up as follows.

The fuzzy model and ABC algorithm balance the resource rivalry between various departments. The acting productivity and degree of administration in the hospital are improved. In the earlier allotment determination, section 6 has the greatest entrance permission ratio about 100% and section 3 has the least entrance permission ratio about 54.80%. In comparison, in the new allotment the greatest entrance permission ratio is 100% in department 6 and the lowest admission rate is 58.08% in section 7. Therefore, in the new allotment, determinations, not only the entrance permission ratios are stable, but also the least entrance permission ratios are notably made better. Almost, resemble outcomes are also informed in nursing hours. As can be noticed, the greatest nursing hours is 40 h in the previous situation, 48 in the new situation.

From an extensive perspective, the general patient entrance permission ratio and nursing hours are grown from 73.01% to 181.8 to 78.48% and 192.45 correspondingly.

Table 3
Comparison between the new and previous allocation decisions.

Dept.	Previous			New		
	N	Pa	Fn	N	Pa	Fn
1	32	66.34%	38.40	40	80.68%	48.00
2	32	64.36%	36.80	40	78.57%	46.00
3	32	54.80%	40.00	34	58.08%	42.50
4	32	64.68%	20.80	34	68.40%	22.10
5	10	99.98%	9.00	7	99.10%	6.30
6	32	100%	17.60	13	100%	7.15
7	32	60.94%	19.20	34	64.51%	20.40
Total	202	73.01%	181.80	202	78.48%	192.45

6. Comparison fuzzy and non-fuzzy solution

The bed allocation objective function and its restrictions can be define as:

$$min\ z = -\left(\sum_{i=1}^{7} c_i * Pa_i(n) + \sum_{i=1}^{7} c_i * Fn_i(n)\right) \tag{19}$$

$$min\ z = -\left(\sum_{i=1}^{7} c_i * \frac{Pa_i(n)}{Pa_i^{max}} + \sum_{i=1}^{7} c_i * \frac{Fn_i(n)}{Fn_i^{max}}\right) \tag{20}$$

Where, Pa_i^{max} *and* Fn_i^{max} is the highest importance of parallel targets which are prized from pre-processing Step (warm-up time) in ABC algorithm series.

As an ultimate outcome, the comparison of act criteria between fuzzy and non-fuzzy explanation for the given hospital scenario is presented by Table 4. The fuzzy solution comparing with non-fuzzy solution showed an improvement in admission rate of patient and nursing hours from 75.45% to 186.95 h to 78.48% and 192.45 h, relatively. It appears to be that *FMOBAP*

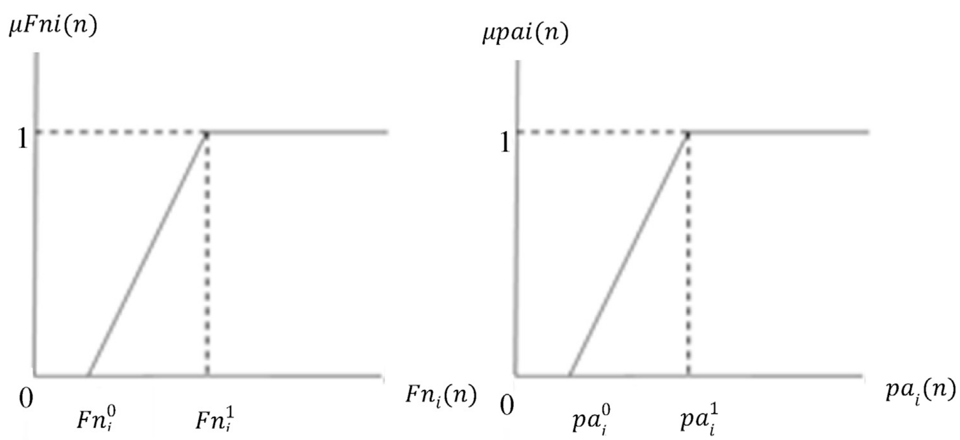

Fig. 1. Membership function for fuzzy objectives.

Fig. 2. Comparisons of patient admission rates.

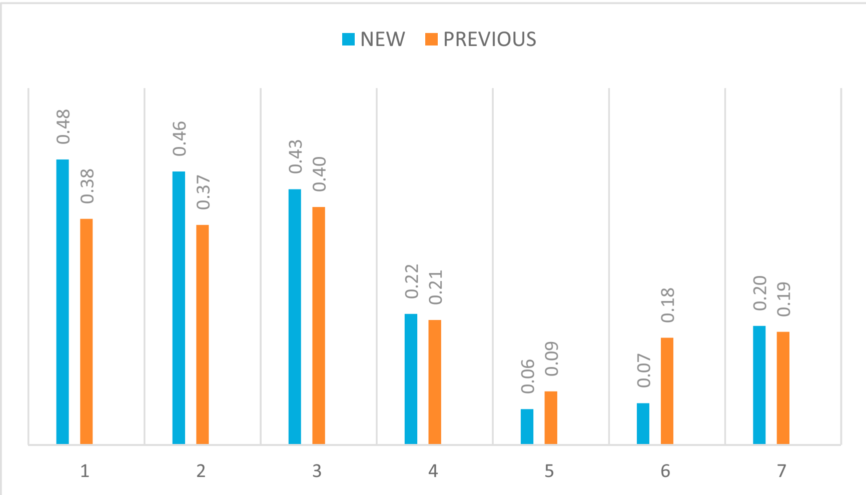

Fig. 3. Comparisons of nursing hours.

Table 4
The comparison between fuzzy and non-fuzzy solution.

Dept.	Non-Fuzzy Sol.			Fuzzy Sol.		
	N	Pa	Fn	N	Pa	Fn
1	30	62.48%	36	40	80.68%	48.00
2	36	71.68%	41.4	40	78.57%	46.00
3	37	62.94%	46.25	34	58.08%	42.50
4	33	66.55%	21.45	34	68.40%	22.10
5	11	100%	9.9	7	99.10%	6.30
6	21	100%	11.55	13	100%	7.15
7	34	64.51%	20.4	34	64.51%	20.40
Total	202	75.45%	186.95	202	78.48%	192.45

model can efficiently directed when the beds should be exchanged, what quantity it is demanded and at which department must be added.

7. Conclusions

This paper proposes a fuzzy multiobjective decision aiding model based on queuing theory for BAP in a hospital. The Artificial Bee Colony (ABC) is used to optimize the proposed model. Solved by ABC, the beds in 202-general hospital in Iraq, is reappropriated. Imitation results explain that resource rivalry between various departments is more stable and the general patient entrance permission ratio and nursing hours in the hospital are both raised. Therefore, the level of service and the resource use in the hospital are made better at the same time.

References

[1] E.P.C. Kao, G.G. Tung, Bed allocation in a public health care delivery system, Manag. Sci. 27 (5) (1981) 507−520.
[2] F. Gorunescu, S.I. McClean, P.H. Millard, A queuing model for bed-occupancy management and planning of hospitals, J. Oper. Res. Soc. 53 (I) (2002) 19−24, https://doi.org/10.1057/palgrave/jors/2601244.
[3] A. Esogbue, A. Singh, A stochastic model for an optimal priority bed distribution problem in a hospital ward, Oper. Res. 24 (5) (1976) 884−898, https://doi.org/10.1287/opre.24.5.884.
[4] S. Lapierre, D. Goldsman, R. Cochran, J. Dubow, Bed allocation techniques based on census data, Soc. Econ. Plan Sci. 33 (1999) 25−38.
[5] M. Cote, A note on bed allocation techniques based on census data, Soc. Econ. Plan Sci. 39 (2005) 183−192, https://doi.org/10.1016/j.seps.2004.01.006.
[6] G. Chryssolouris, K. Dicke, M. Lee, On the resources allocation problem, Int. J. Prod. Res. 30 (2007) 2773−2795, https://doi.org/10.1080/00207549208948190.
[7] X.D. Li, P. Beullens, D. Jones, M. Tamiz, Optimal Bed Allocation in Hospitals, Lecture Notes in Economics and Mathematical Systems, vol. 618, Springer, 2009, pp. 253−265.
[8] S.C. Kim, I. Horowitz, K.K. Young, T.A. Buckley, Flexible bed allocation and performance in the intensive care unit, J. Oper. Manag. 18 (4) (2000) 427−443.
[9] L. Luo, L. Li, X. Xu, W. Shen, L. Xaio, A data-driven hybrid three-stage framework for hospital bed allocation: a case study in a large tertiary hospital in China, computational and math, Methods Med. (2019) 1−12, https://doi.org/10.1155/2019/7370231.
[10] J. Oddoye, M. Tamiz, D. Jones, P. Schmidt, A Simulation Model for Health Planning in a Medical Assessment Unit with Multi-Objective Output Analysis, University of Portsmouth, UK, 2007. Technical report, Management Mathematics Group.
[11] Z.F. Antmen, S.N. Oğulata, The capacity planning of intensive care units via simulation: a case study in university hospital, Int. J. Appl. Math. Stat. 51 (2013) 214−235.
[12] S.M. Ballard, M.E. Kuhl, The use of simulation to determine maximum capacity in the surgical suite operating room, in: Proceedings - Winter Simulation Conference 7, 2006, pp. 433−438, https://doi.org/10.1109/WSC.2006.323112.
[13] H.R. Feili, Improving the health care systems performance by simulation optimization, J. Math. Comput. Sci. 7 (2013) 73−79, https://doi.org/10.22436/jmcs.07.01.08.
[14] J. Oddoye, M. Yaghoobi, M. Tamiz, D. Jones, P. Schmidt, A multi-objective model determine efficient resource levels in a medical assessment unit, J. Oper. Res. Soc. 58 (2007) 1563−1573.
[15] J. Nguyen, P. Six, D. Antonioli, P. Glemain, G. Potel, P. Lombrail, P. Le Beux, A simple method to optimize hospital beds capacity, Int. J. Med. Inform. 74 (I) (2005) 39−49.
[16] F. Gorunescu, S.I. McClean, P.H. Millard, Using a queueing model to help plan bed allocation in a department of geriatric medicine, Health Care Manag. Sci. 5 (4) (2002) 307−312, https://doi.org/10.1023/A:1020342509099.
[17] M.D. Muynck, H. Bruneel, S. Wittevrongel, Analysis of a discrete-time queue with general service demands and phase-type service capacities, J. Ind. Manag. Optim. 13 (2017) 1901−1926, https://doi.org/10.3934/jimo.2017024.
[18] L.A. Zadeh, Fuzzy sets, Inf. Control 8 (1965) 338−353.
[19] H.J. Zimmermann, Fuzzy programming and linear programming with several objective functions, Fuzzy Sets Syst. 1 (1978) 45−55.
[20] H.J. Zimmermann, Fuzzy Set Theory and its Applications, Kluwer Academic Publisher Group, Dordrecht, 1991.
[21] D. Karboga, B. Basturg, Powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm, J. Glob. Optim. 39 (2007) 459−471.
[22] A. Coello, B. Lamon, A. Van Veldhuisen, Evolutionary Algorithms for Solving Multi-Objective Problems, Springer, 2007, https://doi.org/10.1007/978-0-387-36797-2.
[23] K. Deb, B. Basturk, On the performance of artificial bee colony (ABC) algorithm, Appl. Soft Comput. 8 (2008) 687−697, https://doi.org/10.1016/j.asoc.2007.05.007.