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Decision-Making in Healthcare Resources Optimal Management: the Case of Inpatient Bed Occupancy and Associated Costs

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Abstract

The aim of this paper is to explore how efficient is the *Fish School Search* (FSS) algorithm in building a *Decision Support System (DSS)* for healthcare facility managers in order to optimize both the number of beds in their facilities and their budget. We have used a finite capacity queueing model with phase-type service distribution combined with a compartmental model and associated cost model. The *Fish School Search* algorithm was used to optimize the queueing model. To illustrate the proposed approach, we used the available data reported by a department of geriatric medicine of a hospital. Our findings showed that by encoding the whole information provided by the queueing system and the cost model in a fish, the Fish School Search is a potentially beneficial tool for optimizing healthcare resources and the facility's budget. The model can be extended to different medical facilities with respect to the objective parameters.

Keywords: biology inspired models, collaborative decisions, evaluation criteria, health information technology, swarm intelligence.

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1 Introduction

In [1], a historical account was presented about the contribution of IT and automation to human well-being with particular emphasis on intellectual and occupational facets. Another important dimension of

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well-being is good physical and psychical health condition [2]. Over the years, the contribution of healthcare-specific IT methods and tools has been analyzed and debated. Albeit it has been recognized that IT can contribute to improving the physical health condition of the people, it has been admitted that the negative aspects cannot be overlooked. For example, Karsh et al. [3] identified 12 fallacies of the early *Health Information Technologies (HIT)* and proposed measures mainly based on cognitive and human factors engineering research to improve the situation. Since then, new methods and technologies have been devised and numerous practical experiences paved the way for yielding better results. It is worth noting the increasing usage of automation and *Artificial Intelligence* (AI)-based information tools in healthcare [4], including the pacing *Generative AI* (Gen AI) [5], [6]. A particular subclass of problems to be encountered in the healthcare systems is composed of the decision-making actions meant to optimize the usage of various resources of healthcare facilities with a view of the benefit of human health conditions and medical sector sustainability. Optimal inpatient bed occupancy is a resource that received a lot of attention since it has a serious impact on inpatient conditions and healthcare facility costs [7], [8], [9]. It goes without words that an optimal or even satisfactory solution can only be obtained through the collaboration of the involved persons such as investors, facility managers, medical staff, and IT people using the appropriate methods and information tools [10], [11].

Recent developments have made the problems critical. After the COVID-19 pandemic hit mankind in 2020, the healthcare resources allocation problem became more pressing than it had ever been before. The images of COVID patients crowding the hospital hallways, the lack of necessary ventilators and *Intensive Care Unit* (ICU) beds, and people gasping for air, had made a great impact on society. On average, a COVID patient spent 13 days in the ICU [12]. Managing hospitals resources is crucial during pandemics or wars, but it is of high importance in other cases too when the health situation apparently deteriorates. For instance, the number of patients who need to be admitted to hospices has increased over the last few years. In 2018, the number of medicare hospice residents increased by 4% compared to

2017 (http://www.cdc.gov, nhpco.org/hospice-facts-figures). The average *length of stay* (LoS) of a hospice patient was 89.6 days. Besides the increase in the number of people in need of hospices, the number of low-birth-weight premature infants has increased too. The LoS in the *Neonatal Intensive Care Units* (NICU) for an infant of less than 1500 g is 62 days [13].

One potential solution for better management is using optimization techniques such as swarm intelligence to improve bed occupancy and associated costs. In general, the decisions are made using operational research methods, such as queueing theory. The queueing systems are designed to be of finite capacity. For instance, in [14], the authors used a queueing system with a *two-phase Cox* distribution [14] for service and finite capacity buffer to model a geriatric care unit. A simulation model for bed inventory planning in hospitals was developed in [15], while another queueing model was applied in [16]. While in [17], a Coxian phase-type model and multiple absorbing states were used to represent the management of stroke patients, other researchers used a non-homogeneous discrete-time Markov chain with time-dependent covariates for the same task [18]. Different machine learning methods such as linear regression, multilayer perceptron, support vector machine, k-nearest neighbor, and random tree forests, were used to compute the LoS of preterm infants [19].

An uncharted territory in improving hospital resources is the use of queueing models together with *swarm intelligence*. Few medical studies have tackled this issue. For instance, genetic algorithms and artificial immune systems merged with different queueing models were used for managing elderly persons, surgical department patients, mental health patients, or the ICU departments during the COVID-19 pandemic [20], [21].

The aim of this study is to present a new approach for patient management in different healthcare facilities by optimizing queueing models by using the *Fish School Search* (FSS) algorithm. The study is two-fold: *a*) to design a new policy for bed allocation, and *b*) to simulate different scenarios using the newly designed policy. The number of beds in different medical facilities was considered as servers in the queueing model. We used *phase-type distribution* to represent the length of stay.

The patient arrivals were described by Poisson processes, and the cost assessment and bed allocation policy were optimized using the FSS method.

The paper is organized as follows. In Section 2, we present the FSS algorithm and how we merged it with the operational research methods. The experimental results are presented in Section 3, and in the discussion Section 4, we highlight the research findings.

2 The model

The core idea of this study is to optimize the patient throughput in different medical facilities and the associated costs. For this task, we used specific performance measures such as the average length of stay, arrival rate, the size of a potential waiting room, the holding costs, bed inventory, and so on. Depending on the clinical services offered in different medical facilities, the components of the healthcare service were classified as short-term, medium-term, and long-stay care. Technically, the bed occupancy configuration was translated into the patient flow of the clinical system. The patients are not homogeneous, due to the fact that they belong to different categories. Initially, all patients are inbounded into the clinical facility. Some patients might require emergency care, while others need medium or long recovery. Therefore, from the emergency care block, they can either be released or transferred to another compartment, medium care or long care, where they will remain until outbound cured or dead. To model the process, we used a mixed exponential distribution to describe the average LoS, and a compartmental model associated with the different states. The balance between holding and penalty costs and bed policy was optimized by using FSS.

2.1 Compartment model

Even if healthcare facilities are complex and admit different types of patients, we were able to identify comparable patterns, since the context is quite similar. So, we were able to define a common approach to the patient flow. A one-compartment model regards only one type of patients (e.g., acute care), while using two- or three-compartment models, we model two or three types of patients. Obviously, depending on the situation, more than three compartments should be used [22], [23].

The two-compartmental model can be described as follows: let us presume that we have a constant admission rate when the system is in an equilibrium state. We denote each one of the two compartments as A and B, and the number of patients in each compartment as $N_i\left(s\right),\ i=1,2$, where s is the length of stay. The rates of discharge from compartments A and B are r_1 and r_2, making the presumption that the discharge rate from B is smaller than that from A. We denote as v the rate of transfer from compartment A to compartment B. We can mathematically describe the model as follows [24]:

$$N_1\left(s+1\right)=(1-r_1-v_1)N_1(s) \tag{1}$$

$$N_2\left(s+1\right)=v_1N_1\left(s\right)+(1-r_2)N_2(s) \tag{2}$$

The initial condition of the two-compartmental model states that $N_1\left(0\right)=A_0$, $N_2\left(0\right)=0$. The starting point of the two-compartmental model was the empirical observation, that the two-term mixed exponential distribution (phase-type) fits the best the pattern of bed occupancy, $Ae^{-Bs}+Ce^{-Ds}$, where

$$A\frac{\left(1-k\right)A_0}{v_1+r_1},\ k=\frac{v_1}{v_1+r_1-r_2},\ e^{-B}=1-v_1-r_1,$$

$$C=\frac{A_0k}{r_2},\ e^{-D}=1-r_2.$$

In order to use a compartment model in practice, we must assume that:

- The admission rate is random, all being Poisson arrivals. This presumption is quite reasonable if the healthcare facility is stable.

- The models are regarded as phase-type, having a number of compartments equal to the number of components. This assumption lets us describe the time of immersion of a finite Markov chain in continuous time when we have a single immersion state and the stochastic process begins in a transient state.

In this study, we represented the healthcare facilities by using the multiple-server queueing models viewing the hospital beds are servers. An important matter that deserves to be noted is that we assume that the system is in a steady state. We started with *Erlang B* queueing system (M/PH/c/c) [8], which is the simplest model. In this type of model, all patients arrive at the healthcare facility following a Markov/memoryless (M) Poisson process, where the distribution of the service is phase-type (PH), that is the number of phases is equal to the number of compartments. The number of beds with no waiting positions is given by c. The fact that there is no waiting list, means that if a patient arrives at the healthcare facility and finds all the c beds occupied, he is lost for the system. We denote as λ the Poisson arrival rate, making the LoS have the following probability density function:

$$f(t) = \sum_{i=1}^{l} \alpha_i \rho_i e^{-\alpha_i t} \tag{3}$$

with the corresponding average:

$$\tau = \sum_{i=1}^{l} \rho_i / \alpha_i, \tag{4}$$

where l is the number of compartments or phases, α_i $(i = 1, l)$ are the mixing proportions, and ρ_i $(i = 1, l)$ are the transition rates, and $\sum_{i=1}^{l} \rho_i = 1$.

The probability of all c beds to be occupied is computed using Erlang's loss B equation:

$$p_c = \frac{a^c / c!}{\sum_{k=0}^{c} a^k / k!}, \tag{5}$$

where $a = \lambda \cdot \tau$ is the offered load, [25], [26].

It is obvious, that in a real-world scenario, we must have waiting lists. A solution to this problem is having *back-up beds.* We must keep in mind that an extra bed means extra medical personnel, so, the costs rise up in more than one department. If we allocate extra beds and they do not get occupied, the penalty costs rise up too. In this case, we must extend the loss model to estimate how many back-up beds are necessary as buffers. Our queueing model can be extended by having a *waiting room*. Hence, we shall have M/PH/c/N, where $N \geq c$ represents the maximum capacity. Evidently, N is fixed, so, when a patient goes to the healthcare facility and finds out that the maximum N capacity is reached, he/she will be turned away.

Our new queueing model is described by the following two probabilities:

$$P_j = \begin{cases} \frac{a^j}{j!}, \; if \; j = 1, 2, \ldots, c \\ \frac{a^c}{c!} \cdot \left(\frac{a}{c}\right)^{j-c} \cdot P_0, \; if \; j = c+1, \ldots, \; N \end{cases}, \tag{6}$$

where P_j represents the steady-state probability that there are j patients in the system. P_0 is the steady-state probability that the system is empty, no patients, and is computed as:

$$P_0 = \left[\sum_{j=0}^{c} \frac{a^j}{j!} + \frac{a^c}{c!} \cdot \sum_{j-1}^{N-c} \left(\frac{a}{c}\right)^j \right]^{-1}.$$

We compute the long-run fraction of rejected arrivals as follows:

$$P_N = \frac{a^c}{c!} \cdot \left(\frac{a}{c}\right)^{N-c} \cdot P_0. \tag{7}$$

To compute the average number of patients, technically the average bed usage, in the system, we use *Little's* formula $L = \lambda \cdot \tau \cdot (1 - p_N)$. To compute the bed occupancy, we use $\rho = \frac{L}{c}$.

2.2 Cost model design

Our study's aim is to find the trade-off between the maximum usage of resources and the best medical service provided to the patients. Thus, we need to add costs to the queueing mode and also penalties in order to determine a cost-effective strategy. For this, we have used the base-stock policy from inventory theory [27]. For each unused bed, we will consider the cost φ units per day, and for each unused back-up bed, we will consider the cost ψ units per day. If the system turns away a patient, it will pay a penalty cost π units. The average cost per day in a healthcare facility will be computed as:

$$g\left(\lambda, \tau, c, N, \pi, \varphi\right) = \begin{cases} \pi \cdot \lambda \cdot P_N + \varphi \cdot (c - L) + \psi \cdot (N - x)\,, \text{ if } c \geq L \\ \pi \cdot \lambda \cdot P_N + \psi \cdot (N - L)\,, \text{ if } c < L \end{cases} . \tag{8}$$

2.3 Fish School Search for cost optimization

Our aim is to optimize the healthcare facility's bed occupancy and its associated costs. Technically, this implies finding the balance between inventory costs and penalty costs. Using FFS, we will optimize the cost function g and rejection probability P_N. A collection of fish that have gathered in the same place is called an aggregation of fish. A *fish school* consists of individuals of the same species. If a member of the pack stands out with a certain characteristic, it will become a target for predators. That is why, in fish schools, all the members are identical, making the school homogeneous. In a fish school, all fish swim synchronously, having the same speed and the same direction, showing some sort of group intelligence. Fish, that are part of the same school, share information and control the members' behavior from a close distance.

FFS is a swarm intelligence algorithm used for optimization problems [28]. The agents in this algorithm are called fish, and each fish is assigned a weight that measures its success gained during the search. As the weight varies, the individual and collective movements are affected. Different functions such as built-in feeding or coordinate action mechanism, influence the fish school to move in the direction of a positive gradient in order to increase the weight and find the best local or global spot.

Let us imagine an aquarium, in which the walls are the boundaries of the domain of the function definition. The fish need to find the food that is encoded as the problem's solution. The fish weight is the fitness value, that measures how well the fish performed in finding the food. Through the weight, the fish have memory. The FSS algorithm has two types of operators: a) the *feeding operator* that validates how well the search area has been explored, and b) the *swimming operators* that implement migration algorithms for the fish as well as for the entire school.

Through the feeding operator we update the weights of every fish using the formula:

$$W_i\,(t+1) = \; W_i\,(t) + \frac{\Delta f_i}{\max(|\Delta f_i|)}, \tag{9}$$

where $W_i(t)$ is the weight of fish i, Δf_i measures how the fitness has varied between the current and the past position, and $\max(|\Delta f_i|)$ is the maximum value of the fitness variation between all the fish from the school.

Fish move around using movement operators that are of three types: a) individual fish movement, b) collective-instinctive movement, and c) collective-volitive movement. During an individual fish movement, a fish performs a local search in the search space. The fish is moved around using the following equation:

$$x_i\,(t+1) = x_i\,(t) + rand\;\;(-1,1)\,step_{individual}, \tag{10}$$

where $x_i\,(t+1)$ and $x_i\,(t)$ represent fish i's position before and after the individual operator produced its effect, and $step_{individual}$ is a parameter used to define the maximum displacement of the present movement. The fish does not move into the next position unless the fitness is improved, otherwise, the fish keeps the initial position.

The collective-instinctive movement is computed as follows:

$$I = \; \frac{\sum_{i=1}^{N} \Delta x_i \Delta f_i}{\sum_{i=1}^{N} \Delta f_i}. \tag{11}$$

Having computed I, all fish will move in the same direction using the formula:

$$x_i\,(t+1) = x_i\,(t) + I. \tag{12}$$

The third movement operator is the collective-volitive one. It is used to regulate the exploration ability of the entire fish school. The school's barycenter, B, is computed using the position and the weight of each fish:

$$B(t) = \frac{\sum_{i=1}^{N} x_i(t) W_i(t)}{\sum_{i=1}^{N} W_i(t)}. \tag{13}$$

If the school's weight, $\sum_{i=1}^{N} W_i$, has increased since the last movement, then all fish move toward the barycenter using the following formula:

$$x_i\left(t+1\right) = x_i\left(t\right) - step_{vol} rand\left(0,1\right) \frac{x_i\left(t\right) - B\left(t\right)}{distance\left(x_i\left(t\right), B\left(t\right)\right)}. \tag{14}$$

Otherwise, the fish move away from the barycenter using the following formula:

$$x_i\left(t+1\right) = x_i\left(t\right) + step_{vol} rand\left(0,1\right) \frac{x_i\left(t\right) - B\left(t\right)}{distance\left(x_i\left(t\right), B\left(t\right)\right)}, \tag{15}$$

where $step_{vol}$ is the maximum displacement performed with this operator. The distance is computed using the Euclidian distance.

The steps of the FFS algorithm are:

1. Initialize parameters and the fish positions randomly.

2. While the stopping criterion is not reached:

   2.1 compute the fitness of each fish

   2.2 apply the individual operator movement

   2.3 compute the fitness of each fish

   2.4 apply the feeding operator

   2.5 apply the collective-instinctive movement operator

   2.6 apply the collective-volitive movement operator

3 Results

We have used FSS to optimize the queueing model and created a simulation using the data collected from the Department of Geriatric Medicine – St. George's Hospital London, UK [29], [30], and data from the American Hospital Association Annual Survey of Hospitals [31]. The healthcare assistance regarding geriatric patients has three compartments: acute, rehabilitative, and long-stay. Depending on all sorts of factors, such as influenza epidemic in the 70s, economic pressure, etc., the bed allocation, mean LoS, and annual admission changed. Hence, the number of allocated beds per year is 186, with a mean arrival of 5.9 patients/day and a mean LoS of 24.9 days. A patient costs per day £168, out of which the bed costs £50, and £118 – the treatment. The cost of an unoccupied bed is £50 per day, while an unoccupied back-up bed is £15. Given these numbers, if we assume that the total cost of refusing a patient is 25% out of the cost per day multiplied by the expected LoS, we will have $\pi = 168 \times 24.9 \times 0.25 = 1046$£.

We have applied the FFS algorithm to find the best trade-off when it comes to resource utilization. The search space for each fish in the fish school is the following:

- The number of beds $c \in [130,\ 250]$,
- The arrival rate $\lambda \in [4, 9]$,
- The length of stay $\tau \in [17,\ 32]$,
- The cost per day $\varphi \in [35,\ 65]$,
- The penalty cost $\psi \in [730,\ 1370]$.

We have considered that the back-up beds number is computed as 5% of the total number of allocated beds. Please keep in mind, that if the healthcare facility has around 95% of beds occupied, it means that it is fully occupied, and if the beds are occupied in a proportion of 100%, that means that the system is in real crisis. Hence, the 5% extra beds should reduce the pressure.

The aim of this paper is to use the FSS algorithm to minimize the objective function P_N taking into account different constraints. In general, in geriatric medicine, the percentage of lost demands that is considered as being tolerable is obtained if the percentage of occupied beds is above 80%. Therefore, we have considered a maximum rejection rate of 15%, and the bed-occupancy rate ρ between 63% and 97%.

In the cases of bed occupancy optimization, the fitness function for the FSS is represented by the rejection probability P_N, a fish is defined as a single parameter c, while parameters λ and τ have the default values 5.9 and 24.9, respectively. In Table 1, we have the results obtained after applying the FSS method to optimize bed management. We present the rejection probability as a function of c, together with the corresponding bed-occupancy. For our algorithm, we have used 100 generations and 150 fish. We have discovered that the minimum rejection rate, no patient turned away, is reached if we have 192 beds plus extra 10 beds in the waiting ward. It might seem that this is a good outcome, when in fact it is not, because the bed-occupancy is approximately 77%, which is below our acceptable threshold of 85%. Hence, if we increase the bed occupancy to 92%, which benefits economically the management, we will have a rejection rate equaling 1%, which can be realized with 159 beds plus an extra 9 back-up beds. Please note the fact that this is a far better management solution than the geriatric standard.

Table 1. Values (%) of P_N and ρ taking into account the number of beds

c	N	$\mathbf{P}_N$	ρ
192	202	0.00	75.6
159	168	1.01	90.4
154	163	2.22	93.2
148	155	4.44	95.5
139	148	8.52	96.8
135	143	10.34	97.2
131	138	13.11	98.3

The second approach that we tried was considering all parameters as being subjective, hence a fish is represented through (c, λ, τ). This is an imaginary exercise because, in real practice, a manager cannot modify the arrival and LoS as he/she/they please. Nevertheless, we were interested in how our method would work in the given situation. The results are presented in Table 2.

Table 2. Values (%) of P_N and ρ taking into account all queueing parameters

c	N	λ	τ	$\mathbf{P}_N$	ρ
134	141	6.02	25.10	10.65	98
146	155	6.01	25.01	4.56	97
157	164	5.88	24.94	1.34	92
181	191	5.01	22.21	0.34	56
211	221	6.42	21.23	0.00	87
219	232	5.92	20.67	0.00	56

The FSS algorithm computed that for achieving the best scenario, no turned away patients, we would need 211 beds or 219 beds, an arriving rate of 6.42 or 5.92, respectively, and a LoS of 21.23 or 20.67.

Another purpose of this study was to optimize, using FSS, the corresponding healthcare costs. This task can be achieved by minimizing the cost function g, using fish that have the following structure (c, φ, ψ, π), subjective parameters, while λ, τ remain objective, being the default values in a standard geriatric department. The results are presented in Table 3.

We can see that if we use the same bed allocation of 141 beds, with 6 back-up beds, and a rejection probability of 7.16%, it would require different costs ranging from 950 to 527, depending on the holding and penalty costs 60 vs 35, 18 vs 11, and 1360 vs 720. If we were to have the same holding and penalty costs, with different bed allocations of 155 vs 183, it would result in different costs but increased healthcare service. The last two lines show us that improving the bed allocation with lower costs will result in a reduction of the turned away patients percentage, saving at the same time £64.

In conclusion, a manager can simulate different scenarios regarding

Table 3. The values of the fitness function g in terms of c, φ, ψ, π

c	N	φ	ψ	π	g	$\mathbf{P}_N$
141	147	60	18	1360	950	7.16
141	147	35	10	720	526	7.16
155	163	51	15	1046	1172	2.05
183	192	51	15	1046	1180	0.31
135	141	40	18	1240	1190	0.08
194	201	59	18	1262	1254	10.44

bed allocation and other resources to choose the best value of g.

4 Discussion

We were interested in comparing our results with the ones obtained using *evolutionary computation-EC* algorithm on the same dataset [20]. We have found that the results are quite similar, the differences between bed allocation being 1-2 beds, whereas the cost differences are £2. Even if there are no statistically significant differences between the results, the differences between the usage of computational effort and the efficiency of exploration and exploitation of the two algorithms need to be stated. EC requires significant computational resources. The computational effort is influenced by the population size, the number of genes in the chromosomes, and the number of generations. The EC requires more resources as the fitness function complexity increases. FSS, on the other hand, has lower computational requirements, compared to EC, because it relies on the iterative updates of the fish positions and social interactions, whereas EC uses operators such as reproduction and mutation, which require more memory usage and thus increase the computational complexity.

In terms of efficiency of exploration and exploitation, as EC balances searching diverse regions in the solution space with refining the potential solutions by applying mutation, crossover, and selection, the computation effort involves adjusting this exploration-exploitation trade-off dynamically. On the other hand, FSS emphasizes collective movement and coordination in exploring the search space. The trade-off implies the balance between the step size and weight factors.

Another advantage of using FSS, instead of EC, is the fact that while FSS converges more slowly in comparison with EC, it better explores complex and uncertain search space, leading to better solutions.

In conclusion, albeit the results are similar, the FSS is preferable in terms of algorithmic complexity compared to EC.

5 Conclusions

Healthcare management is a growing field for research. New approaches that merge operational research methods and artificial intelligence are making a significant impact on patient and resource management. In order to achieve the best management strategies, healthcare facility managers should be able to understand the patient flow characteristics, have knowledge regarding the financial resources and the healthcare facilities' needs, and be able to effectively collaborate with IT people who maintain the system. The manager must also know how to identify the strategies that mind improve resource usage and be able to get the forecast of different government changes regarding financial support and stocks in order to be prepared to act accordingly. The model must be built or adapted taking into account the patient flow so that the queueing model parameters are correctly estimated, the history of bed allocation so that different scenarios could be prepared, and potential financial cuts. Once all this information is known, different scenarios can be tested and strategies provided.

This paper explored how feasible is the FSS algorithm in such an approach, using empirical knowledge and theoretical results. FSS proved to be efficient in simulation different scenarios taking into account diverse parameters and changing their roles from objective to subjective depending on the case.

We have used the standard M/PH/c/N finite capacity queueing model and FSS to optimize the beds and resources in such a manner that a reasonable number of patients to be turned away, with respect to an affordable budget. Using the base-stock policy we were able to tackle different values for the parameters to optimize the rate of rejection and healthcare costs. The hospital manager can choose the values that keep the percentage of turned-away patients at a minimum.

The FSS algorithm proved to be feasible and demonstrated that our approach can be extended to different medical departments by just changing the values of different objective parameters. The results are potentially useful. In order to make the method become usable and actually used by the relevant actants, the computerized versions of the models and solving algorithms should be "bolt on" the practical *decision*-making *support systems* (DSS) meant to facilitate a collaborative work of the relevant people involved [32].

Future work will focus on exploring other swarm intelligence algorithms and comparing their results.

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References

[1] F. G. Filip, "Automation and computers and their contribution to human well-being and resilience," *Stud. Inform. Control*, vol. 30, no. 4, pp. 5–18, 2021. DOI: https://doi.org/10.24846/v30i4y202101P.

[2] C. Z. Radulescu, M. Radulescu, A. Alexandru, M. Ianculescu, and V. Vevera, "A multicriteria approach for quality-of-life evaluation," *Procedia Computer Science*, (Part of special issue: 7th International Conference on Information Technology and Quantitative Management (ITQM 2019)), Elsevier, vol. 162, 2019, pp. 532–538. DOI: https://doi.org/10.1016/j.procs.2019.12.020.

[3] B.-T. Karsh, M. B. Weinger, P. A Abbott, and R. L Wears, "Health information technology: fallacies and sober realities," *Journal of the American Medical Informatics Association*, vol. 17, no. 6, pp. 617–623, 2010.

[4] A. Ugajin, “Automation in hospitals and health care,” in *Springer Handbook of Automation*(Springer Handbooks), S.Y. Nof, Ed., Springer, Cham, 2023, pp. 1209–1233. DOI: https://doi.org/10.1007/978-3-030-96729-1_56.

[5] P. Lee, S. Bubeck, and J. Petro, “Benefits, Limits, and Risks of G PT-4 as an AI Chatbot for Medicine,” *N Engl J Med*, 388, pp 1233–1239, 2023. DOI: 10.1056/NEJMsr2214184. Available: https://www.nejm.org/doi/full/10.1056/NEJMsr2214184.

[6] Shashank Bhasker, Damien Bruce, Jessica Lamb, and George Stein, “Tackling healthcare’s biggest burdens with generative AI,” McKinsey&Company, June 2023. [Online]. Available: https://www.mckinsey.com/industries/healthcare/our-insights/tackling-healthcares-biggest-burdens-with-generative-ai.

[7] S. McClean and P. H. Millard, “A decision support system for bed-occupancy management and planning hospitals,” *Mathematical Medicine and Biology: A Journal of the IMA*, vol. 12, no. 3–4, pp. 249–257, September 1995, DOI: https://doi.org/10.1093/imammb/12.3-4.249,

[8] S. Belciug and F. Gorunescu, “Improving hospital bed occupancy and resource utilization through queuing modeling and evolutionary computation,” *J Biomed Inf*, vol. 53, pp. 261–269, 2015. DOI: https://doi,.org/10.1016/j.jbi.2014.11.010.

[9] T. K. Vashishth, S. Chaudhary, and V. Sharma, “Optimum utilization of bed resources in hospitals: a stochastic approach,” in *Artificial Intelligence-based Healthcare Systems (The Springer Series in Applied Machine Learning)*, Manju, S. Kumar, S.M.N. Islam, Eds., Springer, Cham, 2023, pp. 101–110. DOI: https://doi.org/10.1007/978-3-031-41925-6_7.

[10] S. Y. Nof, “Collaborative control theory and decision support systems,” *Comput. Sci. J. Moldova*, vol. 25, no. 2, pp. 115–144, 2017.

[11] F. G. Filip, “Collaborative decision-making: concepts and supporting information and communication technology tools and systems,” *Int. J. Comput. Commun. Control*, vol. 17, no. 2, Article Number: 4732, 2022, DOI: https://doi.org/10.15837/ijccc.2022.2.4732.

[12] Y. Alimohamadi, E. Mansouri Yekta, M. Sepandi, M. Sharafoddin, M. Arshadi, E. Hesar, “Hospital length of stay for COVID-19 patients: a systematic review and meta-analysis,” *Multidiscip Respir Med,* vol. 17, no. 1, Article Number: 856, 2022. DOI: 10.4081/mrm/2022.856.

[13] W. T. Lin, T. Y. Wu, Y.-J. Chen, Y.-S. Chang, C.-H. Lin, Y.-J. Lin, “Predicting in hospital length of stay for very-low-birth weight preterm infants using machine learning techniques,” *J of the Formosan Medical Association*, vol. 121, no. 6, pp. 1141–1148, 2022.

[14] K. U. Uzunoglu and S. Ozkar, “M/C2/c/K queuing model and optimization for a geriatric care center,” *Appl. Stoch Models Bus Ind*, vol. 31, no. 6, pp. 892–911, 2015. DOI: https://doi.org/10.1002/asmb.2119.

[15] L. R. Pinto, F. C. Cardoso de Campos, I. H. Oliva Perpetuo, and Y. C. Neves Marques Barbosa Ribeiro, ”Analisys of hospital bed capacity via queuing theory and simulation,” in *Proceedings of the Winter Simulation Conference 2014*, Savannah, GA, USA, 2014, pp. 1281–1292. DOI: 10.1109/WSC.2014.7019984.

[16] M. M. Kembe, P.O. Agada, and D. Owuna, “A queuing model for hospital bed occupancy management: a case study,” *Int J Comput Theor Stat*, vol. 1 no. 1, pp. 13–28, 2014.

[17] J. Gillespie, S. McClean, B. Scotney, L. Garg, M. Barton, and K. Fullerton, “Costing hospital resources for stroke patients using phase-type models,” *Health Care Manage Sci*, vol. 14, no. 3, pp. 279–291, 2011.

[18] L. Garg, S. McClean, B. Meenan, and P. Millard, “A non-homogeneous discrete time Markov model for admission scheduling and resource planning in a cost or capacity constrained healthcare system,“ *Health Care Manage Sci*, vol. 13, no. 2, pp. 155–169, 2010.

[19] Y.-J. Gong, Z. Zhang, and Z. Fan, “A multi-objective comprehensive learning particle swarm optimization with a binary search-based representation scheme for bed allocation problem in general hospital,” in *Proc. IEEE international conference on systems, man*

and cybernetics, (Istanbul, Turkey), 2010, pp. 1083–1088. DOI: 10.1109/ICSMC.2010.5641804.

[20] S. Belciug and F. Gorunescu, "A hybrid genetic algorithm-queuing multi-compartment model for optimizing inpatient bed occupancy and associated costs," *Artific Intel Med*, vol. 68, pp. 59–69, 2016. DOI: https://doi.org/10.1016/j.artmed.2016.03.001.

[21] S. Belciug, S. I. Bejinariu, and H. Costin, "An artificial immune system approach for a multi-compartment queuing model for improving medical resources and inpatient bed occupancy in pandemics," *Advan Electric Comp Engin*, vol. 20, no. 3, pp. 23–30, 2020. DOI: 10.4316/AECE.2020.03003.

[22] G. Taylor, S. McClean, and P. Millard, "Geriatric patient flow-rate modelling," *Mathematical Medicine and Biology: A Journal of the IMA*, vol. 13, no. 4, pp. 297–307, 1996. DOI: 10.1093/IMAMMB/13.4.297.

[23] G. Taylor, S. McClean, and P. Millard, "Stochastic models of geriatric patients bed occupancy behaviour," *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, vol. 163, no. 1, pp. 39–48, 2000.

[24] G. Harrison, "Compartimental models of hospital patient occupancy patterns," in *Modelling Hospital Resource Use*, P. H. Millard and S. I. McClean, Eds. Royal Society of Medicine Press, 1994, pp. 53–61.

[25] H. C. Tijms, *Stochastic Modelling and Analysis: a Computational Approach*, John Wiles & Sons, 1986.

[26] S. M. Ross, *IntroductionTo Probability Theory*, 6^{th} edition, Academic Press, 1997.

[27] W. Stevenson, *Operations Management*, 10^{th} edition, McGraw-Hill Higher Education, 2009.

[28] C. J. A. Bastos Filho, F. B. de Lima Neto, A. J. C. C. Lins, A. I. S. Nascimento, and M. P. Lima, "A novel search algorithm based on fish school behavior," in *2008 IEEE International Conference on Systems, Man and Cybernetics*, (Singapore), 2008, pp. 2646–2651. DOI: 10.1109/ICSMC.2008.4811695.

[29] P. H. Millard, B. Rae, and W. Busby, "Why nosokinetics? Measuring and modelling the process," in *Intelligent Patient Management* (Studies in Computational Intelligence, vol. 189), S. McClean, P. Millard, E. El-Darzi, and C. Nugent, Eds. Berlin, Heidelberg: Springer, 2009, pp. 3–23. DOI: https://doi.org/10.1007/978-3-642-00179-6_1.

[30] R. Vinicchayakul, "Costing Care in Geriatric Medicine," MSc dissertation, University of London, 2000.

[31] "NHPCO Facts and Figures," Reports of 1976, 1981, 1991-2010 editions, Chicago IL, http://www.cdc.gov, https://www.nhpco.org/hospice-care-overview/hospice-facts-figures/.

[32] F. G. Filip, C. B. Zamfirescu, and C. Ciurea, *Computer Supported Collaborative Decision-Making,* (Automation, Collaboration, & E-Services, ACES, vol. 4), Springer Cham, 2017, XVI+ 216 p. DOI: https://doi.org/10.1007/978-3-319-47221-8.

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