IOSR Journal of Mathematics (IOSR-JM)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 20, Issue 2, Ser. 2 (Mar. – Apr. 2024), PP 01-13
www.iosrjournals.org

Utilizing Evolutionary Computation And Queue Modeling To Increase Hospital Bed Occupancy And Resource Utilization

R.K.Mishra And Geetanjali Sharma*
Dept. Of Mathematics & Statistics, Banasthali Vidyapith, Rajasthan.

Abstract:
Carefully crafted policies are necessary to provide appropriate allocating beds, superior medical care, and sufficient financial assistance in the face of limited healthcare resources. This research integrates an optimization method based on evolution, a compartmental model, and a queuing system into a single framework to offer a complicated investigation of the distribution of resources in the medical field. The compartmental model offers a workable hospital division structure according to with defining qualities of the queuing system, and employing a genetic algorithm technique, evolution as a theory offers the tools for managing resource utilization and bed occupancy most effectively. The hospital's patient flow is shaped by the queuing system "What-if analysis" is another area of emphasis in the study. which provides a versatile tool to investigate the implications on the outputs resources are used and the queuing mechanism is examined methodical modifications during input parameters. A model simulation actual data gathered from a hospital's geriatric division in Jaipur, India, was used to demonstrate the methodology. The research also considers the viability of applying the concept to several medical specialties, including surgery, stroke, and mental disease. By demonstrating a simulated application, the study also emphasizes the model's usefulness from the perspective of healthcare.
Keywords: *Customer, Queue, Bed occupancy, Phase type Queuing Model*

Date of Submission: 18-04-2024 Date of Acceptance: 28-04-2024

I. Introduction

A hospital department could experience a circumstance when no more beds are available and patients are turned away, delaying the delivery of the necessary healthcare services because there aren't enough beds. This predicament is frequently brought on by a lack of financial support or bad resource management. A waste of the already few resources would be a surplus of a shoddy health care timeline or beds in hospitals, on the other hand. As a result, in order to better allocate. To make better Using hospital beds for enhance patient support and reduce costs, a complicated process is required that brings together cutting-edge analytical methodologies and machine learning techniques.

The literature contains reports of a wide variety of distinct strategies in use. Gillespie et al.(2011) Uses a combination design for the Coxian phase numerous states that absorb, to present a model of the expense of attending to stroke sufferers inside a hospital. In a medical care system, the movement of patients with financial or capacity constraints, Garget al.(2010) devised a discrete time with non-homogeneity Markov chain that incorporates timing-related covariates. For the problem of allocating beds in general hospitals, Gong et al. (2010) presents a sophisticated gaining knowledge of particle swarm with multiple objectives. Optimization with a representation technique using binary search. To track both between the clinic and hospital, and into the clinic, patient flow Lee et al.(2009) constructed a semi-closed migration network.

Even though queuing models frequently employed in business to enhance customer service, there aren't many instances of them in healthcare. This is most likely because the two realms are so dissimilar from one another, despite how challenging it is for people to accept the client-patient analogy. M/PH/c and M/PH/c/N models of queuing have been established in earlier works Gorunescuet al.(2002) to make the best possible Utilization of medical resources within a model of loss as well as an expanded model with an additional waiting room.Gorunescuet al.(2002) provides a model to aid with multi-objective decision-making. for allocating, Goal-oriented programming and queuing theory are used to allocate hospital beds. To increase an Emergency Department's capacity, Li et al.(2009) employed a queuing strategy depending on irregular patterns of arrival and irregular allocation of service time, and numerous patient classes together the queuing equations that come from it are implemented in a spreadsheet. An Erlang loss model-based decision support system is created in De et al.(2010) to assess the number of nursing units. Prior research has demonstrated that compartmental models, particularly for geriatric care, can accurately describe the patient flow across a hospital division. A mathematical model that has two compartments and is predictable Harrison et al.(1991) was the starting point; however, in the case of stochastic models, combinations of exponential distributions, a Bayesian belief network and a continuous Markov model were developed McClean et al. (1993) additional advancement was made. The two primary features of hospital management that are addressed in this work are (a) the bed distribution policy and (b) effective utilization of financial resources. The patient flow is first modeled using findings from queuing theory, wherein a Poisson procedure occurs depicts the arrival of patients, hospital beds serve as servers, and a distribution of the phase type, models the length of stay. Second, a compartmental model within the hospital division is used in conjunction with the queuing system. Finally, and perhaps most significantly, the prior strategy has been improved by the inclusion of the evolutionist paradigm, which is employed to maximize both bed allocation and efficiency. the use of resources and policies. Additionally, a "What-if" analysis has been carried out to thoroughly examine all of the potential options open to the hospital management. The paper's two key contributions are the evolutionary-based hospital administration optimization and the "What-if" analysis, which allows for the comparison of many accessible solutions.

II. Components And Procedures:

The model of queuing

The hypothetical framework speaks about an M/PH/c queuing system, where M stands for Arrivals of Poisson (Markov) and PH for phase-type Taylor et al.([1997) service distribution, c for how many servers are available, The Poisson arrival rate is represented by k in this loss model, where clients who discover every server is occupied and lost in the system, in addition to The probability density function of the phase-type service is provided by:

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

with the corresponding mean, $\tau = \sum_{i=1}^{l} \rho / \alpha$ where l is the quantity of phases or compartments,
α the mixing proportions, and the ρ the transition rates with $\sum_{i=1}^{l} \rho_I = 1$

The variables constituting The model of queuing mentioned above, λ, τ, and c are seen as changeable things that go through an optimisation procedure to increase bed occupancy and effectiveness of resources.

The mean quantity of arrivals happening during a period of time of length t is provided by λ.t, and as a result, the system's offered load, or the average number of arrivals over a typical duration of stay, is τ is a= λ.τ.Given that the likelihood of having j active servers is:

$$P_j = \frac{a_j / Lj}{\sum_{k=0}^{c} a_k / Lk}$$

The likelihood that each of the c servers is occupied is determined by:

$$P_c = \frac{a_c / Lc}{\sum_{k=0}^{c} a_k / Lk} = B(c,a) \text{ (Erlang's loss formula)}$$

B(c, a) thus symbolises the proportion of clients that the system loses Marshallet al.(2001) It should be noted that the results presented above hold true after the system reaches statistical equilibrium, which occurs when enough time has passed for Pj to be referred to as probabilities of statistical equilibrium or stable state.

Basic queuing characteristics

In general, queuing models are concerned with three key quantities:

- L–Customers in the system on average.
- W–The average time a randomly selected ,client spends in the system.
- q–The availability of servers.

We list a few helpful connections between the aforementioned traits, including:

- The carried load L = a. [1 - B(c, a)], often known as Little's formula, represents the typical number of consumers in the system.
- An arbitrary customer's average time in the system W= s. [1 -B(c, a)].
- The server occupancy $\rho = l/c$ (with $\rho \leq 1$ for steady-state).

One of the study's two main objectives is an optimization of bed occupancy management based on evolution. through parameter estimation for the model's, c, λ and τ,

- An appropriate proportion of patients who are refused that the system is willing to accept is considered the appropriate cutoff for the delay probability B(c, a).
- The equivalent average amount of time spent in the system
- The system's related average consumer count.

The related cost model

Providing the best service to clients while keeping costs to a minimum by making the best use of already available resources is a major consideration when presenting a model to address real-world problems, particularly in the healthcare industry. This might be "translated" into queuing models by keeping the missed requests (lost prospective customers) at a minimal level with minimal expenses. In accordance with Faddyet al.(2007) base-stock guidelines method Cooperet al. (1990) is used to put up an associated cost model to balance the proportion of consumers the system loses against the expense of providing the service.

The variables c, λ ,τ and in the model are meant to be variable, as was mentioned before. In order to provide penalty costs and serving costs are balanced for unmet expectations, this work focuses on determining their (almost) ideal values.

Let's assume that there are c servers. Includes both the quantity of beds and that are occupied and the number of vacant beds that are available to be used in an emergency in order to describe the corresponding cost model.

- Similar to the newsvendor model Rosset al.(2020) the cost model takes into account the following two factors:
- h units of storage per day for every idle (unused) server.
- p units as a fixed penalty fee for unfulfilled orders.

Below the base-stock strategy and using level of the server c, the daily cost could be written based on The parameters of the queuing system, λ, τ, s the cost model's inputs h, π in order to improve server utilisation and resource utilisation ,Departmental activities throughout the long term.

g=(c, λ, τ,h, π)= $\pi . \lambda . B(c, \lambda , \tau)$+h.{c- λ, τ.[1-B($c, \lambda . \tau$)]}

The problem of optimising inventory level, or resource utilisation, according to the cost function g(c, λ,τ,h, π), is analogous to solve a minimization problem, that is, to determine c,λ,τ,h, and π, minimise the fitness function (cost) g .

The turnover for each allotted bed annually, determined based on the proportion between the annual number of beds annually and the number of admissions assigned, is a contentious metric that is still used in the healthcare industry to assess inpatient activity. As a result, T = 366 .λ /c admissions per patient per bed gives the average turnover T.Stevenson et al. (2014)Cost-based function and average turnover are the two primary economic indicators used to gauge how well resources are used.

The compartmental model for patient flow

Consideration of the use of compartmental models, which have been demonstrated to be effective and at least for geriatric medicine, a tested description of patient dynamics Millard et al. (2009), are among the concepts to be brought to impact patient flow modelling. Acute care, for example, is the first compartment into which patients are admitted. Some receive effective care and are released, but regrettably, some pass away. A third group may require more care; therefore, these patients are sent to a different area (like rehabilitation); they may be released from this area or pass away there. Three to six compartments may be taken into consideration at a later stage, depending on the particular caseTayloret al.(1996) Fig. 1 shows the situation representing the traditional two-compartment model, which is the simplest but most typical case.

The admission policy assumes that admissions will happen randomly (i.e., Poisson arrivals), which is a valid assumption for a stable hospital system Such compartmental models, regardless of whether it is continuous-time stochastic or discrete-time deterministic may be viewed as phase-type Tayloret al.(2000) based on the quantity of components equalling the quantity of sections in terms of the service time distribution. When there are only The random procedure begins in a transitory state with only one absorbing state, these distributions explain is a bed occupancy management optimisation method based on evolution.

Evolutionary computing for optimisation

Computer-based patient modelling sounds good but poses serious problems for patient care. Genetic algorithms (GAs) are used in this situation to determine a reasonable the likelihood of a delay B(c, a) cut-off, and to minimise the g(c) cost function.

Genetic algorithm is organic algorithms for computation. made up of Individual chromosome populations, fitness-based selection, crossover to conceive new generations and introduce random alteration to create fresh progeny. The following steps make up the algorithm Eiben et al.(2004)

(Step 0) – Mutation and recombination rates are chosen, and the data are vector-basely encoded;
(Step 1) – A population with n chromosomes is chosen as the study group;
(Step 2) – Each chromosome's fitness function is determined;
(Step 3) –Until n chromosomes are produced, the iteration proceeds via the following steps: selection, crossover, and mutation;
(Step 4) – The previous population being replaced by the new one, and
(Step 5) – The evolutionary process is terminated by the termination criterion.

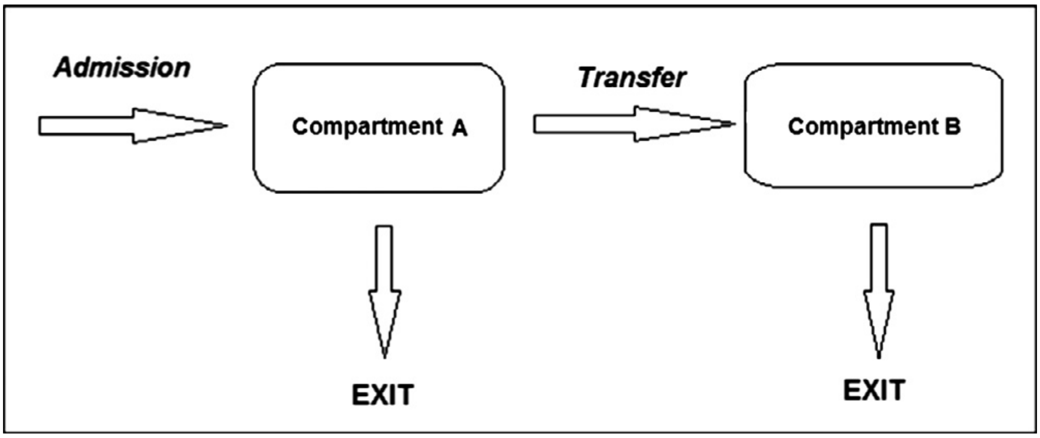

Fig. 1. Model for patient flow with two compartments.

The appropriate evolutionary algorithm is shown below.
Genetic algorithms
1. A group of people made up of n chromosomes or more is randomly selected from a suitable range.
2. One chromosome may appear more than once in the newly formed population since the person in charge of selecting tournaments chooses n chromosomes to be reproduced.
3. Probability of recombination is used to select m parents for reproduction.
4. In place of the parents, there are now m offspring.
5. The (n-m) chromosomes that weren't selected to be reproduced and the freshly created m children make up the new population.
6. This operator for normally distributed mutations is used. to the entire population using the mutation probability PM. If the mutant's fitness is higher than the fitness of the original chromosome, the mutant will take the place of the original in the population.
7. Until the termination requirement is met, the cycle is repeated.

Comment
1The proper selection of population size n is an issue that affects a GA's rate of convergence. The greatest performance was found for n = 100 chromosomes population sizes of 50 to 150 chromosomes are evaluated heuristically.
2. The suitable selection, defining the variations operators of the parameters is another issue that develops in the use of GAs. With the complete (whole) pc = 0.34 for arithmetic recombination with crossover rate and parameter = 0.3, as well as the irregular (distributed regularly) mutation and mutation rate pm = 0.4, we investigated parameter adjustment.
3. The manual analysis of the fitness function values (B or g, respectively) heuristic evaluation with generations between 50 and 150and various thresholds revealed that 100 is the (near) ideal value.
4. The suitable pauses (search area) for the associated chromosomes were computed as< mean 1.85 X SD>, regarded as a replacement for each parameter's mean and the 95% confidence intervals (CI), because Data are not always distributed normally (Poisson arrivals, phase-type service).

Optimisation of resource and bed occupancy based on evolution

Hospital bed management is a crucial responsibility nowadays, and several models have been put out, most of which are operating research-based methodologies (like queuing theory, stochastic systems, etc.) Belciug,and Gorunescu et al.(2015) Because of the statistical and computational character of the majority among these methods, this strategy requires the creation of the associated mathematical model based on resource and time intensive. The employment of GAs is a desirable and practical alternative to this conventional method. There are a number of benefits to using GAs, including the fact that (a) They are able to resolve any optimisation issue pertaining to chromosomal encoding described, (b) The process is simple in order to comprehend and apply without requiring a deep understanding of mathematics, (c) There may be a vast number of parameters., and (d) the fitness function is not subject to any significant restrictions. We have decided to employ GAs as an optimisation strategy for hospital bed occupancy and resource utilisation because of their effectiveness, speed of calculation, and broad range of applicability.

Management of bed occupancy is optimised.

To keep the number of requests that are turned down at a manageable level, the primary goal objective this study is to optimise management of bed occupancy by predicting the necessary number of beds. The GA method uses a vector (c, λ, τ), to represent a chromosome, the genes (c, λ, and τ) being associated with specific domains (84% CI) that are consistent with actual medical data. The delay probability B(c, a) provides the relevant fitness metric.

Since minimising the fitness function's objective, B(c, a) depends on several thresholds, the major aim in this situation is to keep the least amount of rejection is feasible.

Resource utilisation is optimised

The study's second goal is to determine the ideal both holding and penalty fees ratio, or the model parameters that will enable the highest quality medical care for patients while maximising resource utilisation.

The fitness feature is currently technically symbolised by the equivalent cost function g, and the vector represents a chromosome. (c, λ, τ, h, π),

In the end, the model can help healthcare workers predict hospital bed allocation and anticipated healthcare expenses by providing answers to a number of issues about the administration of hospital departments (rules regarding arrivals, average duration of stay, best bed occupancy, costs, etc.).

What-if analysis

Finally, "what-if analysis" has been conducted to examine the effects of systematic changes in the input parameters on the results of resource use and the queue system. This sensitivity evaluation determines how the two primary Performance metrics for models (a) Probability of delay B and (b) where the cost function g is influenced through an input modification variables (c, λ,τ,h, π) and how they may be adjusted to address the management optimisation problem.

Model for a geriatric medicine department

Utilising availability of beds gathered on the part of the Geriatric Medicine Department from January 2022 to 2023, the process described above is demonstrated.

The healthcare support included short-term, long-term, and rehabilitative medical services.

Various admission procedures and inpatient supervision were taken into consideration throughout this time. Seasonal occurrences (Easter, Christmas, the flu epidemic, etc.) as well as management decisions had a yearly impact on admission, which occasionally increased and decreased.

Three alternative management approaches were used for the inpatient population: (a) In 22% of cases, a single-compartment design (combining acute, long-term, and rehabilitative care) (b) In 38% of instances, a two-compartment paradigm (mixed rehabilitative and acute wards with individual long-stay rooms) is used. (c) 25% of the time, a three-compartment model with distinct Long-stay, acute, and rehabilitation wards is used. As may be observed, the most typical situation is the example with two components shown in Fig. 1.

The department allotted 186 beds annually on average as per inventory policy. In any instance, a mean arrival rate equal to

λ = 4.8 patients each day, with a mean stay of the same amount

τ = The data were verified to accurately represent 24.9 days. [5].

Since the NHS, or National Health Service provided the data for the related cost model, it was anticipated that there would be no profit

The cost parameters were determined using the then-current general practise as a guide. Vasilakis et al (2008)

- The entire expense for each patient each day is £58 ($30 for the bed and $$20 for the course of treatment)
- The daily retaining expense is h = £40
- As shown below, the penalty cost p is calculated. We can calculate the penalty cost as follows: π =152 X 24.9 X 0.24 = £1045. Given that the entire The price of turning away a patient could be calculated by multiplying the daily cost by the anticipated duration of stay, and that the penalty expense amounts to 24% of the overall expense incurred by turning a patient away.

It is important to note that this assumption is merely indicative and that the cost estimate is depending on the supposition that the penalty may be widely viewed as revenue lost because a patient was turned away because there are no open beds accessible.

Expanding the strategy to include different medical areas

Geriatric people experience healthcare differently than typical patients do, including various hospital, nursing home, continuing care, nursing care, etc. experiences. This results in varied patterns of flow (admission, Staying time), compartmental type, and cost structures. In this context, although the fundamental paradigm can be maintained when applying the geriatrics model to other medical specialties, practitioners must prepare for a patient flow that is more dynamic. Varying values of the appropriate components of parameters and cost functions. Koizumiet al.(2005)

Theoretically, altering rules could result in a decrease in the average duration of stay (or arrival frequency). Whatever the department speciality, hospital administrators who want to improve patient management find it challenging to put the change into practise. This is especially true when suggested modifications (such duration of stay) have a direct impact on how well patients are treated.

The arrival rate, on the other hand, is influenced by outside causes and is not directly under the control of healthcare experts.

Data pertaining to surgery

The equivalent parameters for procedures were calculated as $\lambda = 15.21$ daily patients $\tau = 6.4$ days, and c = 140 beds - community hospitals (single-compartment arrangement), as per the Indian Hospital Association (IHA) annually hospital survey Gryczynski et al (2005)

Stroke data

The information relates to stroke patients and arises from the Hospital Episode Statistics (HES) database in India Horrocks et al.(1994) The estimated values for the related parameters were: $\lambda= 285.3$ patients per day, $\tau=13.19$ days, and c= 5567 beds in a system with three compartments.

Data on mental health

The Centre for Mental Health Policy and Services Research (CMHPSR), Department of Psychiatry, School of Medicine Agra, is where the data are from. The predicted values for the related parameters were c = 560 beds - three-compartment system, $\lambda =1.9076$patients per day, and $\tau= 365$ days.

Associated costs

Today, most of the wealthy nations' healthcare spending is made up primarily of inpatient hospital charges.

Undoubtedly, the inpatient charges are not assessed consistently. Horrocks et al.(1986) state that the average hospital adjusted cost per inpatient day in the USA was $1620 and £214 in the UK. As a result, each hospital makes an estimate of the real inpatient expenditures. Although the g cost function can be utilised exactly as is, each user may change the values h and p in accordance with the geriatric model's paradigm.

III. Results

The evolutionary based optimisation is applied in the following to give an effective controlling bed occupancy and resource utilisation, allowing the hospital administration to weigh the expense of denying patients access to medical facilities and services against the inventory of beds.

Optimisation of bed occupancy

The experimental findings in this part suggested using the suggested GA to determine the close to optimal the parameter values c, λ and τ and in order to keep the likelihood of unmet demands B(c, a) at a manageable level. In this case, the goal is to minimise the fitness function B's objective while accounting for various restrictions (thresholds) on the possible values for it. There is disagreement among practitioners as to what percentage of unmet requests is acceptable in geriatric medicine, although evidence implies that operating at proportion of occupancy levels above eighty causes appreciable increases in patient rejection Silver et al.(1977)

The highest threshold, equal to 10%, is what we consider to be the greatest rejection level tolerable, with the associated occupancy percentage falling between 88% and 95%.The following are the matching search areas for the chromosomes that encode the parameters of the queuing model:

- Number of assigned beds $c \in [121, 172]$.
- Rate of arrival $\lambda \in [4, 8]$.
- Time spent there $\tau \in [24.5, 25.5]$

Table 1 Shows several values, in ascending order, of the rejection/delay probability B(c, a) as a function of various the parameter values for The system of queuing c, λ and τ, and various limits to demonstrate the GA technique to optimising the queuing model.

The GA approach has shown that 145 beds, an arrival rate of roughly 5.21 patients per day, and an average service duration (length of stay) of equal to 23 days, numbers near according to a geriatric department's standards, can be reached with the smallest rejection probability (1.4% of patients being sent away). It is important to note that the GA technique was only used to generate this prospective managing performance for 146 beds, far fewer than the required 186 beds. It is also important to note that experiment with evolution ,revealed that the queuing system is remarkably adaptable, as the same 5% rejection probability can be reached with either 138 or 164 beds, depending on the service time and arrival rate (5.29/25.7 vs. 5.18/31.04). The management can adjust the number of beds based on the situation after taking this observation into consideration.

Table 1
The values of B(c, a) for different variables in the queuing system.

C	λ	τ	B (%)	ρ(%)
145	5.20	24	1.4	87.03
150	5.50	24.01	3	88.46
135	5.07	25	2	91.21
164	5.10	30.18	5	92.26
137	5.28	24.72	4	91.67
133	5.27	23	7	91.79
131	5.27	24.10	6	92.31
132	5.30	23	9	92.84
128	5.35	22	8	93.32
127	5.06	25.75	10	92.84

Table 2 then lists a few values for the performance metrics L, W, and q of the models as functions of c, λ, and τ

The top row shows the system features that correspond to the smallest percentage of patients who are turned away, as determined by GA.

Additionally, as this table demonstrates, the number of beds is not directly related. Correlated with beds available assigned in the sense that, contrary to what one might anticipate, the bed occupancy decreases as the number of beds increases. For instance, both 132 and 165 beds can have the same bed occupancy of roughly 93%.The other factors naturally playing a key impact. The average amount of Spending time with a patient is roughly average. (23.51 vs. 23.8), regardless of various values for c, λ, and τ and that are comparable with standard practise, whereas the average number of patients varies substantially (from 120 to 152). The complexity of the situation suggests that of the structure, managing bed allocation without using computer simulation and optimisation is challenging.

Optimising the use of resources

The evolutionary-based optimisation of the associated healthcare expenses is demonstrated in the sections that follow, enabling effective access to medical care. According to the experimental findings, the suggested GA might be used to calculate the close to ideal values of the parameters, λ, τ ,h and p in order to keep the cost function g at a minimally viable level while still turning away a respectable number of patients. The objective in this situation is to reduce the objective (fitness) function g. The related average turnover per allotted bed per year (T), in addition to cost minimization, is computed. As functions of varying values of the parameters of the queuing system, λ, and τ and the accompanying costs h and p, Table 3 shows example the cost function g's values arranged in increasing order together with the corresponding turnover per assigned bed. We investigated The penalty's price tag ranges from £1035 to £2040. Gorunescu et al.(2002) the initial value equalling the standard approximation, which is the least penalty cost estimation.

The evolutionary technique has shown that 148 beds, an arrival rate of roughly 5.42 patients per day, average service duration (length of stay) of 25 days, a holding cost of £30, and a penalty cost of £1240 may all be used to minimize the expense of healthcare of £615.80. With the exception of the allotted bed count (149), which is significantly lower than the yearly average (185), and the holding cost ratio (p/h = 40.56), which is higher than the ideal value published in the literature and equals 40, these numbers are rather typical for a geriatric department..

By utilising all the characteristics explaining the system at once, the model we have created, which is based on the advantages of the GAs, may be effectively employed as an aid for enhancing a geriatric department's stock management strategy. It can be expanded to several medical departments without too many big obstacles.

Table 2 L, W, and ρ for various parameter value

C	λ	τ	L	W	ρ
145	5.20	24	121	24.03	83.03
150	5.50	24.03	136	23.47	88.47
135	5.07	25	123	23.22	91.22
164	5.10	30.19	152	28.27	92.27
137	5.28	24.70	141	26.68	93.68
133	5.28	23	122	22.79	91.79
132	5.27	24.11	124	23.21	94.21
130	5.30	23	123	23.94	94.94
129	5.35	22	123	24.42	93.42
128	5.06	25.78	121	26.94	94.94

Table 3 The average turnover T and cost g values for various model parameters

C	λ	τ	h	π	g	T
145	5.20	24	121	24.04	88.04	13.39
150	5.50	25.02	136	23.47	89.47	13.29
135	5.07	25	123	23.22	90.22	13.99
164	5.10	30.19	152	28.27	93.27	15.22
137	5.28	24.70	141	26.68	93.68	12.20
133	5.28	23	122	22.79	92.79	11.20
132	5.27	24.11	124	23.21	93.21	10.20
130	5.30	23	123	23.94	93.94	14.12
129	5.35	22	123	24.42	94.42	14.25
128	5.06	25.78	121	26.94	94.94	14.21

What-if analysis

Making use of 35 simulated data, we envisioned a "What-if analysis" the following scenario: $c \in [124,166]$ (avg. 142 beds), λ∈[5.06, 4] (avg. 4.30 patient/day); $\tau \in [23.8, 32.2]$ (avg. 24.44 days), h∈[31, 114] (avg. £53); $\pi \in [1045, 2052]$ (avg. £1533).

This sensitivity analysis serves two purposes.

(a) First, investigate how varying beds available, arrival time, and mean time served has an impact on the delay probability B. In this regard, two scenarios have been taken into account:

(a) Evaluating B(c, τ) for average constant. = 4.30 patient/day, and (b) assessing B(λ, τ), for avg. c = 142 beds.

For a fixed arrival rate of λ = 4.30 patients per day, This is nearby the typical case, the initial situation allows for simulated trials with various bed counts and mean medical service times. The hospital management can implement these improvements as long as the arrival rate cannot be changed practically. For a predetermined number of c = 142 beds (an inventory that is usually seen in reality), The second case enables for the investigation of the impact of the equilibrium between the average service time and the arrival rate onto the delay probability.

(b) Second, to look into how the department's facilities and policy (For example, the average service time and bed count) and the parameters of the cost model h and π may vary the daily cost under base-stock strategy g. In this regard, two situations have been thought of: (a) Evaluating g(c, τ) for constant avg. π = £1530, h = £62, λ= 4.30patient/day, and (b) evaluating g(,πh), for constant avg. c = 142 beds, λ = 5.30 patient/day, and τ = 24.44 days.

We can examine under what circumstances we are indifferent to neighbouring values of (c, τ), (λ, τ), and (π, h) control variables for The chance of delay as well as the cost function, in light of the prior work and the paradigm of indifference curves

The supporting equations for this strategy, which extrapolates the level/contour curves notion, are as follows: B(c, τ) = B(c + Δc, τ + Δτ), B(λ, τ)) = B(λ + Δλ, τ + Δτ), g(c, τ) = g(c + Δc, τ + Δτ), and g(π, h) = g(π + Δπ, h + Δh), where the growing factor is represented byΔ. In terms of geometry, it resembles "plateaus" with some potential "peaks" and "ravines," illuminating the relative "flatness" g and B, the variables of reaction. Through 3D visualisations created using the open-source R programming language, we have demonstrated the surfaces of indifference. R is a very useful graphical and statistical computing environment. It has substantial documentation and active online community assistance. R is a popular tool for data mining and statistics..

In accordance with the outcomes of the first two possibilities mentioned in Figs. 2 and 3 show examples of (a)

The graph and associated statistics imply that we might not care about the delay probability B if:

- Ranges of beds are available from 124 to 165(Δc = 33) with a 25-day average service period. ($\Delta\tau$ = 0.03), producing an average..B = 2.03%, SD = 0.39%.
- Ranges of beds are available from 124 to 145 (Δc = 9) and the mean service time is 24.35 ($\Delta\tau$ = 1.76), producing an average= 8.87%, SD = 0.82%.

In light of this, the hospital administrator may decide to maintain 130 beds for an anticipated proportion of lost demand that does not exceed, assuming a mean service time, 2% on average of 24 days. However, with an increase in the average service time to 24.25 days, 124 beds are enough to keep the decreased demand percentage at roughly 9%. It is important to note that the relatively slight increase in the mean service time contributed to the considerable increase in the lost demand. These findings are in line with the research that identifies the two "plateaus" of the graph of B based on the indifference surfaces.

The graph, associated data, and indifference surfaces analysis all indicate that we might not care about the delay probability B if:

- The rate of arrival ranges from 5.14 to 5.54. ($\Delta\lambda$ = 0.54),and the average service duration is 25 ($\Delta\tau$ = 0.02), resulting in an average B value of 1.96% and an SD of 0.36%.
- The range of arrival rates is 5.06 to 6 ($\Delta\lambda$ = 0.84), and the average service period is 25.26. ($\Delta\tau$ = 1.78), producing an average B value of 8.88% and a standard deviation of 0.82%.

These outcomes agree with the earlier ones. Thus, depending just marginally on the arrival rate, the average lost demand percentage for mean service duration of 25 days is approximately 1.95%, rising to 8.87% for a mean service time of 24.24 days.

The hospital manager may largely regulate the delay likelihood in both of the aforementioned cases by adjusting the mean service time. Be aware that the arrival rate cannot be directly regulated because it is naturally determined by randomness. According to the aforementioned findings, the relative changes in the quantity of beds and arrival rate have a minimal impact on the delay probability. Instead, the delay probability is primarily sensitive to changes in the mean service time. This fact, regarding the impact of c and k onto the typical number of hospital patients, is also supported by Table 2.

Figures 4 and 5 depict the outcomes associated with the second two situations indicated in (b).

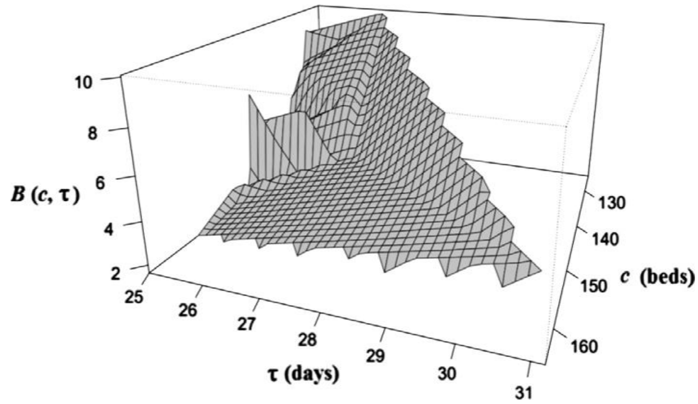

Fig. 2 The delay probability B(c, τ) graph.

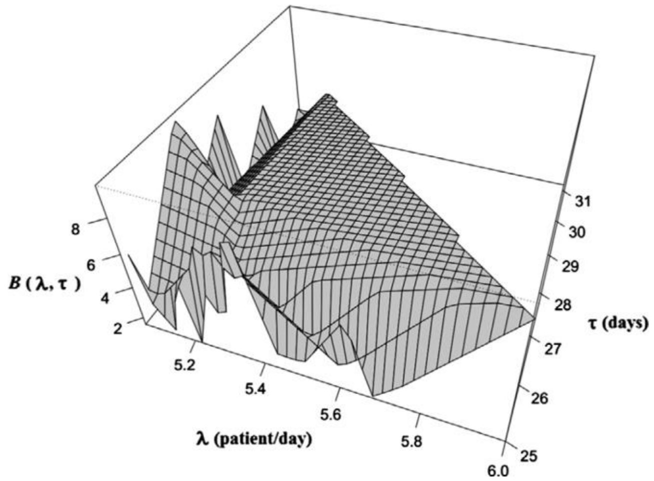

Fig. 3. The delay probability's graph is shown as B(λ, τ).

The graph and associated data, as well as the study of indifference surfaces, indicate that we might not care about the cost function g if:

- The range of beds is from 130 to 165 ($\Delta c = 34$), and the mean service duration is 24 $\Delta s = 0.2$), resulting in an average gross income of £632.15, standard deviation of £14.62.
- The average service time is between 25 and 25.68. ($\Delta\tau = 0.66$) and the number of beds goes from 124 to 143 ($\Delta c = 17$) resulting in an average of £1512.11 and a standard deviation of £90.83.

A balanced approach to the number of beds and the average service time, with a focus on the latter, may result in a lower percentage of lost demand and a corresponding reduced penalty cost, as shown by the first scenario. Similar to this, 130 beds allocated, with an average service time of no longer than 24 days may result in the hospital incurring the fewest losses in demands and the fewest expenses.

The examination of indifference surfaces, this graph, and related data suggest that we might not be concerned with the cost function g if: The holding fees are £30 and the penalty charges range from £1034 to £1640 (avg. π = £1323, SD = £206), resulting in an average of g= £629.19 and a standard deviation of £13.53.

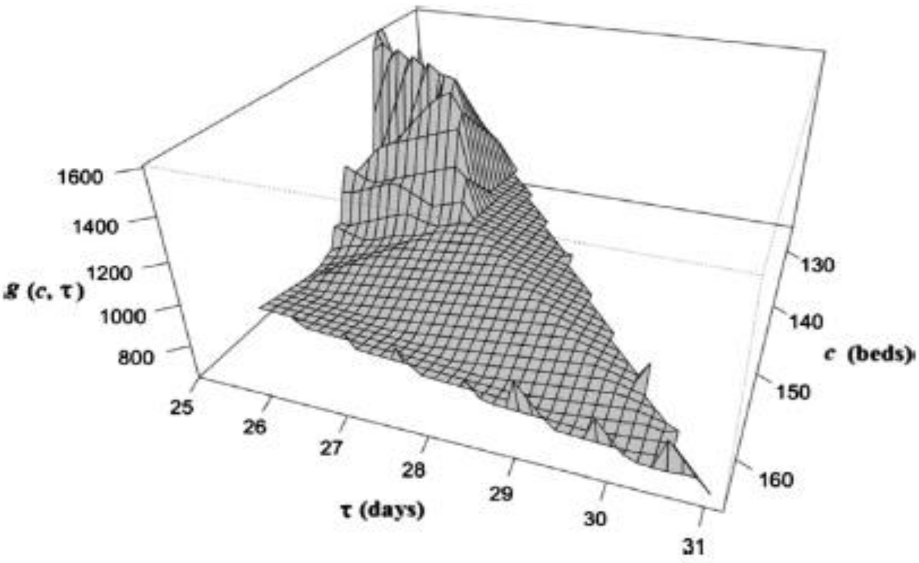

Fig. 4. Graph of the cost function $g(c, \tau)$.

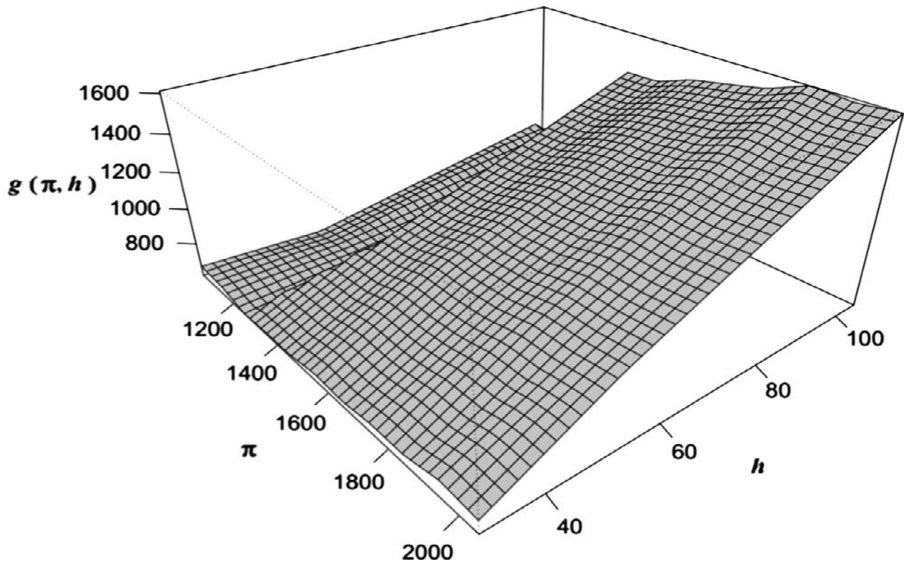

Fig. 5. Cost function's graph, shown as g(π, h).

- The average penalty cost is £1750, the standard deviation is £215, and the holding expenses total £104, resulting in an average of £1530.95, the standard deviation being £84.17.

Therefore, despite the penalty cost not exceeding £1650, the hospital administrator could decide to maintain the holding charges of £32 for an anticipated standard cost function of £617.18.

On the other hand, if penalties rise to £2050, holding charges above £105 may cause a rise in the function cost of up to £1623.25 (avg. g = £1520.45).

Overall, as shown by formula (4), the volume of applications that were declined B greatly exceeds the significance of the quantity vacant beds due to the huge disparity between the penalty cost and the holding cost. In these situations, manager of the hospital can select the appropriate minimal amount of beds and a sufficient mean service time to save costs and ensure competent medical care while maintaining the percentage of lost demands at a manageable level.

Note that the cost of the penalty is merely suggestive and is based on the supposition that the penalty may be seen as a kind of revenue lost any time a patient is rejected (because there are no open beds).

Unlike the prior strategy, which was just concerned with queuing methods .The approach suggested in this research inherits the adaptability and effectiveness of evolution-based computing, encapsulating all the data given by the cost side (h, π) and queuing side (c, λ, τ)in an exhaustive and unitary manner utilising the chromosome. Instead of only taking into beds and the ratio of penalties to holding costs as control variables and only providing partial results regarding the optimisation either the costs or the inventories, we considered all five parameters that define the model's degrees of flexibility, offering solutions for the best inventory and prices as well as potential useful recommendations resulting from "What-if" analysis.

Managing patients whilst utilising the technique

Different strategies emerging from operations research and machine learning techniques made a substantial contribution to offering real-world strategies for managing patients more effectively McClean et al (2009) Inefficient bed allocation, overcrowding in hospital departments, undesirable and potentially damaging cases of rejected patients, improved High-quality medical services and a welcoming environment for patients can all be reduced by an efficient patient flow.

Theoretically, the individuals involved in hospital management must: (a) Grasp and evaluate the financial resources, inventory, and patient flow factors; (b) Determine the actual options for changing the criteria for making the decision (such as the length of stay, the availability of vacant beds, the cost per occupied/unoccupied bed, the cost of the penalty, etc.); (c) Estimate or anticipated adjustments to the government's view on bed availability and supply; and (d) implement the changes as they occur.

The following stages should be included in the model's implementation :Estimating the parameters of the queuing model and the accompanying (GA implementation) searching .it is necessary to (a) analyse the data records pertaining to patient flow, and (b) analyse the history of bed allocation (including constraints on bed stock, bed closures, bed crises, etc.). Permitting the use of hypothetical analyses (or "what-if analysis") for the bed inventory (c) An affordable number of occupied/unstaffed beds is required to calculate an adequate mean service time. an inexpensive daily rate for inpatient care, and (d) It is necessary to analyse modifications to the hospital's management strategy in respect to allotted budget before conducting a time series analysis of the hospital admissions pattern in order to identify its major components , forecast its behaviour, and propose the best future scenarios.

The fundamental queuing model is defined by two different types of parameters. The frequency of arrivals or the average service time (length of stay) is two examples of parameters that a healthcare provider cannot alter. These parameters are what we refer to as "objective" parameters. It is important to note that even these objective metrics can vary under certain conditions. For instance, external factors (such as demography, epidemiology, or perceptions) may cause variations in the number of arrivals. However, even for specific treatments, it was observed that the lengths of stays for two different patients varied by more than a week [34]. The term "subjective parameter" refers to another sort of parameter that medical experts may alter under certain conditions.

(e.g., MATLAB/Genetic Algorithm Solver)

We use a made-up example of three distinct bed allocation procedures to demonstrate the aforementioned points. Think of the "objective" parameters of a steady-state geriatric department. $\lambda \approx 5.30$ patients each day, a stay of $\tau \approx 24$ days, and a "subjective" parameter c between 120 and 170. The penalty fee π is the same as the default amount of £1046 . By utilising the mix queuing/GA model we were able to simulate three distinct scenarios with respect to the selection of the control ("subjective") parameters c and as well as the related rejection probability B, carried load L (average number of inpatients), and incurred expenses, which were calculated as: (a) Total expenditures are calculated by multiplying the average number of inpatients by the cost per patient per day, which is £168; (b) Costs of unstaffed beds; penalty cost PC related to the percentage of lost patients calculated as PC = π X B; UBC equals £50 X c (cost per bed times the quantity y of unstaffed beds).c). Table 4 presents the outcomes.

The managers typically try to distribute the fewest number of beds possible (adding additional beds, if required) in order to cut healthcare expenditures, which are currently the focus of political disputes, while the opposite scenario can also be envisioned.

Table 4: The outcomes of three distinct methods for allocating beds

λ	τ	c	B
5.13	26	132	5.6
		143	2.1
		146	1.6

Assume that c = 130 is the default number of beds in this situation. Using the optimisation model, they could have to choose between the following options:–

Scenario #1: selecting c = 132 as the least amount of beds. The disadvantages of this option include the highest percentage of patients who are turned away (B = 5.7%), which could have a bad impact on how the public perceives them, and the highest prices (TC = £20,520, PC = £58.50);

– Scenario #2: 13 additional beds are added (c = 142 allocated beds). The corresponding benefits of this decision include a reduction in associated expenditures (minus £817 for TC and £73 for PC) and a 2.5 times reduced percent of patients who are refused (B = 2.1%). On the other hand, the price for each bed that was unattended rose by £500.

– Scenario #314 additional beds are added (c = 145 allocated beds). Although the addition of three beds to the preceding scenario's bed count may not seem like much of a difference, the benefits in terms of cost savings are significant. PC fell by £7.32, but TC climbed by £104. Each unstaffed bed now costs £150 more. The price per vacant bed rose by £600. but TC and PC both fell by £921 and £44 in comparison to the previous scenario. The most consistent benefit is a roughly four-fold reduction in the fraction of rejected patients. Additionally, the related cost functions g's are predicted to be g1 = £1485.42, g2 = £632.30, and g3 = £670.85 if we assign, for example, a penalty cost ofπ1 = £1842in the first scenario, π2 = £1440 in the second scenario, and π3= £2040 in the third scenario, respectively .When comparing the first and last models (which have the most beds, , it can be seen that, despite the fact that the number of beds rose by 14, a £100 difference in the penalty cost results in a reduction of around £912 of the associated function cost. This straightforward illustration illustrates the significance of taking into accountancy patient model's related function cost.

IV. Discussion

In this study, we investigate the viability of supporting hospital bed occupancy and resource utilisation with a mix of Artificial intelligence and operations research. The intention is to give medical practitioners a helpful computer-aided tool to help them choose which policies could be implemented with the most impact. It is important to emphasise that this method's primary function is to provide decision-making support, therefore hospital administrators are unlikely to employ it directly.

The paper has three main objectives. First, a novel evolutionary-based technique to optimise hospital management is proposed, beginning from a typical M/PH/c queue paradigm for hospital bed occupancy. This approach offers an effective means to determine controls for the systems as to:

- A manageable number of patients who have been turned away that we are willing to accept.
- The comparable average number of hospital patients. The comparable average number of hospital patients.
- Availability of beds.

Second, we developed a method to optimise resource in accordance with the theory of evolution by taking into account base-stock guidelines frequently employed In inventory management programmes for pricey and slowly moving goods, with the non-profit assumption practise typical to the National Health Service. We have given the hospital administrator the ability to predict the required optimum resource parameters utilisation by including the cost model's attributes as well as the queuing model's properties, contained in a chromosomal vector form. Consequently, by balancing the number of beds available, arrival rate, mean service time, holding charges, and penalties, a hospital department can become more productive.

Finally, we suggested a "What-if" analysis that allows the hospital administrator to practise various scenarios in order to determine the (almost) optimum course of action based on the situation.

We used Availability of beds from the Division of Geriatric Medicine. at Jaipuria Hospital in Jaipur, India, to illustrate the process. Cost modelling was motivated by a prior study with this method intended to be suggestive and real costs dependent exclusively on the hospital.

It is useful and practical to use the theory of evolution to optimise hospital stock and related healthcare in a number of ways:

- The entire information provided by the cost model and the queuing system is encoded in the chromosome.

- The GA strategy is stated openly.
- An appropriate algorithm is straightforward to comprehend and use
- The optimisation procedure is simple and depends on using all of the data at once dash.
- Utilise this technique. in a wide range of these kinds of scenarios.

V. Conclusion

To enhance patient management, queuing models are commonly used in healthcare systems. On the other hand, because to their effectiveness, relative comprehensibility, and ease of use, GAs are natural computing techniques that are primarily used in optimisation tasks. On the task of optimising healthcare and patient management expenses, the usefulness of the unique strategy, which combined queuing models with the paradigm for evolution, was demonstrated. The hospital's geriatric division in Jaipur, India, served as the model's inspiration and it was used in a real-world scenario. Future studies could focus on:

- Using an extensive queuing system of the M/PH/c/N type with a fixed N > c maximum capacity to prevent, when all beds are full, patients are turned away. A (N-c) waiting room may be present with such a setup.
- The configuration of the relevant cost model.
- The enhanced model's evolutionary-based optimisation.

References

[1] Belciug, S., & Gorunescu, F. (2015). Improving Hospital Bed Occupancy And Resource Utilization Through Queuing Modeling And Evolutionary Computation. Journal Of Biomedical Informatics, 53, 261-269.

[2] Cochran, J. K., & Roche, K. T. (2009). A Multi-Class Queuing Network Analysis Methodology For Improving Hospital Emergency Department Performance. Computers & Operations Research, 36(5), 1497-1512.

[3] Cooper, R. B. (1990). Queueing Theory. Handbooks In Operations Research And Management Science, 2, 469-518.

[4] Currie, C. S., & Lu, L. (2009). Optimal Scheduling Using Length-Of-Stay Data For Diverse Routine Procedures. Intelligent Patient Management, 193-205.

[5] De Bruin, A. M., Bekker, R., Van Zanten, L., & Koole, G. M. (2010). Dimensioning Hospital Wards Using The Erlang Loss Model. Annals Of Operations Research, 178, 23-43.

[6] Eiben, A. E., Smith, J. E., Eiben, A. E., & Smith, J. E. (2003). Gray Coding. Introduction To Evolutionary Computing, 265-265.

[7] Faddy, M. (1994). Examples Of Fitting Structured Phase–Type Distributions. Applied Stochastic Models And Data Analysis, 10(4), 247-255.

[8] Faddy, M. J., & Mcclean, S. I. (2007). Using A Multi-State Model To Enhance Understanding Of Geriatric Patient Care. Australian Health Review, 31(1), 91-97.

[9] Garg, L., Mcclean, S., Meenan, B., & Millard, P. (2010). A Non-Homogeneous Discrete Time Markov Model For Admission Scheduling And Resource Planning In A Cost Or Capacity Constrained Healthcare System. Health Care Management Science, 13, 155-169.

[10] Gillespie, J., Mcclean, S., Scotney, B., Garg, L., Barton, M., & Fullerton, K. (2011). Costing Hospital Resources For Stroke Patients Using Phase-Type Models. Health Care Management Science, 14, 279-291.

[11] Gong, Y. J., Zhang, J., & Fan, Z. (2010, October). A Multi-Objective Comprehensive Learning Particle Swarm Optimization With A Binary Search-Based Representation Scheme For Bed Allocation Problem In General Hospital. In 2010 Ieee International Conference On Systems, Man And Cybernetics (Pp. 1083-1088). Ieee.

[12] Gorunescu, F., Mcclean, S. I., & Millard, P. H. (2002). A Queueing Model For Bed-Occupancy Management And Planning Of Hospitals. Journal Of The Operational Research Society, 53, 19-24.

[13] Gorunescu, F., Mcclean, S. I., & Millard, P. H. (2002). Using A Queueing Model To Help Plan Bed Allocation In A Department Of Geriatric Medicine. Health Care Management Science, 5, 307-312.

[14] Gryczynski, J., Schwartz, R. P., O'grady, K. E., Restivo, L., Mitchell, S. G., & Jaffe, J. H. (2016). Understanding Patterns Of High-Cost Health Care Use Across Different Substance User Groups. Health Affairs, 35(1), 12-19.

[15] Harrison, G. W., & Millard, P. H. (1991). Balancing Acute And Long-Term Care: The Mathematics Of Throughput In Departments Of Geriatric Medicine. Methods Of Information In Medicine, 30(03), 221-228.

[16] Horrocks, P. (1986). The Components Of A Comprehensive District Health Service For Elderly People—A Personal View. Age And Ageing, 15(6), 321-342

[17] Koizumi, N., Kuno, E., & Smith, T. E. (2005). Modeling Patient Flows Using A Queuing Network With Blocking. Health Care Management Science, 8, 49-60.

[18] Lee, D. K., & Zenios, S. A. (2009). Optimal Capacity Overbooking For The Regular Treatment Of Chronic Conditions. Operations Research, 57(4), 852-865.

[19] Li, X., Beullens, P., Jones, D., & Tamiz, M. (2009). An Integrated Queuing And Multi-Objective Bed Allocation Model With Application To A Hospital In China. Journal Of The Operational Research Society, 60(3), 330-338.

[20] Marshall, A. H., Mcclean, S. I., Shapcott, C. M., Hastie, I. R., & Millard, P. H. (2001). Developing A Bayesian Belief Network For The Management Of Geriatric Hospital Care. Health Care Management Science, 4, 25-30.

[21] Mcclean, S., & Millard, P. (1993). Patterns Of Length Of Stay After Admission In Geriatric Medicine: An Event History Approach. Journal Of The Royal Statistical Society: Series D (The Statistician), 42(3), 263-274.

[22] Mcclean, S., Millard, P., El-Darzi, E., & Nugent, C. D. (Eds.). (2009). Intelligent Patient Management (Vol. 189). Springer.

[23] Millard, P. H., Rae, B., & Busby, W. (2009). Why Nosokinetics? Measuring And Modelling The Process Of Care. In Intelligent Patient Management (Pp. 3-23). Berlin, Heidelberg: Springer Berlin Heidelberg.

[24] Mishra,R.K, & Sharma, Geetanjali .(2023). A Randomized Clinical Trial Using Artificial Intelligence To Shorten Wait Times And Boost Customer Satisfaction In Pediatric Outpatient Services. Eur. Chem. Bull. 2023,12(10), 13146-13160

[25] Ross, S. M. (2020). Introduction To Probability And Statistics For Engineers And Scientists. Academic Press.

[26] Stevenson, W. J., Hojati, M., & Cao, J. (2014). Operations Management (P. 182). New York: Mcgraw-Hill Education.

[27] Stoean, C., & Stoean, R. (2014). Post-Evolution Of Variable-Length Class Prototypes To Unlock Decision Making Within Support Vector Machines. Applied Soft Computing, 25, 159-173.