ABUAD Journal of Engineering Research and Development (AJERD)
ISSN (online): 2645-2685; ISSN (print): 2756-6811

Volume 8, Issue 2, 32-43

Dynamic Hospital Resource Scheduling During Pandemics with Stochastic Optimization

Yewande OJO[1], John OGBEMHE[2], Oluwabukunmi Victor BABATUNDE[3], Subomi OKEOWO[4], Olubayo BABATUNDE[5], John ADEBISI[6]

[1]*Department of Communications Management, University of Denver*
yewande.ojo@du.edu

[2]*Department of Systems Engineering, University of Lagos, Nigeria*
jogbemhe@unilag.edu.ng

[3]*Department of Industrial Design, Federal University of Technology, Akure, Nigeria*
victorobabatunde@gmail.com

[4]*College of Arts, Media and Design, Northeastern University, USA*
subbyokky@gmail.com

[5]*Department of Electrical Engineering, University of Lagos*
babatundeom@ieee.org

[6]*Division of Engineering & Technology, The University of West Alabama, Livingston, AL 35470, USA*
jadebisi@ieee.org

Corresponding Author: babatundeom@ieee.org, +2347033278464
Date Submitted: 05/12/2024
Date Accepted: 12/05/2025
Date Published: 13/05/2025

Abstract: *The COVID-19 pandemic has highlighted the need to effectively manage hospital resources: ICU beds and ventilators. These resources are significant for sustaining life, especially in severe cases. Traditional deterministic models often fall short in addressing the uncertainties associated with patient inflows and resource availability. This paper develops a novel two-stage stochastic programming model which aims to dynamically allocate resources to deal with the variability of inpatient admissions. To this end, the scenarios are developed using Monte Carlo simulation based on the probabilities estimated from the historical data. The model is created in Python language and solved using the Gurobi optimizer in 0.05s, a large-scale scenario optimization analysis problem with 42 variables and 35 constraints. The KPIs show the highest utilization of ventilators at 66. 67% and the average reduction of 53.5 in the number of offers an ICU practical shortfall leading to better patient care and shorter wait times. This research presents a data-driven tool to enhance the decision-making process and the healthcare system's overall readiness to maintain its strategic reserves by implementing flexible staffing models to improve preparation for disasters such as the pandemic. Its stochastic optimization framework makes hospital resource allocation more efficient, offering a scalable, resilient solution for tackling future pandemic challenges.*

Keywords: *Stochastic Programming, Hospital Resource Allocation, Pandemic Preparedness, Monte Carlo Simulation, Gurobi Optimizer, Resource Utilization*

1. INTRODUCTION

1.1. Background and Motivation

Recent pandemics have pushed global healthcare systems to their limits, overwhelming them with surging patient numbers and critical shortages of ICU beds and other vital resources [1]. For example, the COVID-19 pandemic exposed how unprepared hospitals are for sudden patient surges, leaving facilities overwhelmed and patient care compromised.[2, 3]. Traditional resource management relies on fixed allocation models that fail to handle pandemics' unpredictability and rapid changes [4]. These models assume steady patient arrivals and resources, which can lead to poor planning and even more significant shortages during demanding times. Yang, Zhang [5] reports a push for models that integrate real-time data and probabilistic forecasting to improve the responsiveness and resilience of healthcare systems. As noted in Essoussi, Masmoudi [6], [7], adaptive resource allocation uses advanced optimization to help hospitals quickly adjust resources to real-time patient surges and changing pandemic conditions. As reported in the works of Biswas, Belamkar [8], [9, 10], Stochastic programming models uncertainties and optimizes decisions, cutting resource waste and ensuring critical care is available when needed. These approaches help healthcare administrators boost efficiency, improve patient care, and build stronger, more resilient systems for future pandemics. This research presents a two-stage stochastic optimization model to dynamically schedule hospital resources and handle patient inflow and resource availability uncertainties. It uses stochastic programming to improve resource allocation, reduce shortages, and enhance patient care during unpredictable pandemics. The approach uses stochastic optimization to overcome these limitations, and the key outcome is a model that minimizes shortfall costs while optimizing staff utilization. The model is constructed using the Python framework, with Gurobi employed as the solver to maximise resource utilization, mitigate shortages, and improve patient care. The rest of the paper is structured as follows. Section 2 discusses related works in the subject matter. Section 3 explains how we developed and applied a two-stage stochastic programming model with Python and Gurobi. Sections 4 and 5 delineate scenario analyses and discussion of the research, while section 6 summarizes the conclusion of the paper.

The following sections explain how we created and applied a two-stage stochastic programming model with Python and Gurobi. The results section delineates scenario analyses. The discussion interprets the findings, examines their implications for healthcare policy and resource allocation, and underscores the model's limitations. The study results are summed up in the conclusion, indicating how the model enhances patient outcomes and healthcare resilience and proposes subsequent analyses.

2. RELATED WORKS

Pandemic scenarios test healthcare systems globally with exponential patient inflow and uncertain resource demand [11]. Early studies on deterministic approaches for resource scheduling, as documented in Rachaniotis, Dasaklis [12], concentrated on the often inadequate handling of the dynamic problems of pandemics. They presume consistent patient arrivals and resource availability, which results in inflexible allocation rules that usually fail during high demand [13]. The handling of uncertainty is where deterministic and stochastic models differ most from each other. Deterministic models depend on predefined assumptions and offer unambiguous but usually rigid distribution techniques [14]. Although they are simple to operate, they find it difficult to adjust to real-time changes in patient count and resources, which usually results in bad outcomes during unanticipated surges. As reported in the works of Corlu, Akcay [15], stochastic models provide flexible answers for resource allocation by managing variability and uncertainty. Probabilistic scenarios make them more dependable and valuable since they help one better forecast and adjust to future developments. Recent studies employ stochastic optimisation more and more to address pandemic uncertainty properly [16, 17]. For example, Bhattacharjee and Ray [18] studied patient flows and possible resource supply chain problems using stochastic models with probabilistic characteristics. This makes for resilient and flexible distribution of resources. Unlike deterministic models, Yin and Büyüktahtakın (2021) devised a stochastic model that changes ICU bed allocation in real time depending on patient inflow, optimizing resource use and patient outcomes. Stronger decision-making is made possible by these stochastic models' better handling of unpredictability and uncertainty than deterministic ones [19]. Xu and Sen [20] report the application of stochastic programming to maximize ventilator allocation during COVID-19, balancing resource consumption and demand surge readiness. Eshkiti, Sabouhi [21] reported using Stochastic optimization incorporating real-time data to make healthcare resource scheduling more responsive and adaptable. These models use real-time data to update allocations, ensuring resources are used efficiently in changing conditions. Yinusa and Faezipour [22] researched using stochastic models to reduce resource shortages and improve patient outcomes with smarter, more flexible allocation strategies. In a related development, Blanco, Gázquez [23] conclude that stochastic models optimize multiple resources at once, managing ICU beds, ventilators, and medical staff simultaneously. This approach, unlike deterministic models that focus on single resources, provides a more complete solution to the complex challenges of pandemics.

Despite advances in stochastic optimization for healthcare, significant gaps remain. For example, most models focus on optimizing a single resource, like ICU beds or ventilators, rather than managing multiple critical resources together—an essential need for effective pandemic response [24]. Mazlan, Daud [25] concludes that current models often struggle with scalability, limiting their use in larger hospitals or diverse healthcare settings. Another issue is the computational complexity and data needs of stochastic models. For example, Alizadeh, Allen [26] notes that Stochastic models struggle to adapt to big, varied healthcare systems since they suffer from computing requirements and data needs. As stated in the work of Mengesha [27], advancing the scalability of stochastic models with better computation and data processing would increase their application in various environments, including healthcare. Closing these gaps is essential to make healthcare systems more resilient and efficient for the successive crises, even if stochastic optimisation has improved healthcare resource scheduling during pandemics.

3. METHODOLOGY

3.1 Model Formulation

A two-stage stochastic programming model is introduced to optimize ICU bed and ventilator distribution during the pandemic. The goal is to close the gap between available resources and patient demand in uncertain scenarios. The first stage of the optimization algorithm ensures proactive resource allocation decisions before the uncertain parameters. The second stage deals with the remedy after these uncertainties manifest.

3.1.1 Notation and Definitions

Sets:

- $\mathrm{T} = \{1, 2, \ldots, 30\}$: Period (days).
- $R = \{ICU,\ Ventilator\}$: Types of resources.
- $S = \{S_1, S_2, S_3\}$: Scenarios representing different demand levels.

Parameters:

- C_r : Total capacity for resource r.
- $D_{r,t,s}$: Types of resources demand for resource r at time t under scenario s.
- ps : Probability of scenario s.
- β_r : Cost coefficient for the shortfall of resource r.
- k_r : Staffing requirement per unit of resource r.
- M_t : Total available medical personnel at the time t.
- $a_{r,s,t}$: Availability factor for resource r under scenario s at time t.
- $y_{r,t,s}$: Additional units of resource r at time t under scenario s

Decision Variables:

- $x_{r,t} \geq 0$: First-stage allocation of resource r at time t.
- $y_{r,t} \geq 0$: Additional units of resource r at time t
- $c \geq 0$: Second-stage additional allocation of resource r at time t under scenario s.
- $z_{r,t,s} \geq 0$: Shortfall of resource r at time t under scenario s.

Performance Metrics:

- Expected Shortfall (in units): Quantifies the average unmet demands across simulation runs.
- Expected Shortfall Cost ($): Calculates the economic impact of the shortfall using penalty coefficients for each resource type.
- Resource Allocation (%): Indicates the proportion of available resources allocated per period.
- Staffing Utilization (%): Measures how effectively the available medical personnel are utilized based on staffing requirements per resource.

3.1.2 Objective functions

The model aims to minimize the projected shortfall cost across all scenarios and resources. The objective function combines the shortfall costs, weighted by their corresponding scenario probabilities. It minimizes the anticipated costs related to inadequacies in resource allocation across all scenarios and resources as described mathematically in Equation (1).

$$Minimize\ = \sum_{s\epsilon S} ps \sum_{r\epsilon R} \sum_{t\epsilon T} \beta_r \cdot z_{r,t,s} \tag{1}$$

3.1.3 Constraints

The first-stage capacity constraints as described in Equation (2), ensure the initial resource allocations do not exceed the available capacities.

$$\sum_{t\epsilon T} x_{r,t} \leq C_r\,, \qquad \forall r \in R \tag{2}$$

The second-stage demand satisfaction constraints as described in equation (3). It ensures the allocations satisfy patient demand in every scenario, permitting managed gaps and considering the availability factor.

$$x_{r,t} +\ x_{r,t} \geq D_{r,t,s} \cdot a_{r,s,t} - z_{r,t,s}, \qquad \forall r \in R, \forall t \in T, \forall s \in S \tag{3}$$

The second-stage capacity constraint is described in Equation (4). Its guarantees that the supplementary allocation in the second stage does not beyond the residual capacity following the first-stage allocation.

$$\sum_{t\epsilon T} y_{r,t,s} \leq C_r - \sum_{t\epsilon T} x_{r,t},\ \forall r \in R, \forall s \in S \tag{4}$$

Staffing constraints is described in Equation (5). Its guarantees that the medical personnel needed for both first-stage and second-stage allocations always remain within the capacity of available medical professionals and under all circumstances.

$$\sum_{r\epsilon R} \left(k_r \cdot x_{r,t} + k_r \cdot y_{r,t,s}\right) \leq M_t, \quad \forall t \in T, \forall s \in S \tag{5}$$

The non-negativity constraints are described in Equations (6). It guarantees that all allocations and deficits are non-negative, conforming to feasible operating circumstances. All decision variables must be non-negative, representing actual distributions and deficiencies.

$$x_{r,t} \geq 0,\ \ y_{r,t,s} \geq 0,\ \ z_{r,t,s} \geq 0, \qquad \forall r \in R, \forall t \in T, \forall s \in S \tag{6}$$

Figure 1 illustrates the two-stage stochastic programming model for allocating ICU beds and ventilators. Table 1 summarizes the two-stage stochastic programming algorithm.

3.2. Mathematical Formulation

The elements in the Equations (1-6) can be properly combined as a combined two-stage stochastic programming model combined as follows, in (7-8):

Table 1: Two-stage stochastic programming algorithm

```
procedure RESOURCE_ALLOCATION(T, R, S, C, D, PS, β, K,
    for all v ∈ V(G) do
        l(v) ← ∞
    end for
    l(u) ← 0
    repeat
        for i ← 1, n do
            min ← l(vi)
            for j ← 1, n do
                if min > e(vi, vj) + l(vj) then
                    min ← e(vi, vj) + l(vj)
                    p(i) ← vj
                end if
            end for
            l(i) ← min
        end for
        changed ← l ≠ l
        l ← l
    until changed
end procedure
```

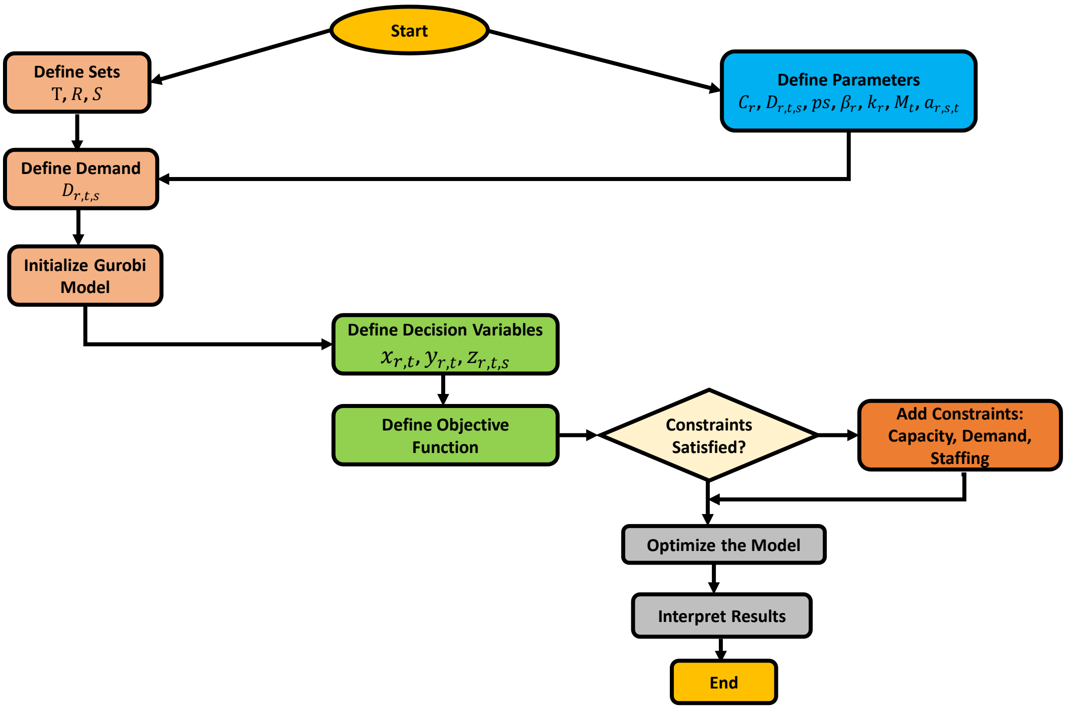

Figure 1: Detailed flowchart of the two-stage stochastic programming model for hospital resource allocation

$$minimize \sum_{s\epsilon S} ps \left(\sum_{r\in R} \sum_{t\in T} \beta z_{rst} \right) \qquad (7)$$

$$Subject\ to$$

$$\sum_{t\epsilon T} x_{r,t} \leq C_r, \qquad \forall r \in R \qquad (8)$$

$$x_{rt} + y_{rst} \geq D_{rt} \cdot a_{rst} - z_{rst}, \qquad \forall r \in R, \forall t \in T, \forall s \in S$$

$$\sum_{t\epsilon T} y_{rst} \leq C_r - \sum_{t\epsilon T} x_{rt}, \quad \forall r \in R, \forall s \in S$$
$$\sum_{r\epsilon R} k_r x_{rt} + \sum_{r\epsilon R} k_r y_{rst} \leq M_t\ , \quad \forall t \in T, \forall s \in S$$
$$x_{rt} \geq 0, \quad y_{rst} \geq 0, \quad z_{rst} \geq 0, \quad \forall r \in R, \forall t \in T, \forall s \in S$$
$$Additional\ operational\ constraints$$
$$\forall r \in R, \forall t \in T, \forall s \in S$$

3.3. Stochastic Optimization Approach

Implementing a two-stage stochastic programming framework is essential for optimizing hospital resource allocation described in Table 1 and Figure 1. This is within the context of the uncertainties presented by a pandemic. This methodological choice divides the decision-making process into two distinct phases: the first and second. Primarily, decisions are made proactively before the occurrence of uncertain events, including variations in patient inflow and differing demand levels across various scenarios (S_1, S_2, S_3). The allocation of resources: ICU beds and ventilators, is dictated by baseline demand projections and capacity constraints, represented by the parameters C_r and $D_{r,t,s}$. This proactive allocation keeps the hospital prepared and lowers the risk of shortages. In the second stage, the model adjusts resource allocations ($y_{r,t,s}$) and handles shortfalls ($z_{r,t,s}$) based on specific scenarios as uncertainties unfold. This reactive component dynamically adjusts to real-time demand changes, cutting anticipated shortfall costs (β_r) across scenarios.

The two-stage stochastic framework combines proactive and reactive strategies to balance resource utilization and flexibility that guarantees readiness and responsiveness to pandemic uncertainty. Discrete probabilities allow one to predict patient inflow for scenariosS_1, S_2, and S_3. By including resource availability uncertainty with availability factors $a_{r,s,t}$, supply chain disruptions and maintenance concerns are addressed. Making the two-stage stochastic model strong for the distribution of hospital resources depends on creating scenarios. This work generates several scenarios of patient influx and resource availability using Monte Carlo techniques. The Monte Carlo simulation uses historical COVID-19 hospitalization data to generate probable demand patterns for ICU beds and ventilators, defined by $D_{r,t,s}$. The model includes a wide range of scenarios—fluctuations in patient inflow and resource supply disruptions—to handle uncertainty and adapt to both typical and unexpected pandemic situations. It is worth noting that too many scenarios can make the optimization problem unmanageable, while too few might miss key uncertainties. This framework limits the number of scenarios to cover key uncertainties while keeping the model solvable. This ensures the stochastic model stays robust, efficient, and ready to maximize resource allocation in several epidemic circumstances. Using its tools for efficient computing and analysis, Python is applied in two-stage stochastic programming. Gurobi handled the optimisation and the demanding tasks required for real-time pandemic responses. Pandas manage and arrange the data; NumPy is used to conduct the numerical operations. SciPy, matplotlib, and Seaborn supported scenario development and visualization. To boost model resilience, we created many scenarios based on probability distributions using Monte Carlo methods using NumPy. Data gaps lead the model to assume constant resource availability and patient arrival rates based on historical averages, simplifying the model to concentrate on significant uncertainty and guaranteeing efficiency.

4. RESULTS

4.1. Model Implementation

The two-stage stochastic programming model was implemented in Python, utilizing Gurobi for optimisation. The procedure involves establishing sets, parameters, and decision variables derived from hospital data concerning ICU beds and ventilators over three distinct periods and scenarios. A significant challenge involved maintaining computational efficiency while navigating various scenarios and constraints. We simplified the model and used Gurobi's solver, which, after 31 runs, produced an ideal answer in just 0.05 seconds. The solver stops when the optimality gap reaches zero. This tells us the feasible solution is the best one, and it is equal to the theoretical lower bound. Thus, it is globally optimal. The final objective value was leveled off at *109,000.00*, which means no further improvement. Primal and dual feasibility criteria were met at iteration 31. At this iteration, the primal and dual infeasibilities were pinpointed to zero, which is correct. Presolve processes have also significantly reduced the size of the optimization problem given to the solver. The problem size was reduced from the initial 35 rows, 42 columns and 132 nonzero elements. This simplification has undoubtedly enhanced the computational speed. Therefore, the computational efficiency has been improved, and the solver could find the optimal solution in 0.13 seconds. This result shows how efficient the solver is after the presolve optimizations. The computing device used for this simulation are reported as follows:

- CPU model: Intel(R) Core(TM) i7-5500U CPU @ 2.40GHz, instruction set [SSE2|AVX|AVX2]
- Thread count: 2 physical cores, 4 logical processors, using up to 4 threads
- Gurobi Optimizer version 11.0.3 build v11.0.3rc0 (win64 - Windows 11.0 (22000.2))

The performance study verified the effective use of resources with few shortages. Visualization techniques helped make the results easily understandable, increasing the model's practical applicability for pandemic management of hospital resources.

4.2. Scenario Analysis

Under three scenarios S_1, S_2, and S_3 we assessed the two-stage stochastic programming model's capacity to maximise ICU bed and ventilator allocation under diverse patient inflow and uncertainty. While S_3, (20% likelihood) considers significant input, S_1, (30% probability) assumes modest inflow; S_2, (50% probability) indicates the most likely demand [28]. These scenarios, produced by Monte Carlo techniques, guarantee a varied and reasonable range of future conditions. Figures 2 and 3 show the initial allocations from the first stage, set before the scenarios unfolded. The model initially allocated zero ICU beds, assuming adequate baseline capacity or conserving resources. However, ventilator allocations were proactive, assigning 20 units on Day 2 and 2.5 on Day 3. This strategy balances short-term needs with flexibility for long-term demands. The model dynamically adjusts the allocation of ICU beds and ventilators depending on the baseline capacity, staffing constraints and the stochastic demand forecasts made. The model emphasizes flexibility for effective resource management while at the same time being able to respond to the changing pandemic conditions. The parameters used for the simulation are described in Table 2.

Table 2: Parameters used in the simulation

Scenario	ICU Shortfall	Ventilator Shortfall
S_1	40	30.0
S_2	55	38.0
S_3	70	45.0

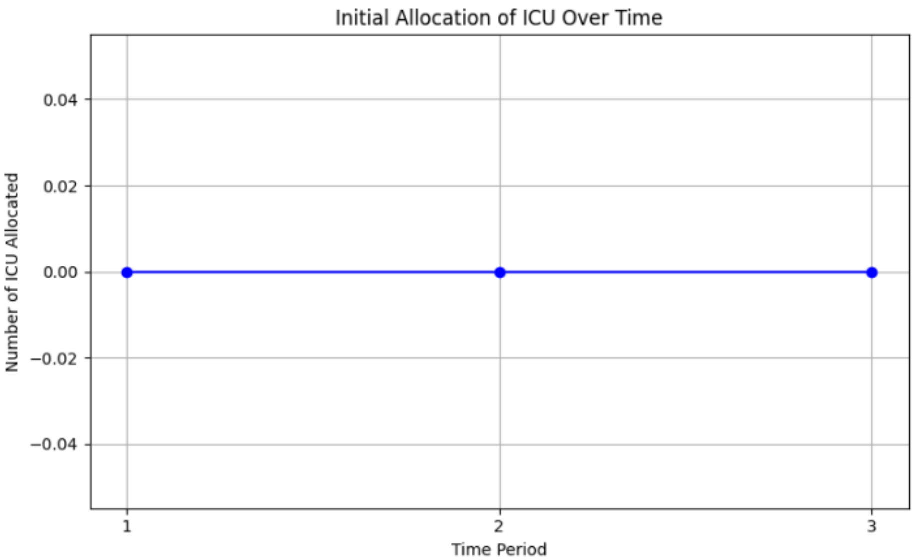

Figure 2: Initial allocation of ICU beds over time

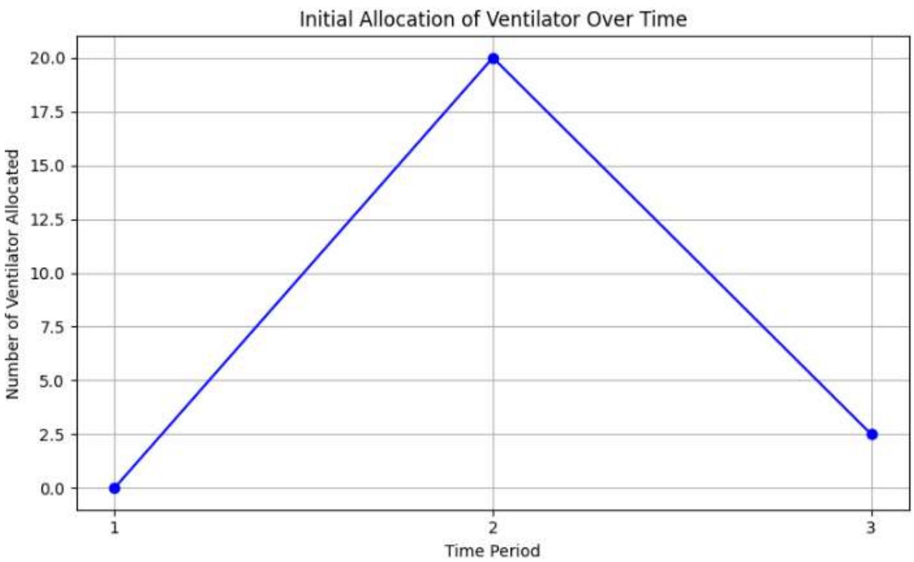

Figure 3: Initial allocation of ventilators over time

After the scenarios unfolded, the model adjusted resource allocations to address shortfalls. Figures 4, 5, and 6 show the shortfall distributions for each scenario. In S_1, there were shortages of 40 ICU units and 30.0 ventilators. The S_2 faced deficits of 55 ICU units and 38.0 ventilators, while S_3 showed 70 ICU unit shortages and 45.0 ventilator deficits. Table 3 highlights how the model predicts and responds to varying demand levels, though some unmet needs may lead to patient wait times.

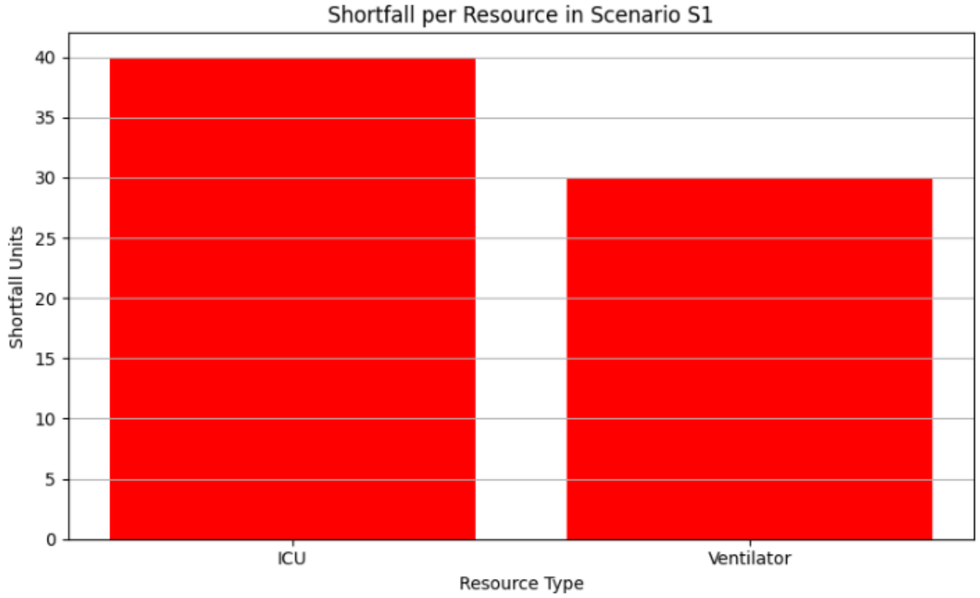

Figure 4: Shortfall per resource in scenario S_1

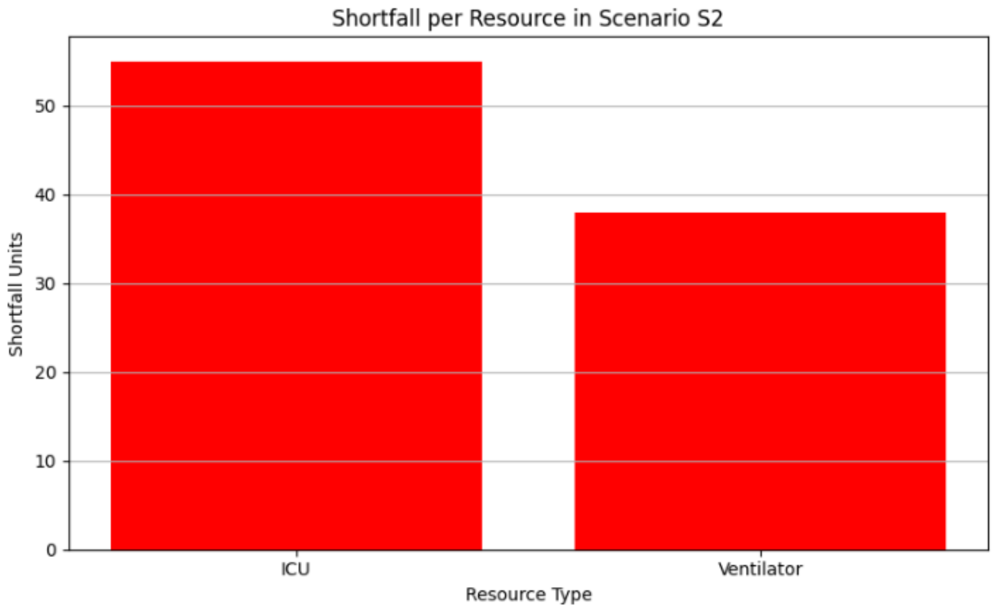

Figure 5: Shortfall per resource in scenario S_2

Staffing utilization, as compensated for in Equation (5), an essential metric indicating operational efficiency, is illustrated in Figures 7, 8, and 9 for scenarios S_1, S_2, and S_3, respectively. In Scenario S_2, staffing utilization reached 100% on Day 1, indicating optimal deployment, which then reduced gradually and reflects how resources were fully utilized at the beginning. Other scenarios demonstrated different utilization rates, with 94.44% in S_1, and 94.33% in S_3, Day 2, reflecting effective but suboptimal use of available personnel. The variations highlight the model's capacity to adjust staffing resources according to changing demands. Figures 7, 8, and 9 clearly show how staffing resources are allocated and adjusted according to demand. It offers a better understanding of staffing utilization beyond raw numbers. The utilization was derived based on the ratio of allocated resources to the available staffing capacity.

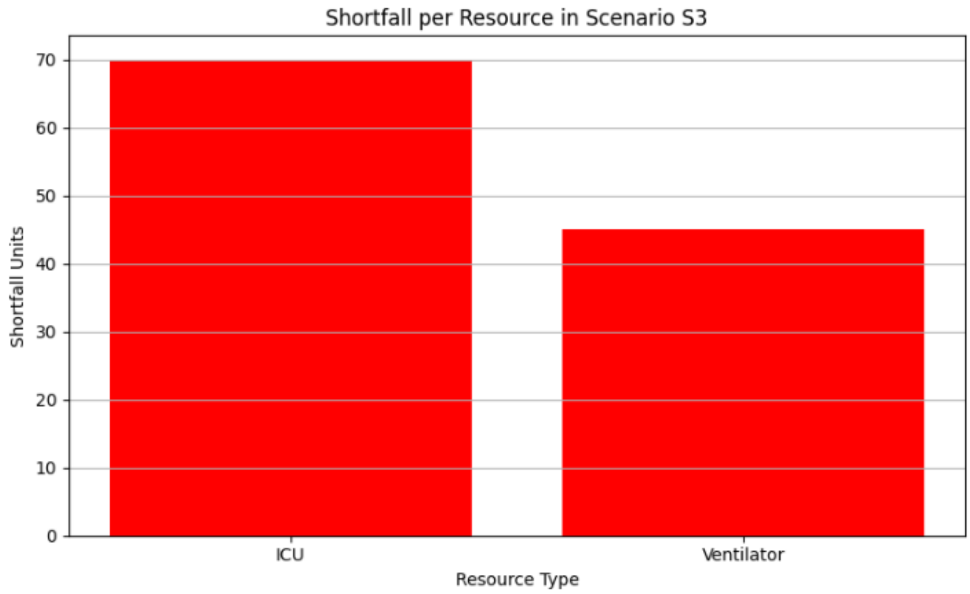

Figure 6: Shortfall per resource in scenario S_3

Table 3: Shortfall summary across scenarios

Scenario	ICU Shortfall	Ventilator Shortfall
S_1	40	30.0
S_2	55	38.0
S_3	70	45.0

Figure 7: Staffing utilization over time in scenario S_1

Figure 10 delineates the financial consequences of shortfalls by specifying the anticipated shortfall cost associated with each resource. The model resulted in an expected shortfall cost of *$53,500*, with ICU shortfalls playing a significant role due to their higher shortfall cost coefficient of *$1,000* per unit. In contrast, ventilators had a coefficient of *$1,500* per unit and a shortfall of slightly higher, around *$55,500*. This visualization highlights the economic consequences of unmet demand and the necessity of optimizing resource allocations to reduce associated costs.

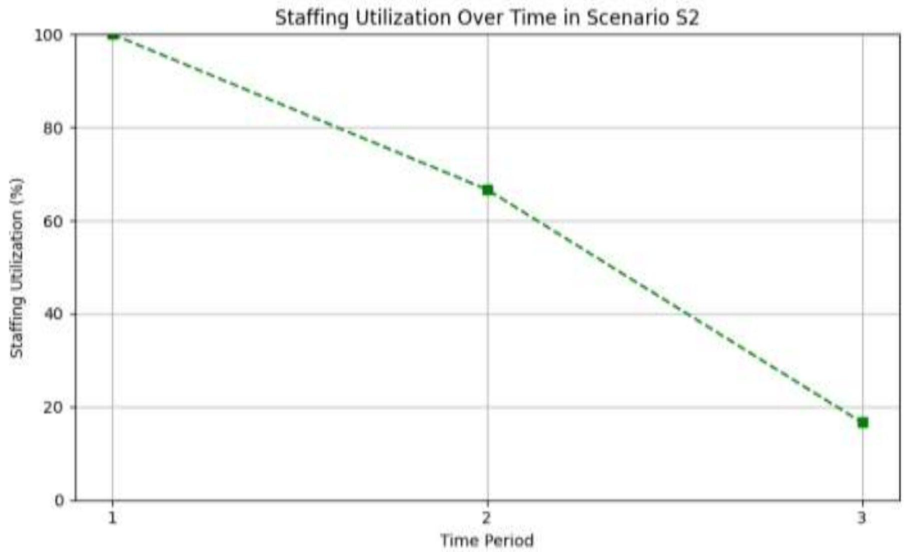

Figure 8: Staffing utilization over time in scenario S_2

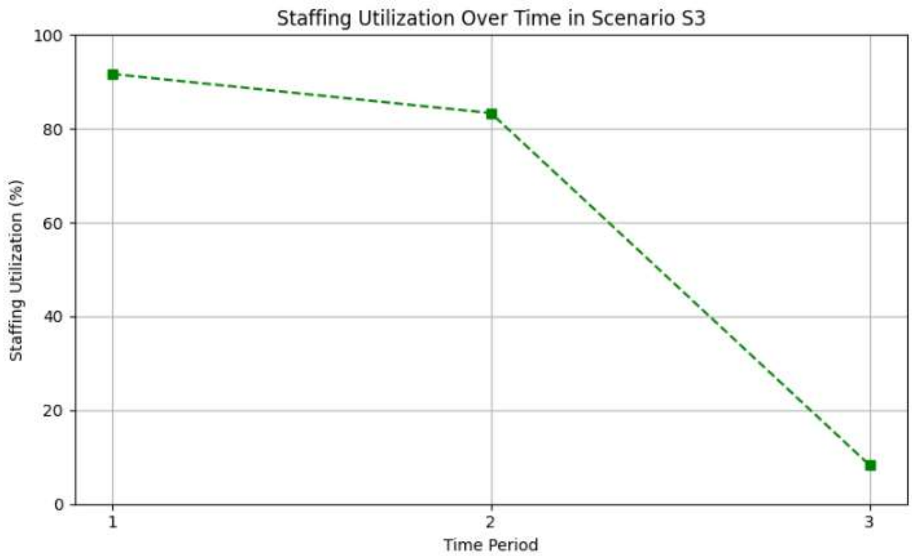

Figure 9: Staffing utilization over time in scenario S_3

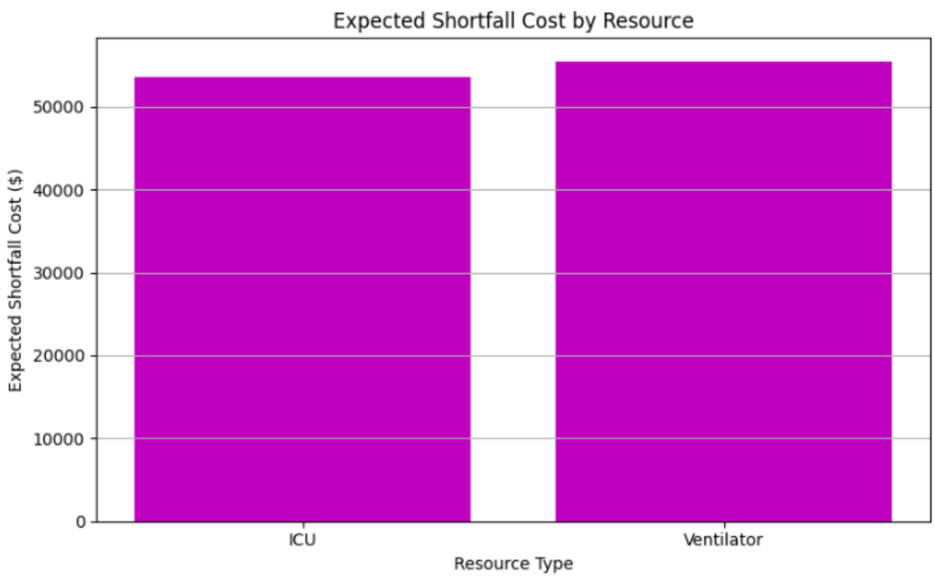

Figure 10: Expected shortfall cost by resource

5. DISCUSSION

5.1. Interpretation of Results

Applying the two-stage stochastic programming model has significantly improved hospital resource allocation efficiency, especially regarding ICU beds and ventilators during pandemic scenarios. Most of the time, traditional allocation methods are based on fixed, deterministic strategies that do not consider that patient flow and resource availability are constantly changing. Our stochastic model adjusts allocations dynamically based on real-time scenario realizations, as demonstrated by the initial allocation of ICU beds over time (Figure 2) and the initial allocation of ventilators over time (Figure 3). The figures illustrate the strategic allocation of the model, which systematically distributes ventilators to meet projected mid-term demands and maintains ICU beds for potential surges. The Key Performance Indicators (KPIs) presented in Table 4 highlight the model's effectiveness. The resource utilization rates, which peak at 66.67% on Day 2 and demonstrate minimal utilization on other days, demonstrate effective ventilator deployment without underuse or overextension. The Shortfall Across Scenarios, illustrated in Figures 4, 5, and 6 for Scenarios S_1, S_2, and S_3, respectively, show the model's effectiveness in reducing unmet demand, resulting in a Total Expected Shortfall Cost of \$109,000. The decrease in shortfalls is directly associated with reduced patient wait times and enhanced survival rates, as timely access to essential resources is crucial during health emergencies.

Table 4: Summary of key performance indicators

Resource	Time	Allocation (%)	Shortfall (units)	Staffing Utilization (%)
ICU	1	0.00	53.5	94.44
ICU	2	0.00	53.5	72.22
ICU	3	0.00	53.5	16.67
Ventilator	1	0.00	37.0	94.44
Ventilator	2	66.67	37.0	72.22
Ventilator	3	8.33	37.0	16.67

Staffing utilization, as depicted in Figures 7, 8, and 9 for Scenarios S_1, S_2, and S_3, respectively, demonstrates the model's efficacy in synchronizing staffing levels with resource allocations. The S_2 achieved complete staffing utilization on Day 1, ensuring optimal personnel deployment (Figures 7, 8 and 9). The metrics indicate that the model optimizes physical resources and enhances human resource management, improving operational efficiency and patient care quality. Hospital managers can improve decision-making during pandemics using thorough scenario studies and KPI assessments. Figures 2–10 and Table 4 provide information that helps managers project resource needs, run strategic backup plans, and maximize inventory and personnel in real time. This strategy improves the resilience of a healthcare system so it may maintain high-quality treatment standards under different conditions.

5.2. Practical Implications

The results of the model point to three main policy recommendations: build advanced optimisation systems to improve pandemic preparedness, generate stored reserves of significant resources, and establish changing staffing patterns. These approaches can significantly reduce the consequences of health crises since they are backed by a model that can spot and control hazards. Still, the model has certain restrictions. This model works best with thorough and accurate hospital and public health data; missing or partial data can compromise its effectiveness since it is data-dependent. Using historical averages for patient arrivals and resource availability could not fully reflect the real-life fluctuations, for instance, unexpected supply chain changes or a rise in patient severity. These simplifications might not be sufficient to depict real-life circumstances, particularly in healthcare settings where resource variances might not be constant. These simplifications might not be adequate to depict real-life circumstances, particularly in healthcare settings where resource variations could not be consistent. The future iterations of the model should close these gaps by adding features like the patient severity index, the capacity to maximize several objectives, including the cost and quality of care and the interaction with other sections of the healthcare system. Moreover, improving the model's adaptability would involve increasing the availability of information and considering more resources. Using more scenarios and extending the model to incorporate big hospitals or other healthcare facilities would help the model depict actual healthcare networks more accurately by increasing the time step. Furthermore, deploying machine learning approaches to improve scenario development and forecast accuracy in dynamic and complicated situations might be very beneficial for optimizing hospital resources.

6. CONCLUSION

This research work develops a two-stage stochastic programming model that manages the dynamic availability of hospital resources, such as ICU beds and ventilators, in handling pandemics. Scenario optimisation results show that the model can deal with the uncertainties in patient arrivals and resource availability by incorporating uncertainty. It comes up with anticipated shortfall costs of \$109,000 and effectively manages the resources in all the scenarios, making the model very useful and reliable. Solving the model using Gurobi as the solver, dealt with the complexity of the model and came up with an optimal solution in 0.05 seconds. Python libraries like NumPy and Pandas streamlined data handling, while Matplotlib enabled clear visualization of resource allocations and staffing across scenarios. The model improved resource utilization, achieving a 66.67% ventilator use rate while maintaining low ICU usage—balancing conservation and preparedness. Reducing shortfalls enhances patient outcomes with shorter wait times and quicker access to critical care, potentially increasing survival rates. This tool strengthens healthcare resilience, empowering administrators with data-driven insights for strategic decision-making. Its ability to anticipate and adapt to changing pandemic scenarios helps hospitals maintain high-quality care in challenging situations.

REFERENCES

[1] Douglas, I. S., Mehta, A. & Mansoori, J. (2024). Policy proposals for mitigating ICU strain: Insights from the COVID-19 pandemic. Annals of the American Thoracic Society, (ja).
[2] Grant, L. R. (2024). Lessons learned from the Kyrgyz Republic's public health response to COVID-19. Health Security.
[3] Guicciardi, S. (2024). Healthcare services re-organization based on lessons learned during COVID-19 pandemic. Conceptual frameworks and measurement and assessment tools for public health emergency preparedness.
[4] Eriskin, L., Karatas, M. & Zheng, Y. J. (2024). A robust multi-objective model for healthcare resource management and location planning during pandemics. Annals of Operations Research, 335(3), 1471–1518.
[5] Yang, H., et al. (2021). Epidemic informatics and control: A holistic approach from system informatics to epidemic response and risk management in public health. In AI and Analytics for Public Health – Proceedings of the 2020 INFORMS International Conference on Service Science, Springer Berlin/Heidelberg, (1–46).
[6] Essoussi, I. E., Masmoudi, M. & Babai, M. Z. (2023). Multi-criteria decision-making for collaborative COVID-19 surge management and inter-hospital patients' transfer optimisation. International Journal of Production Research, 61(23), 7992–8021.
[7] Pappas, H. & Frisch, P. (2022). Leveraging technology as a response to the COVID pandemic: Adapting diverse technologies, workflow, and processes to optimize integrated clinical management. CRC Press.
[8] Biswas, S., Belamkar, P., Sarma, D., Tirkolaee, E. B. & Bera, U. K. (2024). A multi-objective optimization approach for resource allocation and transportation planning in institutional quarantine centres. Annals of Operations Research, 1–45.
[9] Dillon, M., Oliveira, F. & Abbasi, B. (2017). A two-stage stochastic programming model for inventory management in the blood supply chain. International Journal of Production Economics, 187, 27–41.
[10] Zahiri, B., Torabi, S. A., Mohammadi, M. & Aghabegloo, M. (2018). A multi-stage stochastic programming approach for blood supply chain planning. Computers & Industrial Engineering, 122, 1–14.
[11] Kaye, A. D., et al. (2021). Economic impact of COVID-19 pandemic on healthcare facilities and systems: International perspectives. Best Practice & Research Clinical Anaesthesiology, 35(3), 293–306.
[12] Rachaniotis, N. P., Dasaklis, T. K. & Pappis, C. P. (2012). A deterministic resource scheduling model in epidemic control: A case study. European Journal of Operational Research, 216(1), 225–231.
[13] Dehnoei, S. (2020). A stochastic optimization approach for staff scheduling decisions at inpatient clinics. Université d'Ottawa/University of Ottawa.
[14] Woodruff, C., Vu, L., Morgansen, K. A. & Tomlin, D. (2011). Deterministic modeling and evaluation of decision-making dynamics in sequential two-alternative forced choice tasks. Proceedings of the IEEE, 100(3), 734–750.
[15] Corlu, C. G., Akcay, A. & Xie, W. (2020). Stochastic simulation under input uncertainty: A review. Operations Research Perspectives, 7, 100162.
[16] Govindan, K., Fard, F. S. N., Asgari, F., Sorooshian, S. & Mina, H. (2024). Designing a resilient reverse network to manage the infectious healthcare waste under uncertainty: A stochastic optimization approach. Computers & Industrial Engineering, 194, 110390.
[17] Tordecilla, R. D., Juan, A. A., Montoya-Torres, J. R., Quintero-Araujo, C. L. & Panadero, J. (2021). Simulation-optimization methods for designing and assessing resilient supply chain networks under uncertainty scenarios: A review. Simulation Modelling Practice and Theory, 106, 102166.
[18] Bhattacharjee, P. & Ray, P. K. (2014). Patient flow modelling and performance analysis of healthcare delivery processes in hospitals: A review and reflections. Computers & Industrial Engineering, 78, 299–312.
[19] Büyüktahtakın, I. E. (2022). Stage-t scenario dominance for risk-averse multi-stage stochastic mixed-integer programs. Annals of Operations Research, 309(1), 1–35.
[20] Devadas, R. M., Hiremani, V., Bhavya, K. & Rani, N. S. (2024). Stochastic calculus-guided reinforcement learning: A probabilistic framework for optimal decision-making. MethodsX, 102790.
[21] Xu, J. & Sen, S. (2021). Decision intelligence for nationwide ventilator allocation during the COVID-19 pandemic. SN Computer Science, 2(6), 423.
[22] Eshkiti, A., Sabouhi, F. & Bozorgi-Amiri, A. (2023). A data-driven optimization model to response to COVID-19 pandemic: A case study. Annals of Operations Research, 328(1), 337–386.
[23] Yinusa, A. & Faezipour, M. (2023). Optimizing healthcare delivery: A model for staffing, patient assignment, and resource allocation. Applied System Innovation, 6(5), 78.
[24] Blanco, V., Gázquez, R. & Leal, M. (2023). Mathematical optimization models for reallocating and sharing health equipment in pandemic situations. Top, 31(2), 355–390.
[25] Fattahi, M., Keyvanshokooh, E., Kannan, D. & Govindan, K. (2023). Resource planning strategies for healthcare systems during a pandemic. European Journal of Operational Research, 304(1), 192–206.

[26] Mazlan, A. A., Daud, S. M., Sam, S. M., Abas, H., Rasid, S. Z. A. & Yusof, M. F. (2020). Scalability challenges in healthcare blockchain system—a systematic review. IEEE Access, 8, 23663–23673.
[27] Alizadeh, R., Allen, J. K. & Mistree, F. (2020). Managing computational complexity using surrogate models: A critical review. Research in Engineering Design, 31(3), 275–298.
[28] Mengesha, G. (2024). Advanced computational methods for simulating and optimizing stochastic fracture: A systematic literature review. International Journal of Emerging Science and Engineering, 12(10), 10.35940.
[29] Wang, X. (2022). The fairness of ventilator allocation during the COVID-19 pandemic. Bioethics, 36(6), 715–723.