ISSN 2090-3359 (Print)
ISSN 2090-3367 (Online)

ΑΔΣ

Advances in Decision Sciences

Volume 29
Issue 4
December 2025

亞洲大學
ASIA UNIVERSITY

SCIENTIFIC & BUSINESS WORLD

Published by Asia University, Taiwan and Scientific and Business World

Optimizing Repair Allocation in Healthcare: Comparing Volume- and Value-Based Models under Capacity Constraints

Chartchai Leenawong
School of Science, King Mongkut's Institute of Technology,
Ladkrabang, Bangkok, 10520, Thailand
***Corresponding author** Email: chartchai.le@kmitl.ac.th

Received: May 16, 2025; First Revision: July 23, 2025;
Last Revision: November 14, 2025; Accepted: December 5, 2025;
Published: December 11, 2025

Abstract

Purpose: This study compares two optimization models—volume-based and value-based—for allocating repair resources in healthcare equipment maintenance. It introduces a dual-model framework with eligibility-weighted fairness constraints, a combination not previously explored in the literature. The study highlights trade-offs between service volume and strategic value, offering practical and adaptable solutions, including for low-resource settings.

Design/methodology/approach: A linear optimization approach evaluates both models under identical capacity and eligibility constraints. The volume-based model maximizes repair volume, while the value-based model maximizes total repair value based on equipment criticality and facility performance. Both incorporate eligibility-weighted proportionality constraints to ensure fair and feasible assignments. Real-world–inspired data simulate multiple demand scenarios to compare assignment patterns and system outcomes.

Findings: The value-based model prioritized high-impact repairs and achieved a higher total repair value score of 1,157,270 compared to 1,130,998 in the volume-based model, with only a one-unit difference in repair volume. These dimensionless scores reflect strategic benefit rather than monetary value. The results highlight trade-offs between broad service coverage and targeted system impact. This study contributes to Decision Sciences by applying linear programming to optimize repair allocation under resource constraints.

Practical implications: Healthcare administrators can use these insights to align repair strategies with institutional priorities—whether maximizing throughput or clinical value.

Social implications: Timely repair of critical equipment enhances patient safety, service reliability, and health system resilience.

Originality/value: This research presents a novel comparison of volume- and value-based optimization models for healthcare repair. Both models incorporate eligibility-weighted proportionality constraints to support fair, effective planning across diverse facilities.

Keywords: Healthcare equipment maintenance, Optimization model, Repair task allocation, Eligibility-weighted assignment, Capacity-constrained scheduling

JEL Classifications: C44, C61, P36

1. Introduction

The maintenance and repair of healthcare equipment are essential for ensuring uninterrupted clinical operations, patient safety, and overall system efficiency. As health services increasingly depend on advanced diagnostic and therapeutic devices, the complexity, cost, and risk of equipment failure have grown significantly (Zamzam et al., 2021). In this context, equipment reliability is no longer a peripheral concern—it is central to sustaining critical care and the financial viability of healthcare providers (Hillebrecht et al., 2022; Mahfoud et al., 2016). Breakdowns in essential medical equipment can delay procedures, reduce service capacity, and jeopardize patient outcomes.

A structured, data-informed approach to maintenance, grounded in reliability assessments, is therefore indispensable. Hossain et al. (2020) highlighted clinical engineering frameworks that integrate technical performance with patient-centered metrics. Such tools help healthcare organizations prioritize interventions, especially when resource constraints limit what can be addressed at any given time.

In resource-limited environments, maintenance planning is even more complex. Challenges such as insufficient funding, limited technical staff, and fragmented infrastructure hinder effective equipment management (Bahreini et al., 2018). These are exacerbated by diverse equipment types and uneven facility capabilities (Hillebrecht et al., 2022; Mwanza et al., 2022). In decentralized systems, disparities across facilities further complicate timely and equitable task assignment.

To address these issues, researchers have developed mathematical and simulation-based optimization models for maintenance and resource allocation. These models structure decisions around capacity, eligibility, and fluctuating repair demand (Mwanza et al., 2022; Salami et al., 2023). Systems-based optimization also improves coordination of staffing and repairs across networks (Yinusa & Faezipour, 2023).

Complementary techniques such as multi-criteria decision-making accommodate trade-offs among cost, urgency, uptime, and risk (Chakraborty et al., 2023). These frameworks blend quantitative metrics with expert judgment and support transparent prioritization in complex settings.

Preventive maintenance remains central to asset management. Dependability-based models address reliability and maintainability (Mahfoud et al., 2018), while Markov chains assist long-term repair and replacement planning (Liao et al., 2021). Building on these, predictive maintenance enables real-time, data-driven scheduling. Boppana (2023) and Li et al. (2022) demonstrate how analytics and information fusion anticipate failures and streamline repairs. Stodola and Stodola (2020) add classification schemes based on labor intensity to optimize workload distribution.

Cost containment remains a core focus, particularly in developing countries. Hillebrecht et al. (2022) showed that structured maintenance planning reduces life-cycle costs, even in low-resource settings. Additional efficiencies have been documented through audits and process reviews (Laktash, 2015; Pedistat, 2025).

Recently, value-based optimization has gained attention. These approaches emphasize long-term operational and strategic benefit over simple volume or cost goals (De Jonge & Scarf, 2020). For instance, González-Domínguez et al. (2020) proposed models that integrate clinical importance and performance metrics, offering a more nuanced approach than traditional volume-based strategies.

Yet, there remains a notable gap: few studies directly compare volume- and value-based optimization under identical constraints. Moreover, fairness mechanisms that address inter-facility disparities in repair capabilities are rarely incorporated. In decentralized networks, such imbalances can lead to inefficient or inequitable task allocation.

This study addresses key limitations in repair planning by proposing two optimization models for assigning tasks across heterogeneous healthcare facilities. The first maximizes total repair volume under shared capacity and eligibility constraints, while the second maximizes total repair value using a utility matrix reflecting equipment criticality and facility effectiveness. Both models apply an eligibility-weighted proportionality constraint to ensure fair and feasible allocations aligned with each facility's capabilities. Together, they offer a scalable, data-driven framework for efficient and equitable repair planning.

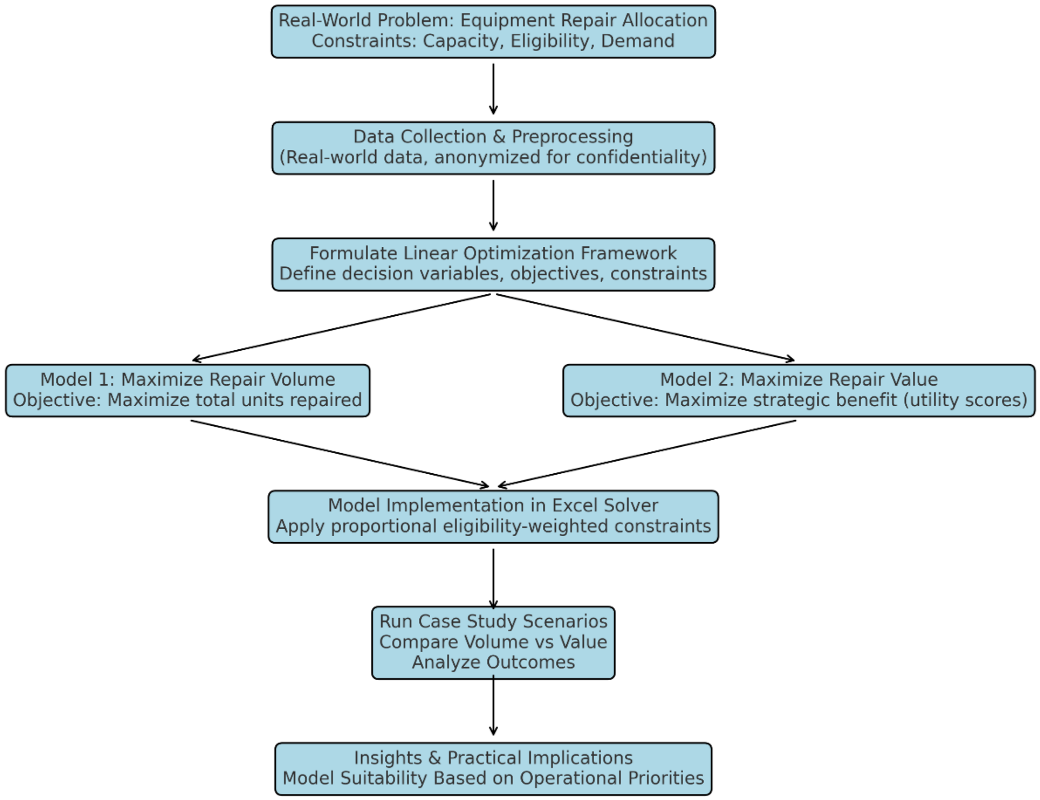
This paper contributes to the literature with a side-by-side comparison of volume- and value-based models under identical constraints—an approach not previously explored. By integrating fairness through eligibility-weighted bounds, it demonstrates how model design affects operational outcomes and advances the field of Decision Sciences through its focus on resource optimization and system efficiency.

2. Methodology

Building on the operational challenges outlined in the introduction—such as facility heterogeneity, equipment diversity, and limited repair capacity—this section presents a structured modeling approach to optimize healthcare equipment repair allocation. Rather than emphasizing cost minimization alone, the proposed models aim to improve both system efficiency and equity by aligning repair decisions with real-world constraints.

The overall modeling framework is summarized in Figure 1, which outlines the key phases from problem definition and data preparation to model formulation, implementation, and evaluation.

Figure 1. Flow diagram of the development process for the volume- and value-based optimization models



While prior studies have focused on minimizing repair costs or maximizing service coverage, they often overlook proportional fairness—particularly in systems where repair tasks must be distributed relative to each facility's eligibility and available capacity (Mwanza et al., 2022; Salami et al., 2023). To address this gap, we introduce a capacity-aware, eligibility-weighted optimization framework designed for decentralized, multi-facility environments with diverse equipment types. The framework features two objective functions: one that maximizes total repair volume, and another that maximizes the total strategic value of completed repairs.

This section is organized as follows. Section 2.1 explains the fundamentals of Linear Programming (LP), the optimization method used in this study, including the formulation process involving decision variables, objective functions, and constraints. Section 2.2 then details the two specific LP models developed for this research: a volume-based model and a value-based model, both applied to the healthcare repair allocation problem.

2.1 The Optimization Method

Optimization methods provide systematic techniques for selecting the best option from a set of feasible alternatives according to defined criteria. They are essential for decision-making in complex systems where trade-offs must be managed under various constraints. Broadly, optimization approaches can be categorized into exact methods—such as linear, nonlinear, and integer programming—and heuristic techniques, such as genetic algorithms, simulated annealing, and hybrid approaches that combine analytical and computational strategies.

LP is widely applied to determine the best possible outcome—such as maximizing output or minimizing cost—under resource and feasibility constraints. Its versatility has made it indispensable across industries: in manufacturing, it supports production scheduling and resource allocation; in finance, it is used for portfolio optimization and risk management (Hillier & Lieberman, 2015; Taha, 2017); and in transportation and logistics, it enables route planning and cost minimization (Leenawong & Ritthipakdee, 2024). These diverse applications underscore the enduring value of LP in addressing real-world decision-making challenges.

This study employs a Linear Programming (LP) framework, a cornerstone of operations research and decision sciences for problems in which both the objective function and constraints are linear (Dantzig, 1963; Hillier & Lieberman, 2015; Taha, 2017). Once formulated, the LP model can be solved using efficient algorithms. The most widely used is the Simplex Method, introduced by George Dantzig in 1947, which systematically explores the feasible region defined by the constraints to locate the optimal solution (Dantzig, 1963).

The following subsection presents the specific LP formulations developed for the healthcare equipment repair allocation problem.

2.2 Optimization Models for Healthcare Equipment Repair Allocation

This study develops two linear programming models to optimize the allocation of repair tasks across healthcare facilities. The models account for capacity limits, equipment demand, and repair eligibility. One model focuses on maximizing total repair volume, while the other emphasizes maximizing strategic repair value. Both are designed to support fair and efficient resource allocation in decentralized settings.

2.2.1 Model 1: Maximizing Total Repair Volume

The first formulation focuses on maximizing the total number of equipment units assigned for repair across all facilities. This is appropriate in contexts where maximizing system throughput is the primary goal, such as in emergency response or backlog clearance scenarios.

The problem is formulated as a centralized assignment model involving a set of healthcare facilities, indexed by $i = 1,\ldots,m$, each responsible for repairing different equipment types $j = 1,\ldots,n$. Not all facilities are capable of servicing all equipment types. Additionally, each facility operates under a limited repair capacity—such as technician availability or workstation limits—while each equipment type has a defined total repair demand.

Let

$i = 1,..., m$: index for repair facilities;

$j = 1,..., n$: index for equipment types;

x_{ij}: number of units assigned to facility i for repairing equipment type j;
S_i: total repair capacity of facility i;
D_j: total number of units of equipment type j that require repair;
$T_{ij} \in \{0,1\}$: binary indicator showing whether facility i can repair equipment type j (1 = yes, 0 = no);
$F_i = \sum_j T_{ij} D_j$: total demand of all equipment types that facility i is eligible to repair; and
$w_{ij} = \left(\frac{T_{ij} D_j}{F_i}\right)$: repair eligibility-based weight.

Objective Function: The primary objective is to maximize the total number of equipment units repaired across all facilities:

$$\text{Maximize } \sum_i \sum_j x_{ij}. \tag{1}$$

This formulation prioritizes repair coverage, which is crucial in contexts where equipment downtime severely affects care delivery and patient safety.

Constraints:

(1) Facility Capacity Constraint

Each facility cannot exceed its repair capacity:

$$\sum_j x_{ij} \leq S_i \ \forall i. \tag{2}$$

This constraint reflects resource limits such as available technicians, repair bays, tools, or daily operating hours.

(2) Demand Fulfillment Constraint

Repair assignments cannot exceed the demand for each equipment type:

$$\sum_i x_{ij} \leq D_j \ \forall j. \tag{3}$$

This prevents over-assignment and ensures that no excess repairs are planned for equipment beyond its demand.

(3) Eligibility and Fair Distribution Constraint

A central innovation of this model is the introduction of a proportional upper bound on x_{ij} based on the share of total eligible workload each facility can claim. The maximum number of units that facility i can be assigned for equipment type j is given by:

$$x_{ij} \leq w_{ij} S_i \ \ \forall i, j. \tag{4}$$

This ensures that if facility i is not eligible to repair type j, where T_{ij} equals zero, then x_{ij} must be zero. If the facility is eligible, the number of units assigned is proportionally bounded by the relative demand share and the facility's capacity.

(4) Non-Negativity Constraint

$$x_{ij} \geq 0 \;\; \forall i, j. \tag{5}$$

Assignments must be non-negative, and in practice, can be restricted to integers if partial repairs are not feasible.

This model ensures fair and efficient allocation while maintaining computational tractability. It can be readily implemented in Excel Solver or open-source optimization platforms. The formulation is extensible to support additional features such as priority scores or time windows.

2.2.2 Model 2: Maximizing Total Repair Value

The second formulation enhances decision-making by shifting the objective from volume to value generation. Here, each assignment is weighted by a unit repair value that reflects the strategic or operational benefit of performing that repair at a particular facility.

Let v_{ij} be the unit repair value for facility i when repairing equipment type j.

The unit repair value v_{ij} is a dimensionless utility score that reflects the strategic benefit or efficiency of assigning equipment type j to facility i. These values are not monetary; rather, they represent normalized, performance-based priorities used to guide optimal allocation under resource constraints.

Objective Function: The primary objective is to maximize the total repair value across all assignments, by prioritizing repair tasks that offer higher unit value at each facility:

$$\text{Maximize } \textstyle\sum_i \sum_j v_{ij} x_{ij}. \tag{6}$$

Subject to the same constraints as Model 1: Capacity, demand, and proportional eligibility constraints.

This formulation prioritizes assignments that yield higher returns in terms of efficiency, cost-effectiveness, or strategic impact. Facilities with high value scores for specific equipment types are favored, while low-impact or inefficient pairings are deprioritized. Like Model 1, this model is linear and scalable, suitable for spreadsheet-based solvers or full-featured mathematical programming tools.

Both models share a common structure that ensures operational feasibility while offering flexibility to address different planning goals. Decision-makers can choose between maximizing throughput or value, or use the models in tandem to support scenario-based analysis. The eligibility-weighted constraint ensures fairness in task distribution, making the framework especially useful in healthcare systems where resource constraints and facility capabilities vary significantly.

Table 1. Summary comparison of volume-based and value-based optimization models

Feature	**Model 1: Maximize Repair Volume**	**Model 2: Maximize Repair Value**
Objective	Maximize the total number of equipment units repaired	Maximize the total repair value across all assignments
Decision Variables	x_{ij}: number of units of type j assigned to facility i	x_{ij}: number of units of type j assigned to facility i
Input Parameters	- Demand per equipment type D_j - Facility capacity S_i - Eligibility matrix T_{ij}	- All parameters in Model 1 - Unit repair value v_{ij} per facility-equipment pair
Key Constraint Types	- Capacity constraints per facility - Demand fulfillment per equipment type - Eligibility-weighted proportionality bounds	Same as Model 1
Optimization Goal	High repair throughput (coverage)	High system benefit (value per unit repaired)
Assignment Behavior	Distributes tasks to maximize volume (even if value is low)	Concentrates tasks on high-impact facility-equipment pairs
Best Suited For	Scenarios with uniform criticality or backlog clearance	Scenarios with limited capacity or high-value prioritization
Strengths	Maximizes utilization and service coverage	Improves operational impact with selective allocation
Potential Trade-offs	May assign low-impact tasks; less strategic	Slightly lower coverage in favor of value

To facilitate comparison, Table 1 summarizes the key characteristics of the two proposed optimization models. While both share a common structure, including identical decision variables and constraint sets, they differ in objective functions and assignment behaviors. The volume-based model emphasizes service coverage by maximizing the number of repair assignments, making it suitable for backlog clearance or uniform-priority settings. In contrast, the value-based model targets system-level impact by prioritizing assignments with higher operational or strategic value, offering a more selective yet impactful allocation. This tabular summary highlights the strategic trade-offs between efficiency and value that healthcare planners must consider.

3. Case Study and Experimental Analysis

The proposed framework is operationalized on a representative multi-facility network. The first part describes the data, including the facility set, equipment categories, capacities, eligibility, demand, and the value matrix. The second part explains how both optimization models were implemented and solved using Microsoft Excel Solver.

3.1 Data Description

The case study uses an anonymized, real-world–inspired dataset from a decentralized repair network comprising 15 facilities and 7 equipment types labeled A through G, as summarized in Table 2. Each facility i has a total repair capacity S_i that ranges from 900 to 1,300 units, and each equipment type j has a total repair demand D_j that ranges from 1,700 to 2,600 units. Aggregate capacity across facilities equals 16,000 units, and aggregate demand equals 15,000 units.

Table 2. Facility eligibility matrix with repair capacities and equipment demand

Facility	A	B	C	D	E	F	G	Capacity
1	1	0	1	0	1	1	1	900
2	1	0	1	1	1	1	1	1,200
3	1	1	1	1	1	1	0	1,000
4	1	1	0	1	1	1	1	900
5	1	0	1	1	1	1	1	1,000
6	1	1	1	1	0	1	1	1,300
7	0	1	1	1	1	1	1	1,000
8	0	1	1	1	1	1	1	1,100
9	1	0	1	0	1	1	1	900
10	1	1	0	1	1	1	1	1,100
11	1	0	1	1	1	0	1	1,300
12	1	1	1	1	0	1	1	1,100
13	1	1	1	1	1	1	0	1,000
14	1	1	1	0	0	1	1	1,200
15	1	0	1	1	1	0	1	1,000
Demand	2,500	1,800	1,800	2,300	1,700	2,600	2,300	15,000/16,000

Note: Columns A–G are equipment types.

Table 2 presents the fundamental input data used in these models. Each row represents a facility, and each column represents whether that facility is capable of repairing a given equipment type. A binary value of 1 indicates eligibility, while 0 indicates ineligibility. This eligibility matrix T_{ij} defines feasible combinations of facilities and equipment types. Additionally, the rightmost column shows each facility's total repair capacity, ranging from 900 to 1,300 units, with a combined capacity across all 15 facilities of 16,000 units. At the bottom of the matrix, the total demand for each equipment type is listed, ranging from 1,700 to 2,600 units, with a combined equipment repair demand of 15,000 units.

Table 3. Normalized weights based on repair eligibility for each facility across equipment types

Facility	A	B	C	D	E	F	G
1	0.23	0.00	0.17	0.00	0.16	0.24	0.21
2	0.19	0.00	0.14	0.17	0.13	0.20	0.17
3	0.20	0.14	0.14	0.18	0.13	0.20	0.00
4	0.19	0.14	0.00	0.17	0.13	0.20	0.17
5	0.19	0.00	0.14	0.17	0.13	0.20	0.17
6	0.19	0.14	0.14	0.17	0.00	0.20	0.17
7	0.00	0.14	0.14	0.18	0.14	0.21	0.18

8	0.00	0.14	0.14	0.18	0.14	0.21	0.18
9	0.23	0.00	0.17	0.00	0.16	0.24	0.21
10	0.19	0.14	0.00	0.17	0.13	0.20	0.17
11	0.24	0.00	0.17	0.22	0.16	0.00	0.22
12	0.19	0.14	0.14	0.17	0.00	0.20	0.17
13	0.20	0.14	0.14	0.18	0.13	0.20	0.00
14	0.23	0.16	0.16	0.00	0.00	0.24	0.21
15	0.24	0.00	0.17	0.22	0.16	0.00	0.22

Note: Columns A–G are equipment types.

To ensure a fair and operationally sound allocation of repair tasks, the model incorporates an eligibility-weighted proportionality constraint. This is calculated in two intermediate stages. First, as shown in Table 3, the weight by eligibility is derived. Each facility's eligible share of the total demand is calculated for each equipment type, such that the weights across all equipment types sum to one for each facility. For example, Facility 1 is eligible for all types except B and D, and its weights are redistributed proportionally across the remaining eligible types. For instance, the weight is 0.23 for Type A and 0.24 for Type F. These weights represent the relative share of each type's demand that the facility can claim, adjusted according to its eligibility pattern.

The resulting proportional upper bounds on decision variables x_{ij} are shown in Table 4.

Table 4. Maximum repair units per facility and equipment type based on eligibility-weighted capacity

Facility	A	B	C	D	E	F	G	Total Max.
1	206	0	149	0	140	215	190	900
2	227	0	164	209	155	236	209	1,200
3	197	142	142	181	134	204	0	1,000
4	170	123	0	157	116	177	157	900
5	190	0	136	174	129	197	174	1,000
6	244	176	176	225	0	254	225	1,300
7	0	144	144	184	136	208	184	1,000
8	0	158	158	202	150	230	202	1,100
9	206	0	149	0	140	215	190	900
10	208	150	0	192	141	217	192	1,100
11	307	0	221	282	208	0	282	1,300
12	207	149	149	190	0	215	190	1,100
13	196	142	142	181	134	205	0	1,000
14	273	196	196	0	0	284	251	1,200
15	236	0	170	217	160	0	217	1,000

Note: Columns A–G are equipment types.

This matrix presents the capacity allocations by facility and equipment type. Each cell represents the maximum number of units of type j that can be assigned to facility i, ensuring that capacity allocations are distributed fairly across the equipment types for which each facility is eligible. For instance, Facility 6, which has a high capacity of 1,300 units and is eligible for all types except E, receives an upper bound of approximately 244 units for Type A and 225 units for Type D. This step ensures that even among eligible facilities, repair assignments are proportionally distributed to reflect demand priorities and local resource limits.

In the second experimental formulation, Table 5 presents the unit repair value matrix, which serves as a core input to the value-maximizing optimization model. In this model, each feasible repair assignment—defined by a specific equipment type from A to G and a facility from 1 to 15—is weighted by a corresponding unit repair value. These values are dimensionless utility scores that represent the estimated benefit of performing a particular repair at a given facility. They are derived from a combination of qualitative and quantitative criteria, such as operational efficiency, technical expertise, turnaround time, cost-effectiveness, and strategic importance. While not expressed in physical units (e.g., dollars or hours), these values offer a consistent, normalized measure of relative priority across facility-equipment combinations.

Higher values indicate more favorable or impactful repair assignments, signaling that a given facility is particularly well-suited to perform certain types of repairs. Conversely, a value of zero signifies that the facility is either ineligible or operationally unsuited for repairing that specific equipment type. The matrix thus captures meaningful variation in facility performance and contextual strengths, allowing the optimization model to prioritize assignments that not only comply with eligibility and capacity constraints but also deliver maximum strategic value to the overall healthcare system.

Table 5. Unit repair value by equipment type and facility (dimensionless scores, not monetary)

Facility	A	B	C	D	E	F	G
1	67	0	89	0	59	59	72
2	98	0	64	85	57	60	60
3	67	87	63	87	97	87	0
4	62	70	0	100	72	95	52
5	71	0	88	95	57	87	64
6	80	64	74	73	0	69	72
7	0	50	57	99	92	97	98
8	0	63	95	98	98	79	94
9	82	0	88	0	92	67	79
10	92	65	0	91	88	68	82
11	74	0	52	55	86	0	72
12	98	64	97	66	0	64	100
13	95	95	76	96	77	56	0
14	82	90	78	0	0	54	53
15	87	0	82	85	75	0	88

Note: Columns A–G are equipment types.

The variation in unit values reflects real-world differences in repair potential, as shown in Table 5. For instance, Facility 6 shows relatively high values for repairing several types, including 80 for Type A and 74 for Type C, suggesting it offers both capability and efficiency for those equipment types. In contrast, Facility 11 exhibits low values for certain types—such as 52 for Type C and 55 for Type D—indicating limited benefit or suboptimal suitability for those assignments. Such insights allow the solver to allocate high-value tasks to facilities best suited to handle them, while avoiding low-impact or infeasible pairings. Overall, the matrix plays a pivotal role in shifting the model's focus from maximizing volume to generating strategic value, enabling healthcare planners to better align repair decisions with broader operational goals.

3.2 Model Implementation

The coverage-maximizing model was implemented to determine an effective repair assignment strategy across 15 facilities and 7 equipment types. The dataset reflects realistic operating conditions with eligibility constraints, facility-specific capacities, and equipment-specific demand. The eligibility matrix and proportional capacity bounds were embedded into the optimization logic to ensure fair and feasible allocations. The objective was to test whether the model could achieve high repair coverage while satisfying all operational constraints. The model was developed and solved in Microsoft Excel Solver to assess practical effectiveness under realistic conditions.

Both models use the same decision variable matrix x_{ij} that records units of type j assigned to facility i. They enforce the same constraint set, namely capacity by facility, demand by equipment type, eligibility-weighted proportional upper bounds $U_{ij} = w_{ij}S_i$ with $U_{ij} = 0$ when ineligible according to T_{ij}, and nonnegativity with optional integrality. They also share the same solution procedure in Excel Solver; only the objective differs.

The spreadsheet organizes a 15 by 7 decision range named NoRepaired. For the coverage model, the objective cell TotalRepaired equals the sum of all x_{ij}. For the value model, the objective equals the sum product of the unit value matrix v_{ij} with the decision range x_{ij}. Solver enforces four constraint groups: first, for each facility i the row sum of x_{ij} does not exceed capacity S_i; second, for each equipment type j the column sum of x_{ij} does not exceed demand Dj; third, each cell satisfies $x_{ij} \leq U_{ij}$ with U_{ij} constructed from eligibility weights w_{ij}; fourth, $x_{ij} \geq 0$ with integrality required when whole-unit assignments are operationally necessary.

Both models are solved with the Simplex LP method in Excel Solver. Solver options select Assume Linear Model and Make Unconstrained Variables Non-Negative. Initialization can start from zeros or any feasible seed since the bounds guarantee feasibility. Integer variables are used when operations require whole units; otherwise, continuous variables preserve LP speed and structure.

In the coverage objective, the model maximizes TotalRepaired to raise throughput while respecting eligibility, capacity, demand, and proportional bounds. In the value objective, the model maximizes the sum product of v_{ij} and x_{ij}, where v_{ij} rates each feasible facility-equipment pairing by strategic or operational benefit. The value matrix referenced in Table 5 captures factors such as turnaround time, technical expertise, cost effectiveness, and service criticality by facility and type.

This common implementation ensures that any difference in solutions arises from the objective choice alone rather than from constraint design or the solution method.

With the data and implementation fixed, the following section reports the optimized assignments for both objectives, compares coverage and total value, and examines how eligibility-weighted bounds shape facility-level workloads and equipment-level fulfillment. The comparative results highlight the trade-offs between maximizing throughput and prioritizing strategic impact.

4. Results and Discussion

This section reports the outcomes of the two optimization models: one maximizing repair coverage and the other maximizing repair value. Results are presented individually, then compared to highlight differences in allocation and strategic implications, followed by a discussion of model validation.

4.1 Results from Model 1: Maximizing Total Repair Volume

Table 6. Optimized equipment repair assignment results from Model 1

Facility	A	B	C	D	E	F	G	#Repairs	Capacity
1	206	0	148	0	140	214	189	897	900
2	227	0	163	209	154	236	209	1,198	1,200
3	196	141	141	181	133	204	0	996	1,000
4	170	122	0	156	115	177	156	896	900
5	189	0	136	174	128	196	174	997	1,000
6	244	175	175	224	0	254	224	1,296	1,300
7	0	144	144	184	136	208	184	1,000	1,000
8	0	158	158	202	149	228	202	1,097	1,100
9	206	0	148	0	140	214	189	897	900
10	208	150	0	191	141	216	191	1,097	1,100
11	306	0	220	282	208	0	282	1,298	1,300
12	206	148	148	190	0	215	190	1,097	1,100
13	196	141	141	181	133	204	0	996	1,000
14	146	196	78	0	0	34	110	564	1,200
15	0	0	0	126	123	0	0	249	1,000
#Repairs	2,500	1,375	1,800	2,300	1,700	2,600	2,300	14,575	Value 1,130,998

Note: Columns A–G are equipment types. Each entry is the number of repair units assigned to the facility–equipment pair. The '#Repairs' column shows the total units assigned to each facility, which must be less than or equal to (≤) the facility's capacity. The bottom row reports column totals across facilities. Value 1,130,998 is the total aggregated repair value (dimensionless score) achieved by the assignments from Model 1. Zero entries indicate no assignment or an ineligible pair.

As summarized in Table 6, the model assigned 14,575 units out of a total demand of 15,000, achieving a coverage rate of 97.17 percent. This result demonstrates the model's efficiency in utilizing available capacity while honoring all eligibility constraints. Each cell in the result matrix indicates the number of units of a specific equipment type assigned to a facility, and all values remain within the proportional upper bounds defined earlier—validating the model's fairness mechanism.

At the facility level, none of the 15 centers exceeded its repair capacity. For example, Facility 6 and Facility 11 were utilized at near full capacity, with 1,296 and 1,298 units assigned, respectively, reflecting the model's preference for high-capacity and broadly eligible facilities. In contrast, Facility 15, which had fewer eligible types, was assigned only 249 units, effectively utilizing its constrained capacity.

From an equipment perspective, demand was fully met for six out of seven equipment types. The only shortfall occurred in Type B, with 1,375 units repaired out of a demand of 1,800—equating to 76.4 percent coverage. This under-assignment was anticipated due to a limited number of eligible facilities for that type. Nonetheless, the model effectively redistributed available capacity to other equipment types to maximize overall system throughput.

These results confirm the model's ability to strike a balance between fairness and efficiency, making it highly applicable for real-world healthcare repair planning where capacity differences and repair eligibility vary widely. By incorporating eligibility-weighted bounds, the model ensures that repair tasks are only assigned to qualified facilities, mitigating risks associated with improper allocations.

From a modeling standpoint, the proportionality constraint plays a dual role. It enforces technical feasibility and introduces a fairness mechanism, ensuring that facilities with broader eligibility and higher demand coverage contribute more, while specialized facilities are assigned appropriately smaller workloads. This behavior is evident in the output: high-capacity, high-eligibility facilities such as Facility 6 and Facility 11 are nearly saturated, while limited-eligibility facilities like Facility 15 are lightly but appropriately loaded.

The near-complete assignment of 14,575 units underscores the model's robustness in maximizing coverage within tight constraints. The unassigned remainder of 425 units reflects systemic limitations—specifically, insufficient eligibility for high-demand equipment types such as Type B—rather than a shortcoming of the optimization logic. This suggests that future improvements could involve increasing facility eligibility through technician training or equipment upgrades.

Overall, Model 1's linear structure and successful implementation in Excel Solver highlight its practicality and accessibility. Beyond its ability to maximize coverage, the framework's flexibility allows for adaptation to alternative objectives. The next section examines this adaptability by applying the model to prioritize repair value, offering a different lens on resource optimization.

4.2 Results from Model 2: Maximizing Total Repair Value

This section presents the results of the second optimization model, which focuses on maximizing the total strategic value of repair assignments rather than simply maximizing repair volume.

Table 7. Optimized equipment repair assignment results from Model 2

Facility	A	B	C	D	E	F	G	#Repairs	Capacity
1	206	0	148	0	140	214	189	897	900
2	227	0	163	209	154	236	209	1,198	1,200

3	5	141	141	181	133	204	0	805	1,000
4	0	122	0	156	115	177	0	570	900
5	189	0	136	174	91	196	174	960	1,000
6	244	175	175	224	0	254	224	1,296	1,300
7	0	144	77	184	136	208	184	933	1,000
8	0	158	158	202	149	228	202	1,097	1,100
9	206	0	148	0	140	214	189	897	900
10	208	150	0	191	141	216	191	1,097	1,100
11	306	0	0	192	208	0	282	988	1,300
12	206	148	148	190	0	215	190	1,097	1,100
13	196	141	141	181	133	204	0	996	1,000
14	272	196	196	0	0	34	49	747	1,200
15	235	0	169	216	160	0	216	996	1,000
#Repairs	2,500	1,375	1,800	2,300	1,700	2,600	2,299	14,574	Value 1,157,270

Note: Columns A–G are equipment types. Each entry is the number of repair units assigned to the facility–equipment pair. The '#Repairs' column shows the total units assigned to each facility, which must be less than or equal to (≤) the facility's capacity. The bottom row reports column totals across facilities. Value 1,157,270 is the total aggregated repair value (dimensionless score) achieved by the assignments from Model 2. Zero entries indicate no assignment or an ineligible pair.

As shown in Table 7, the model assigned 14,574 units out of 15,000—only one unit fewer than Model 1—but achieved a significantly higher total repair value of 1,157,270 compared to 1,130,998 in the previous model. These totals represent aggregate utility scores derived from the dimensionless unit repair values, not monetary costs, and reflect the overall strategic benefit of the assignment pattern. All assignments adhered strictly to the eligibility-weighted capacity bounds and satisfied both facility-level and equipment-type constraints, confirming that the enhanced value was obtained through smarter allocation rather than relaxed feasibility.

The assignment pattern in Model 2 reveals a clear shift from broad distribution to strategic concentration. Rather than pursuing maximum coverage alone, the model prioritizes assignments with higher utility scores, redirecting capacity to facility-equipment pairs with greater operational significance. For example, Facility 11, which handled 1,298 units under Model 1, saw its load reduced to 988 units in Model 2, as lower-value assignments for Types C and D were shifted to other high-impact facilities. Facility 4 experienced a sharper decline—from 896 to 570 units—due to the exclusion of lower-priority tasks like Types A and G. In contrast, Facility 15, minimally utilized in Model 1 with just 249 units, was reassigned 996 units in Model 2, taking on high-value tasks across Types A, C, D, E, and G.

These adjustments demonstrate how the value-based model reallocates tasks to optimize system-level benefits. Assignments with limited strategic value were deprioritized, allowing Solver to concentrate efforts where they generate the highest return. Facility 4's reduced role highlights the model's ability to filter out inefficient pairings, while Facility 15's increased involvement shows that even lower-utilization sites can be leveraged effectively when aligned with high-value tasks. This targeted allocation boosts total repair value without breaching feasibility constraints, underscoring the practical benefits of value-driven optimization in resource-limited settings.

The findings suggest that repair planning should consider not only operational feasibility but also strategic priorities. In environments where equipment varies in criticality or facility expertise is uneven, value-based planning enables more rational allocation of limited resources. This approach better aligns repair activities with organizational objectives, such as reducing service downtime or prioritizing life-critical systems.

This reallocation reflects the model's strategic intent. Rather than distributing tasks evenly, Model 2 channels resources toward high-impact assignments. Remarkably, it achieves a substantial gain in repair value with only a one-unit reduction in total volume, reinforcing its efficiency.

From a planning standpoint, Model 2 is especially suited to situations that demand selectivity—such as during budget cuts, workforce shortages, or urgent clinical needs. In such cases, prioritizing high-value repairs ensures that the most critical equipment remains operational, improving overall system resilience.

Notably, despite its value-maximizing objective, Model 2 preserves the fairness and feasibility structure of Model 1 by enforcing the same eligibility-weighted proportionality constraint. This ensures that no facility is overburdened and that each assignment remains aligned with operational capabilities. The result is a balanced model that achieves strategic prioritization while maintaining structural discipline.

In summary, Model 2 offers a compelling alternative to volume-based repair planning. It shows that strategic prioritization can significantly enhance system value with minimal sacrifice in service coverage, making it a powerful decision-support tool for healthcare administrators seeking to enhance the efficiency and impact of maintenance operations under real-world constraints.

4.3 Comparison of Both Models

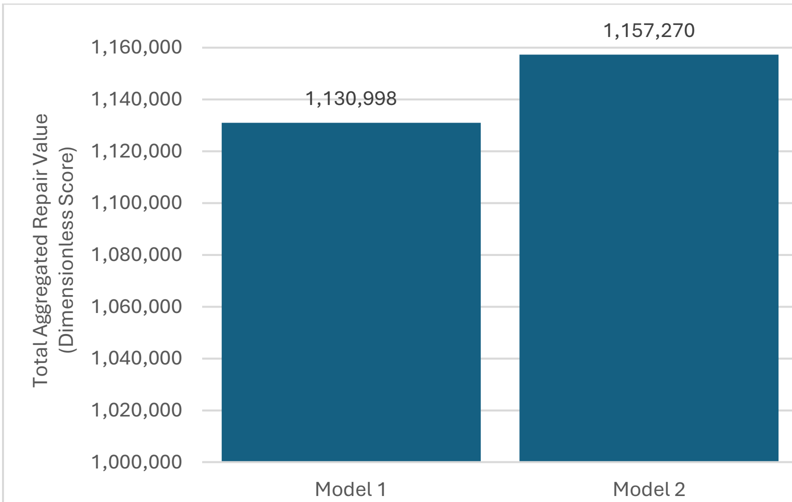
A comparative analysis was conducted to evaluate the performance of the two proposed optimization models: Model 1, which aims to maximize the total number of equipment units repaired, and Model 2, which seeks to maximize the total repair value generated across all assignments. Both models were executed under identical eligibility, capacity, and demand constraints, ensuring a fair and controlled comparison of outcomes.

Table 8. Comparison of optimization results for model 1 and model 2

Feature	Model 1: Maximize Repair Volume	Model 2: Maximize Repair Value
Objective Function	Maximize total units repaired	Maximize total repair value
Total Units Assigned	14,575	14,574
Total Repair Value	1,130,998	1,157,270
Coverage Efficiency	97.17% of demand met	97.16% of demand met
High-Value Allocation Bias	Moderate	Strong
Resource Distribution	Balanced across facilities	Skewed toward high-value cells
Use Case	Service coverage maximization	Strategic value optimization

As shown in Table **8**, Model 1 resulted in 14,575 unit assignments—nearly reaching the system's maximum feasible volume of 15,000—with a total accumulated repair value of 1,130,998. Model 2, in comparison, produced 14,574 unit assignments, representing virtually identical coverage, but achieved a higher total repair value of 1,157,270. These repair value figures are not monetary; rather, they represent the total aggregated utility scores derived from the unitless repair value matrix used in Model 2. This result confirms that Model 2 successfully prioritized higher-value assignments without sacrificing repair volume in any meaningful way. The difference in repair value between the two models is further illustrated in Figure 2.

Figure 2. Total repair value comparison between coverage-based and value-based models



The bar chart visually compares the total repair values of each model, emphasizing Model 2's performance advantage despite nearly identical unit coverage. By adjusting the y-axis scale for clarity, the figure highlights how the value-based model yields greater operational impact while preserving feasibility and fairness.

Table 9. Comparison of repair assignments for each facility and equipment type in Model 1/Model 2

Facility	A	B	C	D	E	F	G	14,575/14,574
1	206/206	0/0	148/148	0/0	140/140	214/214	189/189	897/897
2	227/227	0/0	163/163	209/209	154/154	236/236	209/209	1,198/1,198
3	196/5	141/141	141/141	181/181	133/133	204/204	0/0	996/805
4	170/0	122/122	0/0	156/156	115/115	177/177	156/0	896/570
5	189/189	0/0	136/136	174/174	128/91	196/196	174/174	997/960
6	244/244	175/175	175/175	224/224	0/0	254/254	224/224	1,296/1,296
7	0/0	144/144	144/77	184/184	136/136	208/208	184/184	1,000/933
8	0/0	158/158	158/158	202/202	149/149	228/228	202/202	1,097/1,097
9	206/206	0/0	148/148	0/0	140/140	214/214	189/189	897/897
10	208/208	150/150	0/0	191/191	141/141	216/216	191/191	1,097/1,097
11	306/306	0/0	220/0	282/192	208/208	0/0	282/282	1,298/988
12	206/206	148/148	148/148	190/190	0/0	215/215	190/190	1,097/1,097

13	196/196	141/141	141/141	181/181	133/133	204/204	0/0	996/996
14	146/272	196/196	78/196	0/0	0/0	34/160	110/49	564/747
15	0/235	0/0	0/169	126/216	123/160	0/0	0/216	249/996

Note: Each cell shows the Model 1 result / Model 2 result in repair units for the given facility–equipment pair. Columns A–G are equipment types. The rightmost column lists, for each facility, the total repairs as Model 1 total / Model 2 total aggregated across types; its column header displays the corresponding grand totals for the two models. Zeros indicate no assignment or ineligibility.

Closer examination of the assignment patterns in Table 9 reveals key differences in how each model allocates resources. Model 1 favored a more even distribution of repair tasks across facilities and equipment types to maximize overall throughput. For example, Facility 3 and Facility 13 were assigned substantial volumes across nearly all eligible equipment types, reflecting the model's emphasis on broad and balanced utilization.

By contrast, Model 2 redirected capacity toward higher-impact facility-equipment combinations based on unit repair value. Facility 15, which was underutilized in Model 1 with only 249 units assigned, was allocated 996 units in Model 2—primarily focused on Types A, C, D, E, and G, where it offered strong repair value. Meanwhile, Facility 4 saw a sharp reduction in total assignments, from 896 to 570 units, with Types A and G completely excluded. Facility 11, although heavily loaded in both models, experienced a more targeted allocation in Model 2, dropping from 282 to 192 units for Type D and receiving no tasks for Type C. These shifts demonstrate the model's strategic focus on value maximization, even at the expense of uniformity in distribution.

Both models adhered to all operational constraints, including facility-level capacity limits, equipment-specific demand ceilings, and the eligibility-weighted proportionality bounds. This structural consistency ensures that the differences in results can be attributed entirely to the change in objective—maximizing coverage versus maximizing value—rather than to differences in model feasibility.

The findings highlight a key operational insight: while both models effectively utilize available capacity, the value-maximizing model enables a more selective and strategic allocation of limited resources. It delivers greater overall benefit with only a marginal reduction in repair volume. This demonstrates the flexibility of the proposed framework in adapting to different planning priorities.

Ultimately, the choice between these two models should align with the strategic goals of the healthcare organization. If the priority is to maximize equipment uptime and ensure broad service accessibility, the coverage-based model offers an efficient and equitable approach. Conversely, when operational impact or return on investment is more critical—particularly under constrained budgets or workforce shortages—the value-based model serves as a more effective alternative.

The near-identical repair volumes between the two models also suggest that optimizing for value does not require sacrificing service quantity. This makes the value-driven model especially compelling for healthcare systems that must balance high demand with limited resources, while maintaining fairness and operational transparency.

The comparative results suggest that Model 1 is better suited for scenarios requiring rapid throughput or backlog clearance, such as emergency response or pandemic recovery periods. Its emphasis on broad repair coverage ensures maximum service availability, even when repair impact varies by equipment type. In contrast, Model 2 is preferable in capacity-constrained or high-priority settings, where selectively targeting high-value repairs can yield greater system benefit. For example, in facilities facing technician shortages or high-cost constraints, Model 2 enables strategic prioritization of repairs with the greatest clinical or operational impact. These distinctions offer actionable insights for healthcare administrators selecting between coverage-driven and value-driven planning strategies, depending on institutional context, policy goals, and resource availability.

Traditional models in maintenance optimization often focus on cost minimization or scheduling efficiency without incorporating facility eligibility or strategic prioritization. Compared to these approaches, our dual-model framework offers greater flexibility and fairness. The volume-based model ensures high service coverage even in fragmented systems, while the value-based model emphasizes targeted allocation aligned with institutional priorities. By combining equity, feasibility, and scalability, these models present a practical advancement over purely heuristic or cost-centric approaches.

4.4 Model Validation

This study assesses robustness through post-optimality analysis rather than statistical diagnostics. Because the models are deterministic optimization programs, measures such as residual plots, p-values, or R^2 are not applicable. Validation focuses on sensitivity analysis and stress testing to evaluate whether the optimal solution and its managerial implications remain stable under plausible parameter changes.

For the continuous LP runs, Excel Solver's Sensitivity Report provides shadow prices, reduced costs, and allowable increase/decrease ranges. A stable solution is indicated when proposed perturbations fall within these ranges, which implies the optimal basis and assignment pattern remain unchanged and the objective varies linearly with the relevant shadow prices. When integrality is enforced, standard sensitivity outputs are unavailable; robustness is then checked by re-solving the models under one-at-a-time and combined shocks and tracking changes in objective value, total repairs, facility workloads, and the set of active facility–type assignments.

(1) Facility capacities S_i. If a facility's capacity constraint is nonbinding, small increases or decreases in S_i have no effect. If binding, increasing S_i raises the objective at a rate equal to its shadow price until the allowable range is exceeded, after which the assignment pattern may shift to relieve other bottlenecks. Decreasing S_i when binding forces reallocation and can reduce total coverage or value, often to nearby eligible facilities with slack.

(2) Equipment demand D_j. When D_j is below the system capacity and nonbinding, increases in demand do not change the solution. If D_j is binding, higher demand can increase total coverage only if additional capacity exists or can be reallocated; in the value model, added demand is directed to

facility–type pairs with the highest marginal values. Reductions in D_j may free capacity and shift assignments toward other types that remain constrained.

(3) Unit repair values v_{ij}. In the value-maximizing model, assignments switch when a nonbasic pair's reduced cost approaches zero; increases in v_{ij} above its allowable threshold can bring that pair into the solution, while decreases can drop a marginal pair. Near-tie v_{ij} values can yield multiple optimal solutions with similar totals, so small perturbations may change the pattern without materially changing the objective. In the coverage model, coefficient sensitivity is immaterial because all x_{ij} share unit coefficients; robustness hinges on the right-hand sides and eligibility-weighted bounds.

Overall, the sensitivity checks indicate that the key findings remain stable under moderate and policy-relevant changes in parameters. This form of validation meets common expectations for diagnostic review in optimization studies and reinforces the robustness and credibility of the comparative results.

5. Conclusion

This study was motivated by real-world challenges in managing medical equipment repair within decentralized healthcare systems, where limited capacity, fragmented infrastructure, and uneven repair eligibility complicate maintenance decisions. Our objective was to develop optimization models that allocate repair tasks efficiently while also incorporating fairness and adaptability. The resulting framework provides practical decision-support tools for researchers and healthcare administrators, contributing to improved system resilience and service continuity.

Rooted in the Decision Sciences domain, this research applies mathematical programming to guide healthcare service optimization where constrained resource allocation requires analytical decision-making frameworks. This study proposes a dual-model optimization framework for allocating repair tasks for healthcare equipment across multi-facility networks with heterogeneous capabilities, eligibility constraints, and operational limits. As healthcare systems become increasingly reliant on technologically advanced equipment, the need for robust, scalable, and equitable maintenance planning tools has become more pressing. Rather than focusing solely on cost reduction, this research emphasizes the practical need to ensure equipment uptime, improve operational efficiency, and distribute workloads fairly across facilities with varying capacities and technical qualifications.

The proposed models incorporate key operational elements, including equipment-specific demand, facility-level capacity, and a binary eligibility matrix identifying which facilities are qualified for specific repairs. A central innovation is the eligibility-weighted proportionality constraint, which ensures that allocations are not only feasible but also equitable. This fairness-oriented mechanism enhances transparency in the allocation process and better captures the operational realities of decentralized systems.

Findings from the comparative analysis demonstrate that Model 1 is best suited for scenarios requiring high throughput and broad repair coverage, such as emergency response, pandemic recovery, or backlog clearance. In contrast, Model 2 is more effective when capacity is constrained or strategic prioritization is needed—such as when staffing is limited or critical equipment must be restored quickly. These insights allow healthcare administrators to select models aligned with institutional goals, balancing volume and value under real-world constraints.

The contribution of this study lies not only in its comparative modeling approach but also in the design of a framework that is both scalable and accessible. The linear structure of the models supports implementation in widely available tools like Excel Solver, enabling application even in low-resource environments. The eligibility-weighted constraint further promotes fairness and ensures that no facility is overburdened or underutilized—an essential consideration in decentralized healthcare systems. Beyond healthcare, the framework can be generalized to other service industries, such as fitness centers, where exercise equipment is regularly sent for repair and must be allocated across facilities with varying capacity and specialization.

Future research could extend this framework into multi-objective formulations that simultaneously optimize for coverage, value, cost, and equity—supporting integrated decision analytics for healthcare operations. A promising direction involves developing time-based or dynamic scheduling models that continuously update repair assignments in response to real-time system changes, such as sudden equipment failures, technician unavailability, or shifting clinical priorities. These enhancements would increase the framework's responsiveness and make it suitable for high-volatility environments like emergency response systems or critical care units.

Another key opportunity lies in integrating predictive maintenance data. Leveraging real-time indicators such as failure probabilities, sensor diagnostics, or usage patterns could enable the system to prioritize repairs before breakdowns occur. This proactive approach would shift the model from a reactive allocation tool to a preventive planning system, enhancing uptime, reducing service disruptions, and improving long-term asset performance. Despite current limitations—such as the assumption of static demand and deterministic parameters- the proposed models remain valid and robust for strategic planning in stable settings where constraints are well defined and decisions are made on a periodic or batch basis.

Embedding this logic within simulation tools or intelligent decision-support systems could further enhance its real-time applicability and scalability. Collectively, this study marks a meaningful advancement in maintenance optimization by integrating fairness constraints, comparative modeling, and strategic prioritization. These elements position the framework as a foundational component of digital health infrastructure—capable of minimizing delays, improving maintenance coordination, and strengthening the resilience and reliability of healthcare delivery systems.

References

Bahreini, R., Doshmangir, L., & Imani, A. (2018). Factors affecting medical equipment maintenance management in developing countries: A systematic review. *Journal of Clinical and Diagnostic Research, 12*(4), IC01–IC07. https://doi.org/10.7860/JCDR/2018/31646.11375

Boppana, V. R. (2023). Data analytics for predictive maintenance in healthcare equipment. *International Journal of Business & Management Science, 9*(2). https://doi.org/10.53555/eijbms.v10i1.176

Chakraborty, S., Raut, R. D., Rofin, T. M., & Chakraborty, S. (2023). A comprehensive and systematic review of multi-criteria decision-making methods and applications in healthcare. *Healthcare Analytics, 4*, 100232. https://doi.org/10.1016/j.health.2023.100232

Dantzig, G. B. (1963). *Linear programming and extensions*. Princeton University Press.

De Jonge, B., & Scarf, P. A. (2020). A review on maintenance optimization. *European Journal of Operational Research, 285*(3), 805–824. https://doi.org/10.1016/j.ejor.2019.09.047

González-Domínguez, J., Sánchez-Barroso, G., & García-Sanz-Calcedo, J. (2020). Scheduling of preventive maintenance in healthcare buildings using Markov chain. *Applied Sciences, 10*(15), 5263. https://doi.org/10.3390/app10155263

Hillebrecht, M., Schmidt, C., Saptoka, B. P., Neuhann, F., & Jahn, A. (2022). Maintenance versus replacement of medical equipment: A cost-minimization analysis among district hospitals in Nepal. *BMC Health Services Research, 22*, 1023. https://doi.org/10.1186/s12913-022-08392-6

Hillier, F. S., & Lieberman, G. J. (2015). *Introduction to Operations Research* (10th ed.). McGraw-Hill Education.

Hossain, M. A., Ahmad, M., Islam, M. R., & David, Y. (2020). Mathematical modeling of clinical engineering approach to evaluate the quality of patient care. *Health and Technology, 10*(2), 547–561. https://doi.org/10.1007/s12553-019-00390-9

Laktash, V. (2015, March 4). Medical equipment maintenance: Performing an audit to improve efficiency and savings. *Health Facilities Management*. https://www.hfmmagazine.com/articles/1493-medical-equipment-maintenance

Leenawong, C., & Ritthipakdee, A. (2024). Fuel costs optimization for long-haul flight with refueling layovers. *International Journal of Technology, 15*(6), 1602–1612.

Li, J., Mao, Y., & Zhang, J. (2022). Maintenance and quality control of medical equipment based on information fusion technology. *Computational Intelligence and Neuroscience, 2022*, 9333328. https://doi.org/10.1155/2022/9333328

Liao, H., Cade, W., & Behdad, S. (2021). Markov chain optimization of repair and replacement decisions of medical equipment. *Resources, Conservation and Recycling, 171*, 105609. https://doi.org/10.1016/j.resconrec.2021.105609

Mahfoud, H., El Barkany, A., & El Biyaali, A. (2016). Preventive maintenance optimization in healthcare domain: Status of research and perspective. *Journal of Quality and Reliability Engineering, 2016*, 5314312. https://doi.org/10.1155/2016/5314312

Mahfoud, H., El Barkany, A., & El Biyaali, A. (2018). Dependability-based maintenance optimization in healthcare domain. *Journal of Quality in Maintenance Engineering, 24*(2), 200–223. https://doi.org/10.1108/JQME-07-2016-0029

Mwanza, J., Telukdarie, A., & Igusa, T. (2022). Optimizing maintenance systems of healthcare facilities in low-resource settings through modeling and multi-scenario discrete event simulation. *SSRN*. https://doi.org/10.2139/ssrn.4215608

Pedistat. (2025, March 4). Reduce medical equipment's maintenance cost. *Pedistat Blog*. https://www.pedistat.com/blog/reduce-medical-equipments-maintenance-cost

Salami, A., Afshar-Nadjafi, B., & Amiri, M. (2023). A two-stage optimization approach for healthcare facility location-allocation problems with service delivering based on genetic algorithm. *International Journal of Public Health, 68*, 1605015. https://doi.org/10.3389/ijph.2023.1605015

Stodola, P., & Stodola, J. (2020). Model of predictive maintenance of machines and equipment. *Applied Sciences*, *10*(1), 213. https://doi.org/10.3390/app10010213

Taha, H. A. (2017). *Operations Research: An Introduction* (10th ed.). Pearson Education.

Yinusa, A., & Faezipour, M. (2023). Optimizing healthcare delivery: A model for staffing, patient assignment, and resource allocation. *Applied System Innovation, 6*(5), 78. https://doi.org/10.3390/asi6050078

Zamzam, A. H., Abdul Wahab, A. K., Azizan, M. M., Satapathy, S. C., Lai, K. W., & Hasikin, K. (2021). A systematic review of medical equipment reliability assessment in improving the quality of healthcare services. *Frontiers in Public Health, 9*, 753951. https://doi.org/10.3389/fpubh.2021.753951