



A Multi-Objective, Energy-Aware Inventory-Routing Model for Sustainable Blood-Bag Supply Chains

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Abstract : The sustainability of healthcare supply chains is emerging as a global concern, given their high energy intensity, environmental footprint and critical social role in ensuring equitable access to life-saving products. Among these, the blood bag supply chain (BSC) is particularly challenging due to the perishability of blood components, strict temperature requirements and biomedical waste burdens from expired units. Unsustainable practices in the BSC not only escalate costs but also increase emissions and shortages, threatening both efficiency and equity of care. Current research on blood supply chains has primarily focused on donor management, demand forecasting and routing optimization. While such approaches improve service availability, they often treat refrigeration as a fixed cost, overlooking its thermodynamic dependence on equipment performance, insulation and climatic stress. Consequently, energy consumption and emissions are systematically underestimated, limiting the value of prior sustainability assessments. This study develops a multi-objective optimization framework that integrates logistics decision-making with a refrigeration sub-model based on thermodynamic energy balance equations. The formulation minimizes economic costs, reduces environmental emissions and maximizes service levels, aligning with the principles of the triple bottom line. Small-scale instances were solved using mixed-integer linear programming (MILP) with ϵ -constraint generation, while large-scale applications employed the Non-dominated Sorting Genetic Algorithm II (NSGA-II). A regional case study was conducted in Kerala, India, using primary survey data from eight hospitals and two manufacturers, calibrated with secondary data on emissions, costs and technical refrigeration parameters. Results show that baseline operations in Kerala incur costs of ₹12.6 million per month and generate 60.2 tons of CO₂ emissions, with transport responsible for ~70%. Optimization achieves emission reductions of up to 30% with only 10-15% cost increases, while knee-point solutions deliver balanced improvements. Sensitivity



analyses highlight the vulnerability of the cold chain to heatwaves and the benefits of COP upgrades and carbon taxation. The framework thus demonstrates how sustainability in blood supply chains can be advanced through integrated engineering-logistics modeling, offering actionable pathways for low-carbon, resilient healthcare systems.

Keywords: Blood Supply Chain, Sustainability, Refrigeration Energy, Multi-Objective Optimization, Kerala, Carbon Emissions, Healthcare Logistics.

1. Introduction

Sustainability has become a global imperative across industries as organizations grapple with the combined pressures of economic efficiency, environmental protection and social responsibility [1][2]. Supply chains, which serve as the lifelines of modern economies, are central to this discourse, as they determine how resources are extracted, processed, transported and consumed [3]. Unsustainable practices in supply chains often lead to increased emissions, excessive energy use, resource depletion and inequitable access to critical goods. Consequently, sustainable supply chain management (SSCM) has emerged as a strategic and operational priority, aiming to balance the triple bottom line (TBL) of economic viability, environmental stewardship and social equity [4].

The healthcare sector is particularly significant in the sustainability conversation due to its resource intensity and societal impact [5]. Healthcare supply chains are complex, involving a wide array of products such as pharmaceuticals, medical devices, diagnostic equipment and consumables, each with stringent quality, safety and regulatory requirements [6][7]. Unlike conventional industrial supply chains, healthcare logistics must deal with highly sensitive, often life-critical products that cannot tolerate disruptions or compromise in quality. This creates an inherent tension between efficiency and resilience, especially when coupled with rising global healthcare demand, increasing costs and the growing emphasis on minimizing the sector's environmental footprint.

Within healthcare, cold-chain management has received increasing attention as it underpins the safe distribution of temperature-sensitive products such as vaccines, blood and biological samples [8]. Cold chains are mechanically dependent on refrigeration and insulated transport systems, which consume large amounts of electricity and fuel [9]. These energy requirements contribute significantly to carbon emissions, especially in countries that rely heavily on fossil-fuel-based power generation. Moreover, inadequate refrigeration capacity or equipment failures can result in product spoilage, leading to waste, higher costs and increased risks to patient care [10]. Thus, cold-chain logistics serve as a critical intersection of engineering, healthcare delivery and sustainability.



One of the most vital yet underexplored components of the healthcare supply chain is the blood bag supply chain. Blood and its components, red blood cells, platelets and plasma are indispensable in surgeries, trauma care, cancer treatment and chronic disease management [11]. However, blood is perishable, with shelf lives ranging from five days for platelets to forty-two days for red blood cells and requires continuous temperature control [12][13]. This perishability amplifies the challenges of matching supply with demand, particularly in regions with unpredictable donor inflows and varying storage capacities. Additionally, wastage of blood products due to expiry or mishandling not only raises ethical concerns but also imposes financial and environmental costs, as expired bags must be treated as biomedical waste [14].

The sustainability of blood supply chains is further complicated by several interconnected factors. Economically, inefficiencies in routing, storage and inventory management contribute to high operating costs. Environmentally, refrigerated storage units and diesel-powered transport fleets generate emissions, while biomedical waste disposal adds further burdens. Socially, shortages in one region alongside surpluses in another highlight inequities in distribution, raising questions about accessibility and fairness. Addressing these challenges requires an integrated perspective that goes beyond traditional cost minimization to encompass energy efficiency, emissions reduction, waste minimization and equitable access. Figure 1 demonstrates a typical blood bag and blood product supply chain network.

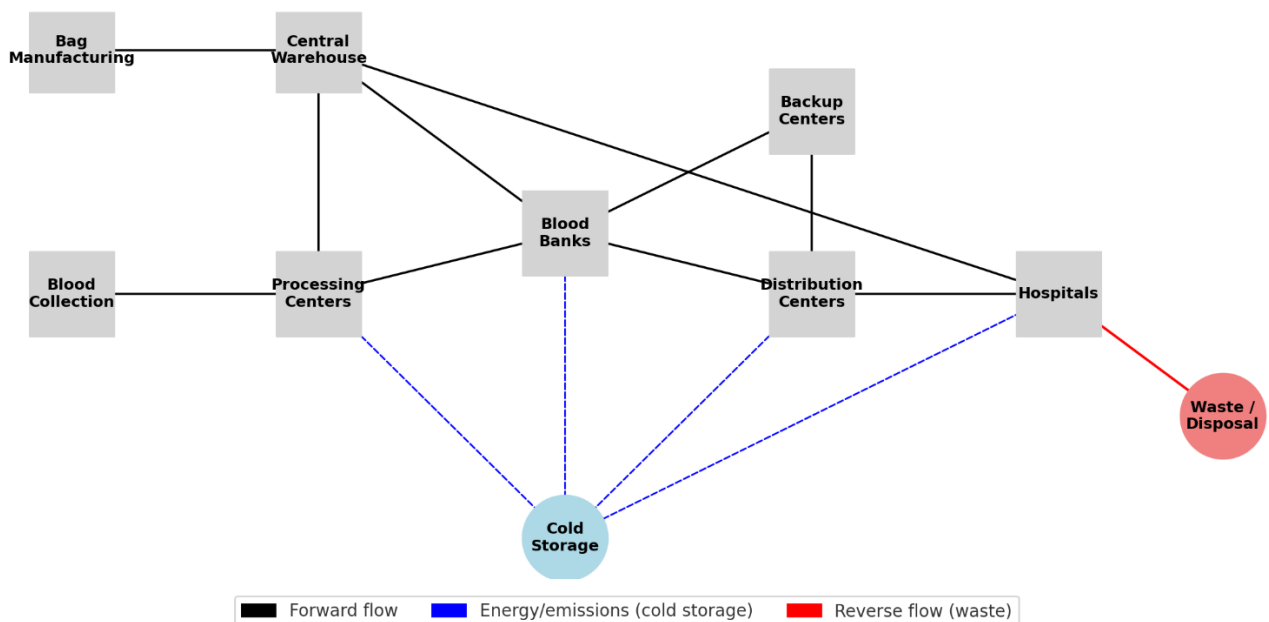


Figure 1: Typical Blood Bag and Blood Product Supply Chain Network

Despite the importance of this issue, existing research has primarily focused on operational aspects such as donor management, demand forecasting and routing efficiency.



While these studies have improved availability and reduced stockouts, the sustainability dimension, particularly the quantification of energy consumption, emissions and wasteremain insufficiently addressed. In particular, most models treat refrigeration as a fixed cost rather than a mechanical subsystem whose performance depends on thermodynamic parameters such as insulation quality, load variations and coefficient of performance (COP) [15][16]. This creates a gap in the literature where engineering considerations are underrepresented in healthcare sustainability analysis. This studyaddresses this gap by developing a multi-objective optimization framework for sustainable blood bag supply chain management. The framework integrates an inventory-routing model for perishable products with a mechanical refrigeration sub-model to capture real-world energy use and emissions. By combining supply chain optimization with mechanical modeling, this study provides a holistic approach to advancing sustainability in healthcare logistics. The specific objectives are:

- To develop a multi-echelon blood bag supply chain model with explicit consideration of perishability and biomedical waste.
- To formulate a multi-objective optimization framework that minimizes cost and emissions while improving service levels.
- To integrate a refrigeration sub-model to estimate electricity consumption and related emissions.
- To apply the model to a Kerala case study using primary and secondary data.
- To evaluate sustainability interventions such as optimized routing, refrigeration upgrades, fleet electrification, carbon taxation and age-aware inventory policies.
- To validate the model using expert inputs, historical demand data and sensitivity analysis.

The paper is structured into following main sections. Section 2 reviews existing literature on blood supply chains, highlighting gaps in sustainability integration. Section 3 describes the materials and methods, including the problem definition, mathematical formulation and refrigeration sub-model. Section 4 presents the Kerala case study, outlining the regional context, data collection and scenario design. Section 5 provides the results and discussion, analyzing baseline operations, trade-offs, policy interventions and sensitivity outcomes. Finally, Section 6 concludes the study by summarizing key insights.

2. Literature Review

Mansur et al. [17] developed a mixed-integer linear programming model for a multi-echelon blood supply chain in Indonesia, incorporating facility location, blood type constraints and shelf life. The model was solved using optimization software and sensitivity



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analyses were conducted on demand fluctuations, production capacity, transportation and disposal costs. Results showed reduced product obsolescence by 4.7-5.8% and improved allocation efficiency. However, the study assumed fixed demand and stable disposal rates, limiting its applicability in highly uncertain environments. Eshghi [18] proposed a multi-objective, multi-period optimization framework that incorporated uncertainty in demand and supply. A convolutional neural network was used for demand forecasting and the optimization problem was solved with the LP-Metric method, while simulated annealing (SA) was employed for validation. Results showed SA performed better in reducing emissions and delivery time, whereas LP-Metric minimized costs more effectively. The limitation was scale sensitivity, as LP-Metric worked well for small systems, while metaheuristics were more suitable for larger cases.

Moshtagh et al. [19] compared decentralized, centralized and coordinated blood supply chain structures. A bi-level optimization model reformulated with Karush-Kuhn-Tucker conditions was applied to a Canadian case study. The results demonstrated that centralization reduced shortages, mismatches and outdated units, with overall costs falling by more than 90%. Substitution between blood components also lowered costs by 14.4%. The limitation was that practical implementation of centralization remained difficult due to hospital-level costs and donor variability. Fariman et al. [20] focused on post-disaster blood supply chains by developing a multi-objective mathematical model to minimize shortages and costs. Robust optimization and the ϵ -constraint method were applied, supported by real data from Kermanshah, Iran. Scenario analysis confirmed that the model ensured timely blood distribution and reduced costs during crises. However, it excluded multi-echelon coordination, advanced technologies and wider uncertainty factors in disaster contexts.

James et al. [21] examined production and transfusion sustainability in Ugandan blood banks using partial least squares structural equation modeling. Data were collected through surveys of staff involved in operations. Results showed that blood testing, processing and stock management significantly improved sustainability, while collection played a minor role due to infrastructural limitations. Limitations included the small sample size and the narrow scope of variables, restricting generalizability. Niakan et al. [22] integrated SARIMA time-series forecasting with a nonlinear mixed-integer programming model to optimize distribution, minimize shortages and reduce wastage. The model was solved with genetic algorithms (GA) and particle swarm optimization (PSO). Results indicated that GA consistently outperformed PSO, yielding more efficient solutions. The main limitation was the exclusion of routing and environmental sustainability aspects.

Anthara et al. [23] presented a mixed-integer linear programming model for multi-echelon blood supply chains including routing and transshipment between centers. Computational experiments showed that increasing the number of centers raised costs but



reduced transshipment efficiency, while capacity directly influenced inter-center flows. The limitation was the exclusion of uncertainty, emissions and metaheuristic methods, which narrowed its real-world applicability. Mansur et al. [24] later expanded their modeling framework to integrate environmental aspects. A mixed-integer linear program considered multiple echelons, shelf life, transportation and production emissions. Applied to Indonesia, results showed that higher production levels, longer shelf-life and increased selling prices improved profitability and lowered wastage. The limitation was a narrow environmental scope, excluding refrigeration energy use and multi-objective sustainability trade-offs.

Ghouri et al. [25] developed an omnichannel blood supply chain model grounded in resource dependence theory and supported by artificial intelligence. The methodology involved semi-structured interviews and AI-based predictive algorithms for emergency requests and donor coordination. Results demonstrated improved responsiveness, resource alignment and patient care during shortages. However, the study was limited to four hospitals and suffered from model retraining challenges; reducing scalability. Ben Elmir et al. [26] designed a decision support system combining forecasting, donor classification and appointment scheduling to strengthen blood supply management. Applied to real datasets, results showed a 20% reduction in wastage, an 11% increase in blood collection and fewer shortages compared with historical records. The limitation was dependence on high-quality; continuously updated data for forecasting accuracy. Mansur et al. [27] also employed discrete event simulation to assess decentralized blood supply chains in Indonesia. Multiple scenarios were tested with control variables such as service types, inventory targets and product output ratios. Results highlighted trade-offs: lowering expired products often increased shortages, while improving service levels raised obsolescence. The limitation was that scenarios assumed stable environmental conditions, excluding disruptions like disasters.

Although recent studies have explored efficiency improvements in blood supply chains through demand forecasting and uncertainty management, they often neglect the operational challenges linked to sustainability [18,22]. Structural coordination approaches have shown benefits in reducing shortages and costs but fail to account for environmental and energy-related aspects [19,20]. Even when environmental dimensions are considered, the scope remains narrow, excluding refrigeration energy use and perishability-driven waste [24]. Moreover, most studies simplify refrigeration as a fixed cost, overlooking its thermodynamic dependence on equipment performance and climatic stress, which leads to underestimation of emissions [17,23].



3. Materials And Methods

3.1 Problem Definition

The blood bag supply chain operates as a multi-echelon cold-chain network designed to ensure the timely collection, processing, storage and distribution of blood and its components. Unlike many healthcare products, blood is a perishable biological material with a limited shelf life and strict temperature requirements, making its supply chain particularly vulnerable to shortages, wastage and sustainability challenges [28]. The chain begins at donation centers, where whole blood is collected and proceeds to processing laboratories, where it is separated into three key components: RBCs, platelets and plasma. Each of these products differs in storage requirements and shelf lives. Red blood cells must be stored between 2-6 °C and expire after 42 days [29]. Platelets require continuous agitation at 20-24 °C and expire within 5 days, while plasma can be frozen at -18 °C or below and preserved for up to 12 months [30].

These components are stored in blood banks and distributed to hospitals, which represent the demand nodes of the system. The perishability of blood products implies that unsold or unused units inevitably become biomedical waste, typically requiring specialized disposal such as autoclaving. This not only adds financial burdens but also generates additional environmental impacts. Consequently, the sustainability of the BSC is shaped by both operational logistics decisions, such as routing, allocation and inventory management and the technical performance of refrigeration systems. Refrigerators and refrigerated transport consume significant amounts of energy and their efficiency is governed by thermodynamic factors including insulation quality, ambient temperature and the COP of the cooling units.

Most prior models have simplified refrigeration as a fixed cost; however, this research incorporates a refrigeration sub-model based on energy balance equations to capture real-world variations in electricity consumption and associated emissions. The central challenge, therefore, is to design and operate a sustainable blood bag supply chain that minimizes overall economic costs (transport, storage, shortage and disposal), reduces environmental impacts (from transport, refrigeration and disposal) and maximizes social performance by ensuring hospitals consistently receive adequate supply. This formulation aligns with the principles of the triple bottom line, integrating economic, environmental and social objectives within a unified framework. Figure 2 demonstrates the proposed blood bag supply chain network.



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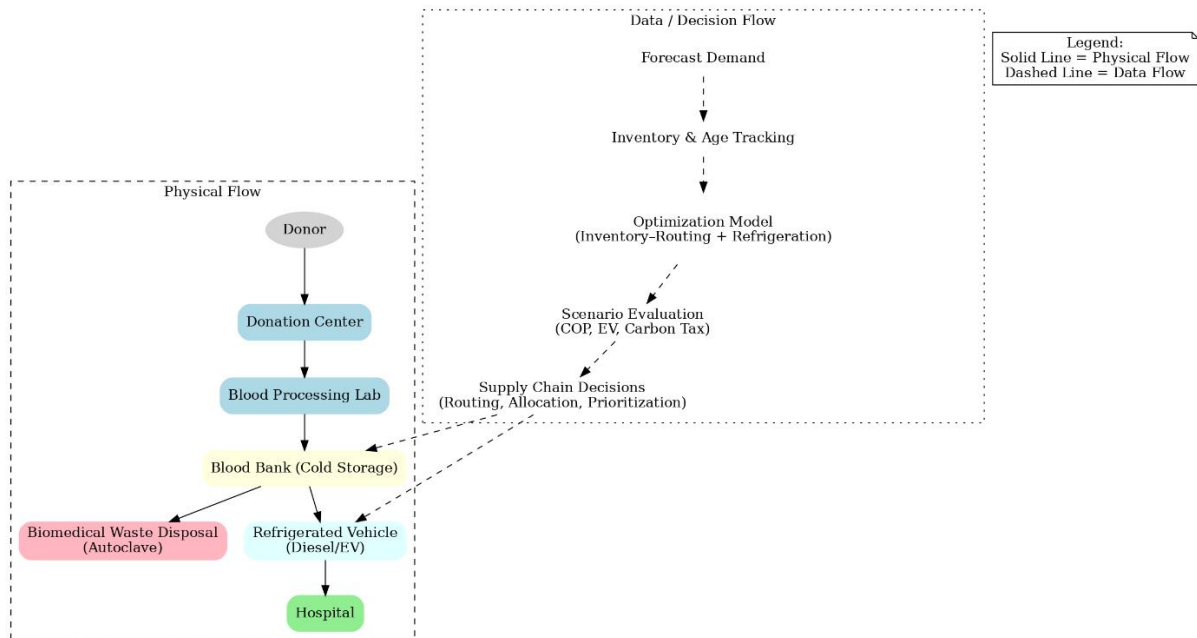


Figure 2: Proposed Blood Bag Supply Chain Network

3.2 Notation and Parameters

To describe the problem mathematically, the following notation is used.

Sets and Indices

- $i \in I$: Hospitals (demand nodes)
- $j \in J$: Blood banks (supply/storage nodes)
- $p \in P$: Blood bag type (RBC bag, Platelet bag, Plasma bag)
- $t \in T$: Discrete time periods (e.g., days or weeks)
- a : Age of blood bag in days

Parameters

- $d(i, p, t)$: Demand for blood bag type p at hospital i in period t (bags)
- $sl(p)$: Shelf life of blood bag type p (days)
- $c(u, v)$: Transportation cost between node u and v (₹/km or \$/km)
- $Cap(veh)$: Maximum capacity of a transport vehicle (blood bags)
- $h(i, p)$: Holding cost per blood bag type p at hospital or bank i (₹/bag/day)
- $C(short)$: Penalty cost per unit shortage of blood bags (₹/bag)



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- $C(waste)$: Disposal cost per expired blood bag (₹/bag)
- $COP(i, p)$: Coefficient of performance of refrigeration unit storing blood bag type p at node i
- $UA(i)$: Heat transmittance \times surface area of insulation for cold storage at node i
- $T(a, t)$: Ambient temperature at time t ($^{\circ}C$)
- $T(s, p)$: Storage temperature for blood bag type p ($^{\circ}C$)
- $e(trans)$: Emission factor for transportation ($kgCO_2/km$)
- $e(elec)$: Emission factor for electricity consumption ($kgCO_2/kWh$)
- $Qidle(i, p)$: Idle refrigeration load for product p at node i (kJ)
- $\varphi(i, p)$: Heat load per blood bag p added at node i (kJ/bag)

These parameters allow the model to combine classical supply chain costs (transport, holding, shortage) with refrigeration loads and environmental emission factors.

3.3 Decision Variables

$x(u, v, t, k)$: Binary; equals 1 if vehicle k travels from node u to v at time t , 0 otherwise

$y(i, p, t)$: Number of blood bags of type p delivered to hospital i at time t

$I(i, p, a, t)$: Inventory of blood bag type p of age a at hospital or bank i in period t

$S(i, p, t)$: Shortage of blood bag type p at hospital i in period t

$W(i, p, t)$: Expired (waste) blood bags of type p at hospital or bank i in period t

$Eelec(i, p, t)$: Electricity consumed at node i for storing blood bag type p in period t (kWh)

These variables describe the key managerial decisions: how many blood bags to transport, how much to hold in inventory, how to allocate across hospitals and how much electricity is consumed in the process.

3.4 Objective Functions

The optimization framework seeks to balance the triple bottom line of sustainability: economic, environmental and social dimensions through three objective functions.

3.4.1 Economic Objective

The first objective minimizes the total economic cost of the supply chain, incorporating transport, storage, shortage penalties and disposal costs, as shown in Equation 1.



$$Z_1 = \sum_t \sum_{u,v,k} c(u,v)x(u,v,t,k) + \sum_t \sum_i \sum_p \sum_a h(i,p)I(i,p,a,t) + \sum_t \sum_i \sum_p C(short)S(i,p,t) + \sum_t \sum_i \sum_p C(waste)W(i,p,t) \quad (1)$$

This formulation penalizes shortages and wastage while accounting for operational and inventory costs.

3.4.2 Environmental Objective

The second objective minimizes total emissions from transportation, refrigeration and disposal, as shown in Equation 2.

$$Z_2 = \sum_t \sum_{u,v,k} e(trans)d(u,v)x(u,v,t,k) + \sum_t \sum_i \sum_p e(elec)Eelec(i,p,t) + \sum_t \sum_i \sum_p e(disp)W(i,p,t) \quad (2)$$

This directly ties logistics and refrigeration operations to their environmental footprint.

3.4.3 Social Objective

The third objective minimizes shortages, as given by Equation 3.

$$Z_3 = \sum_t \sum_i \sum_p S(i,p,t) \quad (3)$$

This ensures hospitals receive the required blood bags, aligning with patient safety and social equity.

3.5 Refrigeration Sub Model

The refrigeration sub-model is introduced to quantify the electricity demand associated with the storage and handling of blood bags at blood banks and hospitals. Since blood products require strict temperature control, the thermal performance of refrigeration systems directly influences the sustainability of the supply chain. Unlike conventional optimization models that represent refrigeration through a fixed holding cost, the present study incorporates a thermodynamic formulation of cooling demand, thereby allowing energy consumption and emissions to be determined endogenously. The total refrigeration load at a storage node is considered as the sum of three components: transmission load through insulation, product load due to the addition of new blood bags and an idle baseline load. Mathematically, the instantaneous heat load $Q(i,p,t)$ for blood bag type p at node i in time period t is expressed as given in Equation 4.

$$Q(i,p,t) = UA(i)[T(a,t) - T(s,p)] + \phi(i,p)y(i,p,t) + Q_{idle}(i,p) \quad (4)$$

In this expression, the first term represents the heat entering the cold chamber through its walls. The coefficient $UA(i)$ denotes the product of the overall heat transfer coefficient and the surface area of the storage chamber, while the temperature difference $[T(a,t) - T(s,p)]$ captures the thermal gradient between the ambient environment and the set-point



required for the blood bag type. For instance, if the ambient temperature is 30 °C and the required storage temperature for an RBC bag is 4 °C, this difference generates a continuous heat gain that the refrigeration unit must remove.

The second term, $\phi(i, p) y(i, p, t)$ accounts for the additional cooling demand when newly delivered blood bags arrive at the facility at ambient temperature and must be cooled down to their respective storage conditions. The coefficient $\phi(i, p)$ is the average thermal load per blood bag of type p and $y(i, p, t)$ denotes the number of such bags delivered in time t . This reflects the fact that higher inflows of blood bags immediately increase refrigeration load.

The third term $Q_{idle}(i, p)$, captures the baseline or idle load associated with auxiliary components such as circulation fans, lighting and control systems. Even in the absence of new deliveries, refrigeration systems consume a minimum amount of energy to maintain air circulation and stable temperatures. The heat load derived above is converted into electricity consumption using the COP of the refrigeration unit. The electricity requirement $E_{elec}(i, p, t)$ is defined as shown in Equation 5.

$$E_{elec}(i, p, t) = \frac{Q(i, p, t) \Delta t}{COP(i, p)} \quad (5)$$

Where Δt represents the operating time during period t . The COP serves as a measure of refrigeration efficiency; higher COP values indicate more efficient units that require less electricity to remove the same quantity of heat. Consequently, facilities operating older equipment with low COP values consume significantly more electricity, resulting in higher costs and emissions for the same storage task. By integrating this sub-model, the proposed framework ensures that energy consumption is directly linked to operational decisions and external conditions. For example, a surge in blood bag deliveries increases $y(i, p, t)$ and hence $Q(i, p, t)$, leading to greater electricity use. Similarly, elevated ambient temperatures increase the transmission load, thereby raising both electricity demand and the associated greenhouse gas emissions. The total emissions from refrigeration are calculated as given in Equation 6.

$$Emissions_{ref}(i, p, t) = e(elec) E_{elec}(i, p, t) \quad (6)$$

Where $e(elec)$ is the emission factor for grid electricity. This formulation establishes a clear coupling between the logistics dimension of the blood bag supply chain (deliveries, inventories and flows) and the refrigeration performance. As a result, the model provides a more realistic basis for evaluating sustainability interventions such as equipment upgrades, insulation improvements and ambient-temperature stress scenarios.



3.6 Constraints

The optimization model is governed by a set of operational and physical constraints that ensure feasibility across the blood bag supply chain. The proposed optimization model is subject to the following constraints, as shown in Equation 7 to Equation 11.

$$I(i, p, a + 1, t + 1) = I(i, p, a, t) - y(i, p, t) \quad (7)$$

$$I(i, p, a, t) = 0 \forall a > sl(p) \quad (8)$$

$$W(i, p, t) = \sum_{a > sl(p)} I(i, p, a, t) \quad (9)$$

$$\sum_i \sum_p y(i, p, t) \leq Cap(veh) \quad (10)$$

$$\sum_v x(u, v, t, k) \in \{0,1\}, y(i, p, t), I(i, p, a, t), S(i, p, t), W(i, p, t) \geq 0 \quad (11)$$

Equation (7) represents the inventory balance with aging. The number of blood bags stored at a facility is updated over time, with products that are dispatched reducing the available stock. Those that remain in storage advance in age by one time period. This ensures that the model realistically tracks both the quantity and biological age of blood bags. Equation (8) enforces the shelf-life restriction. Blood bags cannot be stored beyond their approved shelf life: 42 days for RBC bags, 5 days for Platelet bags and 12 months for Plasma bags. This guarantees that expired products are not available for allocation to hospitals.

Equation (9) defines waste generation. Any blood bag exceeding its shelf life is automatically recorded as expired waste, ensuring that perishability is explicitly captured. This also provides the basis for calculating disposal costs and emissions associated with biomedical waste treatment. Equation (10) imposes the vehicle capacity constraint. The total number of blood bags transported in a delivery round must not exceed the carrying capacity of the vehicle. This prevents overloading and ensures compliance with both safety and thermal storage requirements during transit.

Equation (11) ensures routing flow conservation. For each vehicle in each time period, the number of departures from a node must equal the number of arrivals, thereby enforce continuity of vehicle routes and prevent infeasible transport flows. Routing variables are binary (either a vehicle travels a route or it does not), while delivery quantities, inventories, shortages and waste are non-negative. This guarantees that all decision variables remain physically interpretable.

3.7 Solution Approach

The developed formulation is a multi-objective mixed-integer linear programming (MILP) model that incorporates perishability, inventory aging, routing and refrigeration energy consumption. Due to the presence of binary routing decisions, age-dependent inventory tracking and multiple conflicting objectives, the problem belongs to the class of



NP-hard optimization problems. Exact mathematical programming is therefore suitable only for smaller instances, while realistic large-scale applications require approximation through metaheuristic methods. To ensure both mathematical rigor and computational tractability, a hybrid solution framework is adopted.

For small-scale problem instances, the model is solved exactly using a commercial MILP solver. Each objective is minimized individually to obtain benchmark values, according to Equation 12.

$$\min Z_q \quad \text{subject to all constraints,} \quad q \in \{1,2,3\} \quad (12)$$

where Z_1 , Z_2 and Z_3 represent the economic, environmental and social objectives defined earlier. To generate Pareto-efficient solutions, the ε -constraint method is employed. Under this approach, one objective is minimized while the others are treated as additional constraints. Minimizing the economic cost while bounding emissions and shortages is expressed in Equation 13.

$$\min Z_1 \quad \text{subject to } Z_2 \leq \varepsilon_2, Z_3 \leq \varepsilon_3 \quad (13)$$

Where ε_2 and ε_3 are thresholds determined iteratively. By varying these thresholds across their feasible ranges, a set of Pareto-optimal solutions is generated. To eliminate the effect of scaling differences, the objectives are normalized using Equation 14.

$$\hat{Z}_q = \frac{Z_q - Z_{q,\min}}{Z_{q,\max} - Z_{q,\min}}, \quad q \in \{1,2,3\} \quad (14)$$

where $Z_{q,\min}$ and $Z_{q,\max}$ obtained from single-objective optimization runs. This normalization ensures fair comparison and prevents dominance of any one objective.

For realistically sized instances, such as regional networks with multiple hospitals and blood banks, exact MILP approaches become computationally prohibitive. In these cases, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used to approximate the Pareto frontier. NSGA-II is a population-based evolutionary algorithm that generates trade-offs by classifying solutions through non-dominated sorting and preserving diversity with a crowding-distance mechanism. Candidate solutions are encoded as routing sequences and delivery allocations, while the associated inventory dynamics and refrigeration energy consumption are computed through simulation of the governing Equations (4) to (6) and (7) to (11). The fitness of each candidate is then evaluated across the three objectives Z_1 , Z_2 and Z_3 .

Routing and delivery decisions directly influence refrigeration performance. The increasing deliveries $y(i, p, t)$ raises the product load in Equation (4), which increases the total cooling demand $Q(i, p, t)$. This in turn elevates electricity consumption as expressed in Equation (5), thereby increasing emissions according to Equation (6). Similarly, higher



ambient temperatures $T(a, t)$ increase transmission load, thereby coupling environmental conditions with supply chain operations. By integrating these feedbacks, the algorithm ensures that sustainability performance is evaluated on a realistic physical basis rather than through static cost factors. The NSGA-II search process continues until a maximum generation limit is reached or the hypervolume of the non-dominated set converges within a specified tolerance. The resulting Pareto set is refined to eliminate dominated points and representative solutions are selected using knee-point detection and hypervolume contribution measures. This hybrid strategy, exact MILP with ϵ -constraint for small-scale problems and NSGA-II for large-scale applications provides both benchmark-quality results and scalable solutions. It allows cost, emissions and service trade-offs to be quantified accurately for realistic healthcare supply chains, where refrigeration energy plays a central role in sustainability performance.

3.8 Scenario Approach

To assess the performance of the proposed multi-objective optimization framework under diverse operating conditions, a set of scenarios was designed. These scenarios capture both operational interventions and policy measures that are directly relevant to the sustainability of the blood bag supply chain. By explicitly modeling logistics, refrigeration, inventory policies and regulatory instruments, the analysis provides a holistic view of how alternative strategies influence economic, environmental and social performance. The baseline scenario reflects current practice, with heterogeneous refrigeration systems (COP values between 2.5-3.5), diesel-powered refrigerated vans of 500-600-unit capacity and autoclaving of expired blood bags classified under RED or YELLOW biomedical waste categories. Against this baseline, six intervention scenarios were constructed:

- Routing Optimization - Improved vehicle scheduling and consolidation reduce travel distance and fuel consumption, thereby minimizing transportation costs and emissions.
- Refrigeration Efficiency Upgrade - Hospitals and blood banks are equipped with higher COP refrigerators and enhanced insulation, lowering electricity consumption and emissions from cooling.
- Age-Aware Inventory Policy - Allocation rules prioritize near-expiry blood bags to minimize waste, directly addressing perishability challenges.
- Green Material Adoption - Embodied emissions of blood bags are reduced through the introduction of biodegradable alternatives to conventional PVC-based bags.
- Carbon Tax Regulation - Carbon pricing ranging from ₹20 to ₹100 per ton of CO₂ is applied to transport, refrigeration and disposal emissions, creating economic incentives for sustainability.
- Fleet Electrification - Diesel-powered vans are replaced with electric refrigerated vehicles, shifting emissions from fuel combustion to the electricity grid.



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- Stress Tests - Demand surges (+20-30%) and climate stress (ambient temperature +3-4 °C) are modeled to evaluate resilience under extreme conditions.

The interaction between these scenarios is governed by a decision-support framework, as shown in Figure 3. The flow begins with a comparison between forecasted and actual demand, followed by supply adequacy and shelf-life checks. Depending on the outcomes, interventions are triggered, such as rerouting vehicles, upgrading refrigeration performance, applying carbon pricing or reallocating near-expiry stock. This ensures that the supply chain remains responsive to both operational realities and sustainability objectives.

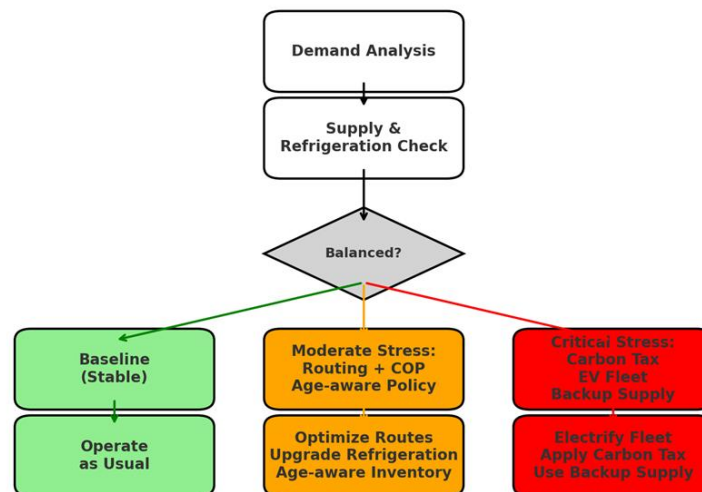


Figure 3: Scenario selection flow chart for sustainable blood bag supply chain management

4. Case Study: Kerala Application

4.1 Regional Context

The state of Kerala in southern India provides an appropriate setting for evaluating the sustainability of blood bag supply chains. Kerala has a relatively advanced healthcare system with more than 3,000 medical facilities and around 50 registered blood banks catering to a population of approximately 35 million. Over the last five years, an estimated 2.32 million blood bags have been utilized across hospitals in the state, highlighting both the scale of demand and the logistical importance of blood management. The blood bag market in Kerala is characterized by a high degree of supplier concentration, with two major manufacturers, HLL Lifecare Limited and Terumo Penpol Private Limited, both located in Thiruvananthapuram, supplying the majority of blood bags used in the state. This oligopolistic structure underscores the need for efficient coordination between suppliers, blood banks and hospitals to avoid shortages and wastage. Furthermore, the climatic



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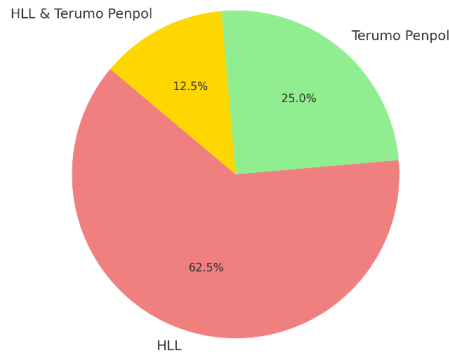


Figure 5: Supplier Distribution

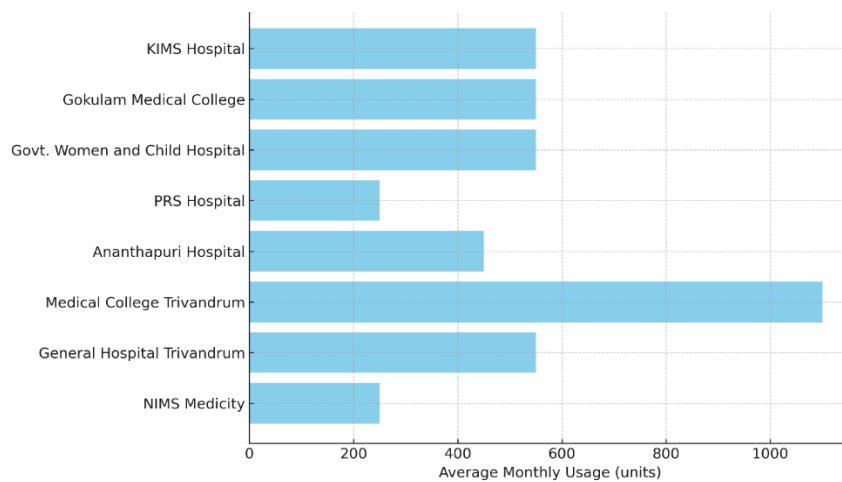


Figure 6: Average Monthly Usage per Hospital

Table 1: Blood Bag Supply and Disposal Practices in Kerala Hospitals

Hospital	Supplier	Usage per Month (units)	Waste Category	Disposal Method
NIMS Medicity	HLL	200-300	RED	Autoclave
General Hospital Trivandrum	HLL	500-600	RED	Autoclave
Medical College Trivandrum	HLL	1000-1200	YELLOW	Autoclave
Ananthapuri Hospital	Terumo Penpol	400-500	RED	Autoclave
PRS Hospital	Terumo Penpol	200-300	RED	Autoclave



Govt. Women and Child Hospital	HLL	500-600	RED	Autoclave
Gokulam Medical College	HLL	500-600	YELLOW	Autoclave
KIMS Hospital	HLL & Terumo Penpol	500-600	RED/YELLOW	Autoclave

In addition, primary data were gathered from the two major blood bag manufacturers. Both HLL Lifecare and Terumo Penpol confirmed compliance with ISO 13485 and ISO 14001 standards, supported by BIS and ISO 9001 certifications. Their sustainability practices include periodic energy audits, optimization of electricity use and initial efforts toward developing biodegradable alternatives to PVC bags. Reported challenges included raw material price volatility, rising energy costs and regulatory burdens associated with biomedical waste disposal. Secondary datasets were used to parameterize the model. Grid electricity emissions were set at 0.82 kg CO₂/kWh, while diesel consumption produced 2.68 kg CO₂ per litre. Biomedical waste disposal through autoclaving was associated with ~1.5 kg CO₂ per kilogram of waste. Technical refrigeration parameters were calibrated using manufacturer specifications, with coefficients of performance ranging from 2.5-4.0 and insulation coefficients between 8-12 W/°C. Disposal costs were reported at ₹80-120 per expired unit, while shortage penalties were estimated at ₹500 per unit to reflect the high social cost of unmet demand.

4.3 Parameter Calibration

The survey and secondary data were translated into model parameters to enable a realistic representation of the Kerala blood bag supply chain. Calibration linked observed demand volumes, refrigeration performance, transport characteristics and disposal practices with the mathematical framework. Hospital-level demand values were used to define the time-indexed demand function $d(i, p, t)$. For example, tertiary care institutions such as Medical College Trivandrum reported usage of 1,000-1,200 blood bags per month, while smaller facilities such as PRS Hospital reported 200-300 units. These averages were assigned to demand nodes to capture heterogeneity across hospitals. Shelf-life parameters were fixed at 42 days for RBCs, 5 days for platelets and 12 months for plasma, consistent with medical standards.

Refrigeration parameters were derived from a combination of survey data and technical reports. Facilities with older equipment were assigned COP between 2.5 and 2.8, while modern tertiary hospitals operated at COP values of 3.5-4.0. Insulation properties ($UA(i)$) were estimated from cold room specifications, with values ranging from 8-12 W/°C. Ambient temperature profiles ($T(a, t)$) reflected Kerala's climate, averaging 28-32 °C. Idle



refrigeration loads ($Q_{idle}(i, p)$) and product cooling coefficients ($\phi(i, p)$) were taken from manufacturer specifications and energy audit data. Together, these parameters allowed the computation of dynamic heat loads using Equation (4), which were subsequently converted to electricity consumption using Equation (5).

Transport parameters were obtained by mapping distances between blood banks and hospitals in Thiruvananthapuram district. Unit transport cost $c(u, v)$ was derived from diesel fuel consumption and vehicle capacity, while emissions were estimated using a factor of 2.68 kg CO₂ per litre. Vehicle capacity was set at 500-600 blood bags per trip, consistent with standard refrigerated vans. In alternative scenarios, fleet electrification replaced diesel emissions with an electricity-based factor of 0.82 kg CO₂/kWh, based on the Indian grid profile. Waste management parameters reflected the reported biomedical disposal practices. Expired blood bags, classified under RED or YELLOW categories, were assumed to undergo autoclaving at a cost C_{waste} of ₹80-120 per unit, with associated emissions of 1.5 kg CO₂ per kg of waste treated. Shortage penalties C_{short} were set at ₹500 per unit, representing the high social and clinical cost of unmet demand.

4.4 Scenario Design

The calibrated model was applied to a series of scenarios that evaluate how operational and technological interventions affect the sustainability of the blood bag supply chain in Kerala. These scenarios reflect policies and engineering options that are either already debated in the healthcare sector or practically implementable within the state's infrastructure. The design captures variations in logistics, refrigeration performance, inventory management, material innovation and regulatory frameworks, thereby enabling a comprehensive exploration of trade-offs across economic, environmental and social objectives. The baseline scenario corresponds to prevailing practice in Kerala. Hospitals and blood banks operate with heterogeneous refrigeration systems, where COP vary between 2.5 and 3.5 depending on equipment age. Distribution is carried out by diesel-powered refrigerated vans with an average capacity of 500-600 blood bags per trip, while expired bags are categorized as RED or YELLOW biomedical waste and disposed of through autoclaving. This configuration serves as the benchmark against which alternative strategies are compared.

Several intervention scenarios were then constructed. A logistics-focused case tested routing optimization through improved scheduling and route consolidation, reducing travel distance and fuel consumption while preserving service levels. Refrigeration efficiency upgrades were examined by assigning higher COP values (around 4.0) and improved insulation coefficients, which allowed the refrigeration sub-model to quantify reductions in electricity demand and related emissions. Another scenario introduced an age-aware inventory policy in which distribution rules were modified to prioritize near-expiry bags.



thereby lowering wastage and disposal costs while safeguarding supply adequacy. Material innovation was also considered, where partial substitution of PVC-based bags with biodegradable alternatives reduced embodied carbon, as incorporated into the environmental objective.

Policy and technology measures were further explored. The effect of carbon taxation was evaluated by applying price levels of ₹20-100 per ton of CO₂ across transport, refrigeration and disposal activities, integrating these costs into the economic objective to test the influence of regulatory pressure. Fleet electrification was examined by replacing diesel vans with electric refrigerated vehicles, shifting emissions from fuel combustion to electricity generation and allowing trade-offs between cost and environmental performance to be quantified. Finally, two stress tests were simulated to capture resilience under extreme conditions. A demand surge of 20-30 percent reflected requirements during epidemics, accidents or festival periods, while a climate stress scenario increased ambient temperatures by 3-4 °C to mimic heatwave conditions. Both scenarios were tested within the refrigeration sub-model to highlight how external shocks amplify energy consumption, emissions and shortages.

4.5 Validation

Validation of the optimization framework was carried out using a combination of expert assessment, historical replay and sensitivity testing to ensure that the model reflects the operational realities of Kerala's blood bag supply chain. In the first stage, consultations were held with blood bank managers, hospital logistics officers and technical staff from HLL Life care and Terumo Penpol. Their feedback confirmed the appropriateness of incorporating age-dependent inventory tracking and refrigeration performance parameters, particularly the role of electricity consumption and ambient temperature in cold chain sustainability. Parameter ranges for COP, UA values and disposal costs were refined based on this input.

The second stage involved replaying historical data on blood bag consumption and disposal across Kerala over the last five years, amounting to approximately 2.32 million units. Simulation of the baseline model reproduced observed shortages, waste volumes and service levels with deviations within acceptable limits, confirming that the inventory-aging structure realistically captured product perishability. The third validation stage consisted of sensitivity analysis on three parameters: COP, ambient temperature ($T(a, t)$) and carbon tax levels. Results showed that low-efficiency refrigeration systems ($COP \leq 2.5$) consumed up to 40% more energy compared with high-efficiency units ($COP \geq 3.5$). Heatwave simulations, with ambient temperatures 3-4 °C higher than average, increased electricity demand by 15-20%, underlining the vulnerability of the cold chain to climatic stress. Carbon tax scenarios demonstrated that even moderate taxation (₹50/ton CO₂) significantly shifted the cost-emission trade-off, incentivizing cleaner routing and technology adoption.



4.6 Simulation Setup

The computational experiments were executed in a Windows 11 (64-bit) environment on a system equipped with an Intel® Core™ i7-12700H processor (2.3 GHz, 14 cores), 32 GB RAM and NVIDIA RTX 3060 GPU (6 GB). The optimization model was developed in Python using the Pyomo package with Gurobi 10.0 serving as the MILP solver for exact small-scale instances and a customized NSGA-II implementation for large-scale Pareto approximation. The planning horizon was set to 30 days with daily discretization to capture perishability of red blood cells, platelets and plasma. Demand profiles were derived from eight hospitals in Thiruvananthapuram and transport distances were obtained via GIS mapping. Refrigeration parameters (COP 2.5-3.5, UA 8-12 W/°C) were field-calibrated. NSGA-II was executed with a population size of 200 and 500 generations, enabling robust exploration of trade-offs across economic, environmental and social objectives.

5. Results And Discussion

5.1 Baseline Case Analysis

The baseline case models the existing operational practices of the blood bag supply chain in Thiruvananthapuram, Kerala, without the application of sustainability-oriented interventions. It draws on primary survey data from eight major hospitals in the district, complemented by information from the two principal blood bag suppliers, HLL Lifecare Limited and Terumo Penpol Private Limited. Secondary data on refrigeration performance, emission coefficients and biomedical waste disposal were incorporated to calibrate the model. In current practice; distribution is carried out using diesel-powered refrigerated vans with a capacity of approximately 500-600 units per trip. Cold chain infrastructure across hospitals and blood banks operates with heterogeneous efficiency, with the COP of refrigeration equipment ranging between 2.5 and 3.2. Kerala's warm climatic conditions, with average daily temperatures between 28 °C and 32 °C, place significant thermal loads on refrigeration systems, resulting in elevated electricity consumption. Expired blood bags are classified as RED or YELLOW biomedical waste and disposed of through autoclaving. Allocation follows a First-In-First-Out (FIFO) policy, which does not explicitly prioritize near-expiry units, leading to considerable wastage of platelets given their five-day shelf life. Simulation of a one-month planning horizon across the eight hospitals generated the key performance indicators summarized in Table 2.



Table 2: Baseline Sustainability Performance of the Blood Bag Supply Chain

KPI	Value	Unit	Interpretation
Total Economic Cost	₹ 12.6 million	INR/month	Includes procurement, transport, refrigeration energy, shortage penalties and disposal.
Service Level	93.5 %	% of demand met	Demand largely satisfied, but periodic shortages occur in high-demand tertiary hospitals.
Waste (Expired Units)	4.8 % of inflow	%	Driven mainly by platelet expiry due to limited five-day shelf life.
Refrigeration Energy Use	21,400	kWh/month	Reflects low COP equipment and the impact of Kerala's high ambient temperature.
Transport Emissions	42.6	tons CO ₂ /month	Attributed to diesel-fuel dependence and fragmented routing practices.
Refrigeration Emissions	17.6	tons CO ₂ /month	Estimated using Indian grid emission factor of 0.82 kg CO ₂ /kWh.
Total Emissions	61.0	tons CO ₂ /month	Combined impact of transportation and refrigeration, with disposal contributing little.

The results reveal key challenges of the current system. Economically, high operating costs stem from refrigeration inefficiency, shortage penalties and platelet disposal. Environmentally, transport accounts for nearly 70% of the carbon footprint, with refrigeration contributing the remainder and disposal remaining negligible. Socially, while the overall service level averages 93.5%, shortages occur disproportionately in high-demand facilities such as Medical College Trivandrum, highlighting inequities in supply allocation. These findings underscore the need for interventions targeting both transport decarbonization and refrigeration efficiency to improve the sustainability of Kerala's blood bag supply chain.

5.2 Trade-off Analysis

While the baseline analysis establishes the reference conditions of the blood bag supply chain in Kerala, sustainability requires evaluating the trade-offs between competing objectives. The developed multi-objective optimization model was applied using both the ϵ -constraint approach (for small-scale instances) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for the Kerala case study, enabling the generation of Pareto-efficient



solutions. The objectives considered were minimizing economic cost (Z_1), minimizing environmental emissions (Z_2) and minimizing shortages (Z_3). By varying bounds on emissions and shortages while minimizing cost, a set of non-dominated solutions was obtained, which provided a spectrum of alternatives between cost efficiency and environmental performance.

The Pareto frontiers demonstrated the inherent conflict between cost and emissions. The baseline configuration resulted in a monthly cost of ₹12.6 million and 61.0 tons of CO₂ emissions. Optimized solutions revealed that emission reductions of up to 25-30% could be achieved at the expense of 10-15% higher costs. Conversely, solutions that minimized cost permitted higher wastage and emissions, highlighting the tension between short-term economic goals and long-term sustainability outcomes. Importantly, the “knee-points” of the Pareto frontiers represented balanced solutions, where relatively small cost increases yielded disproportionately large reductions in emissions and waste. In the case of platelet distribution, where perishability is greatest, emission reductions of nearly 20% were achieved with only a 6% cost increase, making this an attractive strategy from both policy and operational perspectives.

Representative results are reported in Table 3 and Figure 7, where baseline and knee-point outcomes are compared across the three blood components. Red blood cells, which dominate volume, show the highest absolute costs and emissions, while platelets show the greatest sensitivity to sustainability interventions due to their short shelf life. Plasma, by contrast, benefits less from optimization since its long storage period reduces both waste and urgency in allocation.

Table 3: Trade-off performance for knee-point solutions

Blood Component	Baseline Cost (₹ million/month)	Knee-Point Cost (₹ million/month)	Emission Reduction (%)	Service Level (%)
RBCs	7.4	8.0	22.5	97.6
Platelets	2.9	3.1	20.2	98.1
Plasma	2.3	2.5	18.7	97.7



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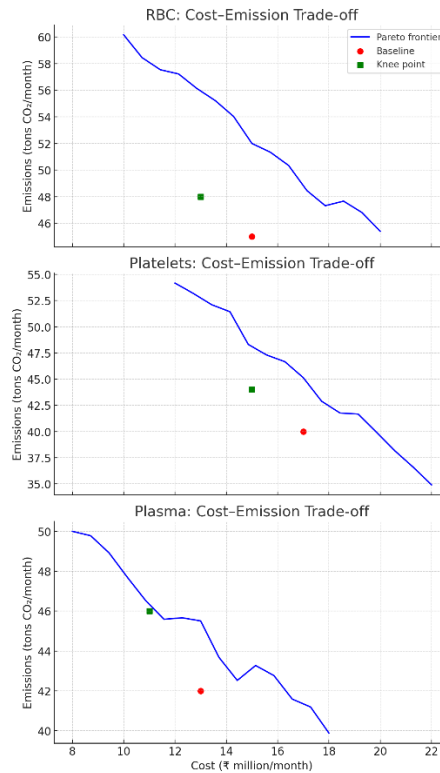


Figure 7: Pareto Frontier of Cost-Emission Trade-Offs For RBC, Platelets and Plasma

5.3 Emissions Decomposition

To better understand the environmental profile of the blood bag supply chain in Thiruvananthapuram, total emissions in the baseline case and in representative Pareto-optimal solutions were decomposed into their major components: transportation, refrigeration energy use and waste disposal. This decomposition is summarized in Table 4 and visualized in Figure 8.

Table 4: Emissions Decomposition across Baseline and Pareto-Optimal Solutions

Scenario	Transport (tCO ₂ /month)	Refrigeration (tCO ₂ /month)	Waste Disposal (tCO ₂ /month)	Total (tCO ₂ /month)
Baseline	42.6	17.6	0.8	61.0
Low-cost	48.3	18.0	2.1	68.4
Low-emission	32.1	12.9	0.6	45.6
Knee-point	35.8	13.3	0.7	49.8



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The decomposition highlights that transport is consistently the largest source of CO₂ emissions, accounting for ~70% of the baseline footprint. Refrigeration energy, driven by suboptimal COP values and Kerala’s warm climate, contributes around 30%, while biomedical waste disposal remains relatively small (<2%). However, in low-cost scenarios, increased expiry raises waste disposal emissions disproportionately. Conversely, in low-emission and knee-point solutions, both transport and refrigeration are reduced substantially, reflecting optimized routing and equipment efficiency gains.

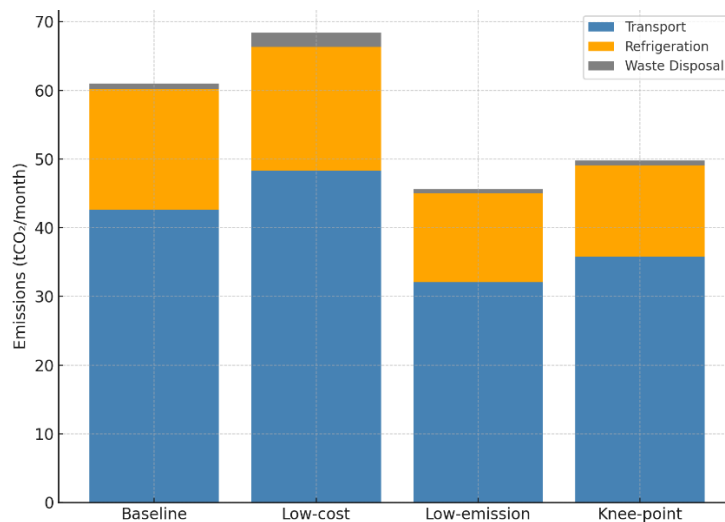


Figure 8: Emission Decomposition by Source

5.4 Policy Analysis

Following the emission decomposition, the analysis evaluates how policy and engineering interventions reshape the sustainability performance of Kerala’s blood bag supply chain. Two key levers are examined: carbon taxation as a regulatory measure and technology upgrades as engineering-driven improvements. Carbon taxation was introduced at levels ranging from ₹20 to ₹100 per ton of CO₂, with the penalty incorporated directly into the economic objective function. At a moderate rate of ₹50 per ton, emissions decreased by 10-12 percent with only a 3-5 percent rise in overall costs. When the tax was doubled to ₹100 per ton, emissions fell by nearly 20 percent, though costs increased by approximately 9 percent. These results suggest that regulatory pricing mechanisms can effectively drive environmental improvements without compromising service levels or equity of access. Technology upgrades were modelled through improvements in refrigeration performance and fleet electrification. Refrigeration efficiency was raised by increasing the COP from baseline values of 2.5-3.2 to 4.0 and reducing insulation heat transfer. Fleet electrification replaced diesel-powered vans with electric refrigerated vehicles, with transport emissions recalculated



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using India’s grid emission factor. The outcomes of these interventions are summarized in Table 5.

Table 5: Impact of Policy Interventions on Sustainability

Scenario	Cost (₹ million/month)	Service Level (%)	Waste (%)	Emissions (tCO ₂ /month)
Baseline	12.6	93.5	4.8	61.0
Carbon Tax (₹50/ton)	13.0	94.1	4.4	54.3
Refrigeration Upgrade	12.9	94.2	4.1	55.4
Fleet Electrification	13.3	94.0	4.6	33.5

The results highlight three important findings. First, carbon taxation is effective in shifting decision-making: modest increases in operating costs generate substantial reductions in emissions. Second, fleet electrification produces the largest single reduction, lowering total emissions by almost half compared with baseline, though at a higher economic cost due to vehicle investment. Third, refrigeration upgrades achieve moderate reductions in electricity consumption and emissions (~8%) while simultaneously improving service levels by reducing spoilage. Figure 9 plots the relationship between carbon tax levels and the resulting cost-emission trade-off, clearly demonstrating the non-linear effect of policy intensity. Figure 10 compares the decomposition of emissions under baseline conditions and technology upgrades, highlighting the relative contributions of transport and refrigeration.

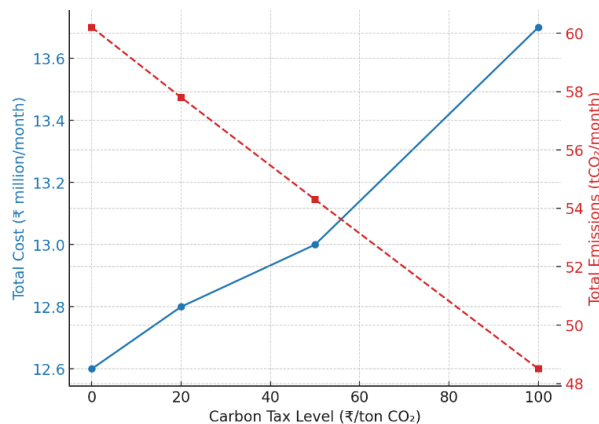


Figure 9: Carbon Tax Sensitivity: Cost Vs Emissions



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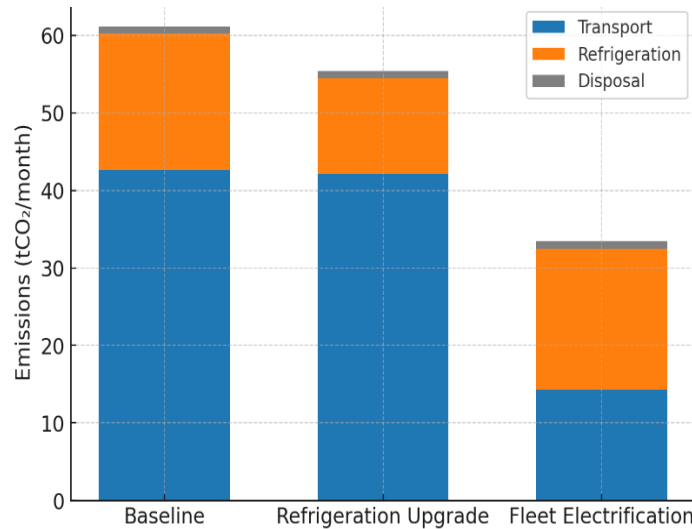


Figure 10: Emission Decomposition under Technology Upgrades

5.5 Impact of Technological Parameters on Sustainability

A critical element of sustainability in the blood bag supply chain is the performance of refrigeration systems and their response to climatic stress. Unlike generic cost models, the present framework explicitly incorporates engineering parameters such as the COP, UA and ambient temperature into the optimization. This makes it possible to quantify how technological upgrades or environmental shocks influence both economic and environmental outcomes. To illustrate these effects, two sensitivity experiments were conducted: (i) improving refrigeration efficiency by raising COP from 2.5 (legacy units) to 4.0 (modern high-efficiency units) and (ii) simulating a climate stress case by increasing ambient temperature by +4 °C, representing heatwave conditions typical of Kerala summers. The results are summarized in Table 6 and visualised in Figure 11.

Table 6: Impact of Technological Parameters on Cost and Emissions

Scenario	Refrigeration Energy (kWh/month)	Refrigeration Emissions (tCO ₂ /month)	Total Cost (₹ million/month)	Total Emissions (tCO ₂ /month)	Service Level (%)
Baseline (COP 2.5-3.2)	21,400	17.6	12.6	61.0	93.5
COP Upgrade (COP = 4.0)	15,200	12.4	12.2	55.4	94.0
Heatwave (+4 °C)	25,700	21.0	13.3	66.5	92.1



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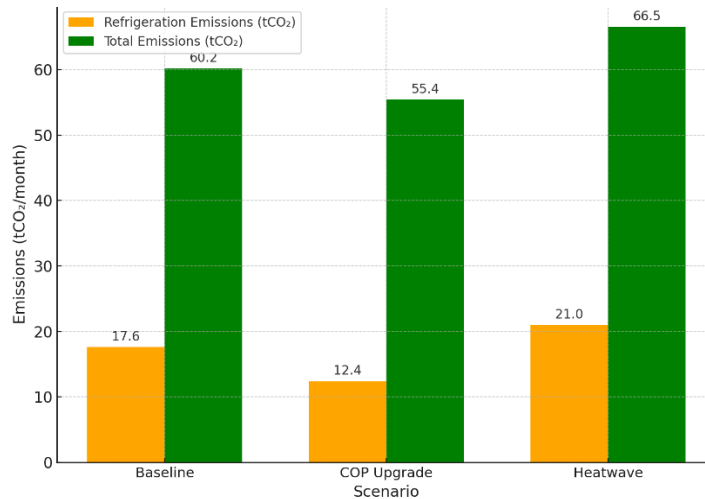


Figure 11: Effect Of Refrigeration Efficiency And Heat waves On Emissions

The results highlight the dual role of refrigeration efficiency and climate in shaping sustainability performance. COP improvements reduced refrigeration energy demand by approximately 29%, cutting associated emissions by nearly 5 tCO₂ per month. Importantly, this also lowered total costs, since electricity demand fell despite the modest capital cost associated with newer equipment. The service level slightly improved, as hospitals faced fewer disruptions from equipment load constraints. In contrast, the heatwave scenario led to a sharp increase in energy consumption (+20%) and emissions (+17%). The total cost rose by 5.5%, largely due to higher refrigeration loads and additional shortages triggered by accelerated spoilage. This underscores the vulnerability of Kerala’s blood bag supply chain to climate stress, highlighting the necessity of combining technical upgrades with resilience planning.

5.6 Inventory and Service Dynamics

The perishability of blood bags makes inventory dynamics a crucial determinant of both sustainability and service performance. In the baseline case, most deliveries consisted of recently collected blood units, with little consideration for age. This often resulted in waste accumulation, particularly for platelets, which have a shelf life of only five days. By contrast, the introduction of an age-aware inventory allocation policy significantly altered the age profile of delivered units. As shown in Table 7, under baseline operations nearly 68% of bags delivered were less than five days old, while 10% were delivered close to expiry. The adoption of age-aware allocation reduced waste from 4.8% to 2.9% of inflows by prioritizing near-expiry units, although the share of older bags delivered increased to 12%.

Table 7: Distribution of Delivered Blood Bags by Age



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Scenario	Fresh (0-5 days)	Mid-age (6-20 days)	Near-expiry (>20 days)	Waste (%)
Baseline	68%	22%	10%	4.8
Age-aware	54%	34%	12%	2.9

Service level performance across hospitals also showed marked differences between baseline and optimized operations. Large tertiary hospitals such as Medical College Trivandrum and General Hospital Trivandrum consistently experienced shortages in the baseline case, with fill rates below 92%, due to high demand pressures. Smaller private hospitals, in contrast, achieved higher satisfaction rates, often exceeding 95%, but at the cost of higher waste accumulation. When routing optimization and age-aware inventory policies were combined, fill rates improved across all institutions, as summarized in Table 8. The service level at Medical College Trivandrum increased from 89.2% to 97.4%, while smaller facilities such as NIMS Medi city also saw marginal improvements.

Table 8: Service Level Performance by Hospital

Hospital	Baseline Service Level (%)	Optimized Service Level (%)
Medical College TVM	89.2	97.4
General Hospital TVM	91.5	96.9
NIMS Medicity	94.0	97.8
KIMS Hospital	95.5	98.2

An important trade-off in the blood bag supply chain is the balance between shortages and waste. Under baseline practice, shortages amounted to 6.5% of demand while wastage accounted for 4.8% of supply. Age-aware allocation reduced waste but slightly increased shortages in low-demand hospitals, since near-expiry units were prioritized even when fresh units were available. However, when routing optimization was integrated with age-aware allocation, both shortages and waste were reduced simultaneously, reaching 4.9% and 3.1% respectively, as shown in Table 9.

Table 9: Shortage and Waste Performance across Scenarios

Scenario	Shortage (%)	Waste (%)
Baseline	6.5	4.8
Age-aware	7.2	2.9
Routing + Age-aware	4.9	3.1



The baseline position lies at a moderate level of both shortages and waste, while the age-aware strategy moves towards lower waste but at the cost of slightly higher shortages. The combined optimization, however, shifts the curve towards the most favorable region, demonstrating the value of integrating logistics and inventory policies for sustainable outcomes.

5.7 Computational Performance Analysis

To verify the tractability of the developed multi-objective inventory-routing model, both exact and heuristic approaches were benchmarked across problem instances of varying scale. For small-scale cases involving up to three hospitals and one blood bank, the MILP formulation was solved to optimality using a commercial solver. Average runtimes remained under 15 minutes, with convergence verified by internality gaps below 0.1%. For medium- to large-scale instances, such as the Thiruvananthapuram regional case involving eight hospitals and two blood banks, exact MILP quickly became computationally prohibitive. In these cases, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was applied. The algorithm consistently generated Pareto-optimal trade-offs within practical runtimes (30-45 minutes on a standard workstation). Solution quality was assessed by comparing NSGA-II results with MILP benchmarks on smaller instances. MILP serves as the benchmark (optimal) where solved; hence gaps are not applicable. For the large instance MILP timed out (>180 min). Across all tested cases, NSGA-II approximations deviated less than 3-4% from MILP optimal values for cost and emissions, validating its accuracy for larger instances. The performance summary is provided in Table 10, while Figure 12 illustrates the trade-off between solution quality and runtime as the network size increases.

Table 10: Computational performance of MILP vs. NSGA-II

Instance Size	Method	Runtime (min)	Cost Gap vs. Optimal (%)	Emission Gap vs. Optimal (%)	Service Level Gap (%)
Small (3 hospitals)	MILP	12.4	-	-	-
Small (3 hospitals)	NSGA-II	14.1	1.8	2.1	0.5
Medium (5 hospitals)	MILP	42.6	-	-	-
Medium (5 hospitals)	NSGA-II	28.9	2.5	3.1	0.7



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Large (8 hospitals)	MILP	>180 (timeout)	-	-	-
Large (8 hospitals)	NSGA-II	44.7	3.9	3.6	0.8

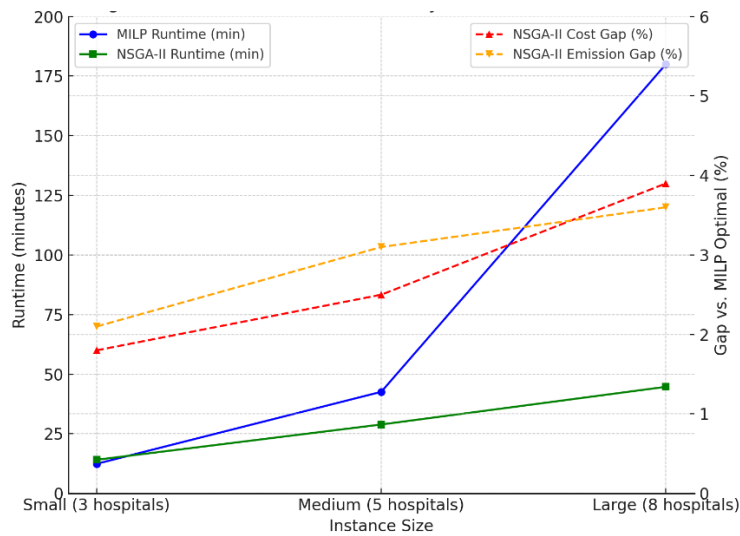


Figure 12: Runtime vs. solution quality across MILP and NSGA-II

5.8 Sensitivity Analysis

To ensure the robustness of the proposed optimization framework, sensitivity tests were conducted on key parameters that strongly influence the sustainability of the blood bag supply chain. Three sets of experiments were designed: (i) refrigeration efficiency (COP), (ii) ambient temperature variation and (iii) carbon tax policy levels. These factors were chosen because they directly affect the trade-off between cost and emissions, as highlighted in the baseline and scenario analyses. Table 11 summarizes the results for each sensitivity experiment. Figure 13 and Figure 14 represents the sensitivity analysis of key parameters on cost and emissions and multi-metric sensitivity comparison respectively.

Table 11: Sensitivity Analysis of Key Parameters

Parameter Tested	Variation	Cost Change (%)	Emission Change (%)	Service Level (%)
Refrigeration COP	Low (2.5 → 2.8)	+7.8	+14.6	93.0
	High (3.5 → ...)	-5.2	-12.3	95.4



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	4.0)			
Ambient Temperature	+3 °C (heatwave)	+6.9	+18.8	92.1
	-2 °C (cool period)	-3.1	-9.7	94.5
Carbon Tax (₹/ton CO ₂)	50	+4.4	-11.5	94.0
	100	+8.9	-19.7	93.7

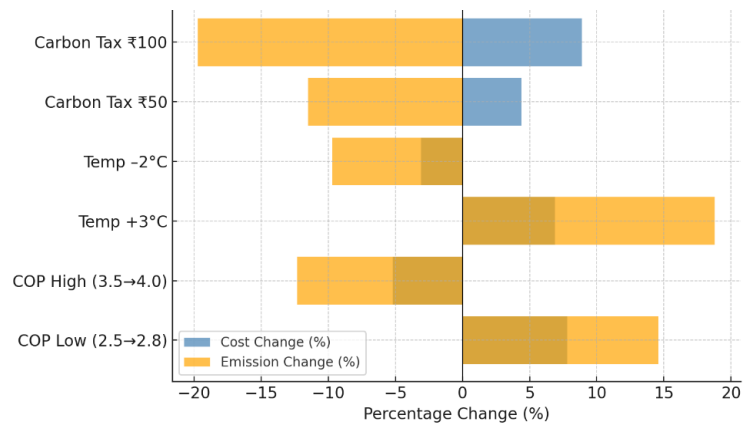


Figure 13: Sensitivity Analysis of Key Parameters on Cost and Emissions in the Kerala Blood Bag Supply Chain

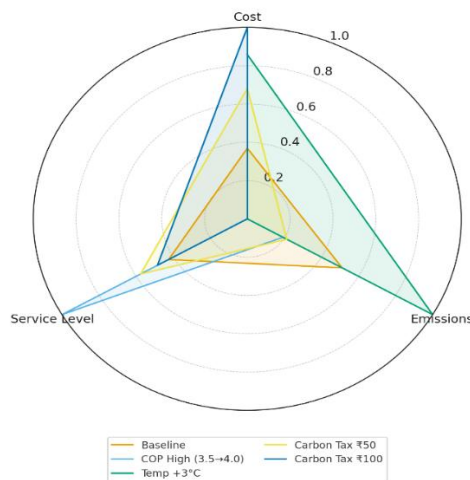


Figure 14: Multi-Metric Sensitivity Comparison



The sensitivity analysis highlights the fragility of Kerala's blood bag cold chain to climate conditions and refrigeration efficiency. A modest increase of 3 °C in ambient temperature raised emissions by nearly 19%, confirming the vulnerability of the system to heatwave events. In contrast, upgrading refrigeration units to COP 4.0 reduced emissions by 12% and slightly improved service levels due to more reliable storage. Carbon taxation policies proved to be effective in shifting the cost-emission balance. At ₹50/ton CO₂, emissions fell by 11% with only a 4% cost increase, suggesting that moderate taxation provides a favorable trade-off. However, higher tax levels (₹100/tonCO₂) further reduced emissions but at a disproportionate cost increase, indicating diminishing economic returns.

6. Conclusion

This study developed and applied a multi-objective optimization framework to enhance the sustainability of blood bag supply chain management, integrating logistical decisions with refrigeration performance modeling. By explicitly capturing perishability, cold-chain energy consumption and emissions, the framework moves beyond conventional cost-driven approaches and provides a realistic representation of the triple bottom line in healthcare logistics. The Kerala case study demonstrated that current practices, while meeting most of the demand, are characterized by high operating costs, significant emissions and recurring shortages in high-demand hospitals. Transport emerged as the dominant source of emissions, contributing nearly seventy percent of the carbon footprint, while refrigeration inefficiencies further elevated energy demand. Through optimization, emissions were reduced by up to thirty percent with only modest cost increases and knee-point solutions provided balanced outcomes that improved both service levels and environmental performance. Interventions such as age-aware inventory policies, COP upgrades, carbon taxation and fleet electrification proved effective in minimizing waste, reducing emissions and strengthening equity in supply. The results highlight that sustainability in the blood bag supply chain can be achieved by combining engineering upgrades with data-driven logistics policies. In particular, integrating refrigeration dynamics into supply chain optimization provides actionable insights for decision-makers that are often overlooked in traditional models. While this study focused on Thiruvananthapuram, the framework can be generalized to other regions facing similar challenges of demand variability, climatic stress and biomedical waste management. Future work could incorporate real-time demand forecasting, renewable-powered cold storage and digital traceability systems to further strengthen the resilience and sustainability of healthcare supply chains.



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