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RESEARCH PAPER

Robust Organ Transportation via Cold Chain and Commercial Flight Networks

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Abstract

Organ transplantation logistics demand rapid, reliable, and medically viable delivery solutions, especially when relying on commercial flight networks. The viability of an organ is severely constrained by its cold ischemia time—the duration an organ can remain functional outside the human body under refrigeration. This study formulates deterministic and robust mathematical models to optimize organ transport routing under uncertainty. The transportation network is modeled as a directed graph, where airports serve as nodes and scheduled flights as arcs, integrating constraints such as flight eligibility, connection handling time, and air traffic control prioritization. Building on a deterministic Resource-Constrained Shortest Path (RCSP) model, a model using Mulvey et al.'s robust optimization approach is extended. This allows the model to account for various real-world disruptions, including departure delays and scheduling inconsistencies, using multiple predefined scenarios. Furthermore, a penalty-based objective function is used to minimize arrival time and deviation across scenarios, ensuring stable and feasible routing decisions. The model is implemented via CPLEX, with experiments conducted on synthetic data for multiple organ types. Results demonstrate that the robust model, while more computationally intensive, yields significantly more resilient and feasible solutions across delay scenarios. Sensitivity analyses further highlight the critical roles of connection time and flight segment penalties. Overall, the proposed model offers a practical, scalable decision-support tool for transplant networks facing operational uncertainty.

Keywords:
Organ Transportation; Robust Optimization; Cold Ischemia Time; Commercial Flight Network; Mulvey Approach; Healthcare Logistics.

1. Introduction

Organ transplantation is a highly time-sensitive and medically critical procedure. Once an organ is harvested, it must be delivered to the recipient within a strict cold ischemia time (CIT), beyond which the organ loses its viability. For instance, a heart must be transplanted within 4–6 hours, while kidneys may remain viable for up to 36 hours. This narrow viability window introduces complex logistical challenges, particularly when relying on commercial air networks for transport.

Current organ transportation logistics often involve multiple flight segments and transit

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nodes, none of which are designed for emergency medical cargo. Unlike dedicated medical flights, commercial air systems face operational uncertainties such as departure delays, prioritization policies, and cargo eligibility constraints. These disruptions can render otherwise optimal transport routes infeasible, risking both patient outcomes and scarce medical resources.

This study addresses the core logistical challenge of identifying transportation paths that deliver transplantable organs within their CIT while remaining robust to potential disruptions in commercial flight networks. Traditional deterministic models fall short in these dynamic environments. Hence, there is a need for a model that integrates real-world operational constraints and uncertainty while optimizing for time and feasibility. We propose a robust optimization model that combines deterministic modeling with scenario-based uncertainty analysis. The model incorporates two real-world factors: (1) flight eligibility for organ transport, and (2) air traffic control (ATC) prioritization levels. Using a directed graph to represent the network, the model seeks to minimize total transport time and variability while maintaining medical feasibility.

This paper is structured as follows: Section 2 reviews existing literature on organ transport, uncertainty modeling, and logistics frameworks in healthcare. Section 3 presents the problem definition. Section 4 presents the deterministic and the robust mathematical models. Section 5 details the model implementation, computational setup, and experimental results. Section 6 concludes with key findings, limitations, and suggestions for future research.

2. Literature Review

The transportation of transplantable organs is one of the most time-critical logistics challenges in modern healthcare systems. Mathematical modeling and optimization methods have been extensively applied to improve decision-making in organ procurement, allocation, and delivery.

The broader healthcare supply chain context provides the foundation for organ logistics modeling. Kwon et al. (2016) outlined key risks and bottlenecks in healthcare logistics, identifying delays, inefficiencies, and cost drivers that also impact organ transport systems. Misra et al. (2022) explored cadaveric organ procurement systems using incentive-based mechanisms, improving organ recovery rates through supply chain optimization. Similarly, Ash et al. (2022) developed a robust model for medicine distribution during the COVID-19 crisis, offering techniques transferable to organ logistics.

Ahmadvand et al. (2018) and Goli et al. (2022) applied fuzzy and multi-objective models for resilient healthcare planning. Their work emphasizes the importance of integrating uncertainty and sustainability into logistics design. Also, case studies have demonstrated the value of optimization in real-world transplant systems. Caruso and Daniele (2017) developed a linear programming model for organ and medical team transport in Italy. Da Silva et al. (2013) used simulation to assess transport coordination in Brazil, showing how communication and storage impact transplant outcomes. Cacchiani et al. (2018) addressed aircraft placement in air medical services, using mixed-integer programming. Rognlie et al. (2007) simulated the U.S. kidney transplant network and examined allocation policies including paired donations. Their work highlighted the trade-offs between equity and efficiency. Zhang et al. (2024) proposed hierarchical location and allocation strategies for multi-organ systems, reinforcing the need for systemic design in organ logistics.

Ethical constraints are inseparable from organ logistics. Bertsimas et al. (2013) used simulation and optimization to improve fairness in kidney exchanges. Chellappa et al. (2023) addressed geographic inequality in liver allocation using GIS-based spatial analytics. Cole (2022) critiqued current transplant infrastructure for prioritizing urban centers and disadvantaging rural areas.

Angel et al. (2024) proposed an international ethical redistribution system for global organ

exchange, calling for policy support and funding from wealthier countries. Similarly, Nikzad et al. (2021) and Abaku et al. (2024) examined sustainability and social justice within healthcare logistics, suggesting integrated frameworks to balance efficiency with moral responsibility. Transportation infrastructure significantly impacts transplant feasibility. Bergiante and Maciel (2024) mapped geographic disparities in Brazil's logistics system. Nguyen et al. (2019) benchmarked developing countries' logistics capacity and its effect on organ availability. Akenroye et al. (2023) discussed how poor infrastructure and limited staff contribute to black-market activity and transplant delays in Africa. These studies underline the need to include geographic, infrastructural, and capacity-based constraints in mathematical models to ensure realistic and equitable solutions.

Digital innovations are reshaping organ logistics. GIS tools (Savaşer et al., 2021), smart containers (O'Brien et al., 2024), and drone transport (Bhayje et al., 2024) offer capabilities for cold chain monitoring. Artificial intelligence (Umoren et al., 2025; Kumar et al., 2025) is increasingly used for predictive modeling, resource allocation, and dynamic routing in emergency logistics. Decision support systems (Ferreira et al., 2023; Riascos et al., 2024) have improved allocation transparency and matching efficiency, while simulation tools (AbuKhousa et al., 2014; Senna et al., 2024) support scenario planning and policy evaluation in transplant systems.

Locational optimization plays a critical role in minimizing transport time. Belien et al. (2011) and De Oliveira et al. (2020) modeled transplant center locations to improve access and reduce transport delays. Yousefi Nejad et al. (2024) used queue-based bi-objective models to plan facilities under uncertainty. Rouhani and Amin (2023) focused on equitable location strategies using convex optimization, while Arefi and Firouzi (2024) considered environmental factors in facility planning.

Routing under CIT constraints is a defining feature of organ transport problems. Balster et al. (2025) applied shortest-path algorithms to minimize delivery time. Franco et al. (2023) introduced real-time route optimization under road and air disruptions. Mirzapour Al-e-hashem et al. (2023) developed time-dependent ambulance routing to reduce delays in urban contexts.

Despite advances, many studies lack robustness under real-world disruptions such as flight delays, weather changes, or sudden demand spikes. On the other hand, robust optimization has gained traction as a way to handle operational uncertainty. Zahiri et al. (2014) used fuzzy logic and stochastic modeling for organ allocation. Aghazadeh et al. (2018) incorporated natural disaster risk into logistics models using scenario planning. Jalilvand et al. (2023) included environmental and cold chain constraints in a bi-objective model prioritizing high-risk recipients. Salimian and Mousavi (2022) proposed a dynamic response system that adapts to disruption while ensuring transplant feasibility. While many studies have addressed key elements of organ transport, few models:

- Integrate real-world flight-level operational constraints
- Capture uncertainty using robust optimization
- Account for eligibility, ATC priority, and cold chain stability simultaneously

Moreover, real-time data usage, dynamic decision-making, and multi-organ routing remain underexplored. This study aims to bridge these gaps by developing a robust, constraint-sensitive model for organ transport using commercial flight networks.

3. Problem Definition

The core logistical challenge in organ transplantation lies in minimizing transport time while ensuring that every routing decision respects the medical viability of the organ involved. This viability is primarily governed by the cold ischemia time (CIT)—the maximum duration an organ can remain outside the human body under refrigeration before the risk of irreversible

tissue damage becomes unacceptably high. This period begins immediately upon the surgical removal of the organ and continues until it is reconnected to blood circulation in the recipient's body. If this window is exceeded, the organ's functional integrity rapidly deteriorates, leading to a higher probability of rejection, postoperative complications, or complete transplantation failure. Managing the so-called "cold chain"—the uninterrupted logistical process that ensures the organ remains preserved and in transit—is, therefore, not merely a technical constraint but a medical imperative. Each organ type has a specific CIT threshold based on its sensitivity to ischemic damage. Hearts are among the most fragile, typically remaining viable for only 4 to 6 hours, while kidneys may endure up to 24 to 36 hours in cold storage, and livers fall somewhere in between. Given these narrow and varied windows, transport timing must be meticulously synchronized with flight schedules and transfer operations. The problem becomes particularly challenging when attempting to design a routing plan that not only minimizes cumulative travel time but ensures that every organ arrives within its unique CIT constraint. The use of commercial flight networks introduces further complexity, because the model relies on commercial passenger flights, we assume that each aircraft provides sufficient cargo capacity for transporting organ preservation containers. These containers occupy only a negligible volume relative to the available cargo hold of commercial aircraft; therefore, cargo capacity is not expected to be a binding constraint in practice and is not explicitly modeled in the formulation. Unlike dedicated medical transport, commercial flights follow rigid schedules and are susceptible to operational uncertainties such as delays, rerouting, and variable handling times. In this context, airports are modeled as nodes and flights as directed arcs in a time-dependent network. Every additional connection requires handling time, which erodes the remaining viable transport window. The routing task must therefore account for cumulative flight durations, intermediate transfer penalties, and the timing of departures and arrivals across a multi-leg network. The challenge intensifies when multiple organ types are transported simultaneously. Each organ requires a feasible, medically safe path that may intersect or compete with others in terms of route availability, node capacity, and timing. The objective extends beyond finding shortest paths—it must ensure conflict-free coordination, respect logistical constraints, and maintain feasibility under stress. The presence of disruptions such as unexpected flight delays can further invalidate deterministic solutions. Thus, the problem addressed in this model is how to design a robust, time-aware transportation strategy across commercial air networks that reliably delivers multiple organs to their destinations within their medical time limits, despite structural complexity and operational uncertainty. The model must not only optimize routing decisions under ideal conditions but also remain resilient when faced with unpredictable disruptions that could otherwise compromise feasibility and patient outcomes.

4. Mathematical Model

This project builds upon the mathematical formulation presented by Balster et al. (2025). The underlying model frames organ transportation as a resource-constrained shortest path problem (RCSP), in which airports are modeled as nodes and commercial flights as directed arcs within a network graph. The primary objective of this optimization is to determine the fastest viable sequence of flights to transport an organ from a donor location (source node) to a recipient location (sink node), while rigorously respecting biological and logistical time constraints. Among these, the most critical is the cold ischemia time (CIT), a parameter that fundamentally shapes the feasibility and success of organ transplantation. While Balster et al. (2025) addressed the deterministic routing of organs under ideal conditions, this study extends the model to incorporate uncertainty in flight delays through robust optimization techniques. Additionally, two practical constraints—flight eligibility for medical cargo and air traffic prioritization—

were introduced to better reflect real-world operational requirements.

4-1-Assumptions

In this study, to preserve computational tractability in the deterministic optimization model, each organ's clinically reported cold ischemia time (CIT) range was represented by a nominal planning parameter. Rather than using the midpoint of the range, a conservative approach was adopted: the lower bound of each organ's viability window was used as the planning deadline. This ensures that any route deemed feasible by the model remains well within the clinically acceptable range, providing a safety buffer against unmodeled operational delays. For example, the heart's documented viability window of approximately 4–6 hours was modeled using a conservative baseline threshold of 240 minutes (4 hours), representing the lower end of the clinical range. This value should be interpreted as a modeling abstraction that enables linear deadline constraints, rather than as a strict physiological cutoff, since actual transplant feasibility remains inherently sensitive to time variability within the full clinical range. Future extensions of the model may incorporate interval-based or distributional CIT representations to more explicitly capture clinical time variability. This means that once a heart departs from the source node, the time remaining to reach the destination is immediately reduced by the duration of each subsequent flight and connection. Similar midpoint approximations were applied for other organs, with the understanding that This modeling choice was adopted to maintain a tractable optimization structure and to allow the incorporation of clear deadline constraints within the routing formulation. The nominal CIT parameter therefore serves as a planning reference for the optimization model rather than an exact representation of clinical tolerance. In practice, organ viability is influenced by multiple factors such as donor condition, preservation quality, and operational delays, which may shift the effective time window within the clinically reported range. In addition to simplifying organ-specific viability thresholds, certain structural assumptions were also introduced to manage the size and complexity of the transport network. One key assumption was that each pair of airports is connected by only a single flight per day in each direction. This constraint limits the number of possible flight combinations in the model, reducing computational burden and making the network graph more interpretable. By narrowing the range of options, the model focuses on capturing high-level strategic trade-offs, such as timing, route length, and feasibility under tight time constraints. These assumptions reflect a deliberate balance between operational realism and mathematical solvability, allowing the core optimization framework to function efficiently while still reflecting the most critical biological and logistical constraints.

4-2- Indices, Parameters, and Decision Variables

The notations used in the mathematical models are given as follows.

Indices and Sets:

i, j: nodes
o: organ
a: flight
s: delay scenarios,
$sink(o,i)$: set of sink nodes for organ i
$source(o,i)$: set of source nodes for organ i
A: set of fights from node i to node j, $(i,j,a) \in A$
O: set of organs, $o \in O$
S: set of scenarios, $s \in S$ (for robust condition)

Parameters:

h_{ij}^{a}: Departure time of flight *a* from node *i* to node *j*

$h_{ij}^{a,s}$: Departure time of flight *a* from node *i* to node *j* under scenario *s* (for robust condition)

d_{ij}^{a}: Duration time of flight *a* from node *i* to node *j*

τ_{ij}: Handling time between node *i* and node *j*

$\delta_{ij}^{a} \in \{0,1\}$: Eligibility of flight *a* for organ transportation between node *i* and node *j*

$\pi_{ij}^{a} \in \{0,1\}$: ATC priority status for flight *a* between node *i* and node *j*

$H_{available}^{o}$: Organ availability time

$H_{t_max}^{o}$: Nominal maximum delivery time for organ *o*, derived from its clinically reported cold ischemia time (CIT) range and used as a planning deadline in the optimization model.

*P***:** Penalty of using additional flight segments

M: A positive large value

p^{s}: Probability of scenario *s*

ρ: Weight of robustness penalty (A higher ρ places more emphasis on robustness and less on average performance, while a lower ρ prioritizes optimality in expectation**)**

ε: A small positive operational tolerance parameter (in minutes).

Parameter ε denotes a small operational tolerance used to differentiate the deadline feasibility between prioritized and non-prioritized flights. In the implementation, ε is set to a very small constant time value, ensuring that the constraint remains logically strict without materially affecting the feasible solution space or the optimization results. The parameter is intentionally calibrated to act solely as a tie-breaking buffer rather than as a structural tightening of the deadline.

Decision Variables:

$x_{ij}^{a,o} \in \{0,1\}$: Binary variable, 1 if flight *a* is used from node *i* to node *j* for organ *o*

$x_{ij}^{a,o,s} \in \{0,1\}$: Binary variable, 1 if flight *a* is used from node *i* to node *j* for organ *o*, under scenario *s* (for robust condition)

$xavg_{ij}^{a,o}$: Continuous variable representing the average routing decision across all scenarios, defined as the probability-weighted mean of all scenario-specific decisions
(it lies between 0 and 1)

T_{i}^{o}: Arrival time of organ *o* to node *i*.

$T_{i}^{o,s}$: Arrival time of organ o to node *i* under scenario *s* (for robust condition)

$dev_{ij}^{a,o,s}$: Difference between each scenario-specific decision $x_{ij}^{a,o,s}$ and $x_{avg}{}_{ijao}$ (for robust condition)

4.3. Deterministic Model

The deterministic mathematical model serves as the foundation of the organ transportation optimization framework. This model assumes all flight times and handling operations are known in advance and disruption-free.

$$\min z = \sum_{o} \sum_{i \in sink(o,i)} T_{i}^{o} + P \sum_{i} \sum_{j} \sum_{(i,j,a) \epsilon A} \sum_{o} x_{ij}^{a,o} \quad (1)$$

S.to:

$$\sum_{i \in source(o,i)} \sum_{j} \sum_{(i,j,a) \epsilon A} x_{ij}^{a,o} = 1 \qquad \forall\, o \quad (2)$$

$$\sum_{i}\sum_{j\in sink(o,j)}\sum_{(i,j,a)\epsilon A} x_{ij}^{a,o} = 1 \qquad \forall\, o \qquad (3)$$

$$\sum_{i}\sum_{(i,j,a)\epsilon A} x_{ij}^{a,o} = \sum_{i}\sum_{(j,i,a)\epsilon A} x_{ji}^{a,o} \qquad \forall\, o, j \notin source\ (o,j)\ \&\ sink(o,j) \qquad (4)$$

$$T_j^o \geq T_i^o + d_{ij}^a + \tau_{ij} - M\left(1 - x_{ij}^{a,o}\right) \qquad \forall i,j,o,(i,j,a)\epsilon A \qquad (5)$$

$$\sum_{i\in source(o,i)} T_i^o \geq H_{available}^o \qquad \forall\, o \qquad (6)$$

$$\sum_{i\in sink(o,i)} T_i^o \leq H_{t_max}^o - \varepsilon \sum_{i}\sum_{j}\sum_{(i,j,a)\epsilon A} x_{ij}^{a,o}\left(1-\pi_{ij}^a\right) \qquad \forall\, o \qquad (7)$$

$$x_{ij}^{a,o} \leq \delta_{ij}^a \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (8)$$

$$T_i^o \geq h_{ji}^a x_{ji}^{a,o} + d_{ji}^a + \tau_{ji} - M\left(1 - x_{ji}^{a,o}\right) \qquad \forall i,j,o,(j,i,a)\epsilon A \qquad (9)$$

$$T_i^O \leq h_{ij}^a + M\left(1 - x_{ij}^{a,o}\right) \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (10)$$

$$x_{ij}^{a,o}\epsilon\{0,1\} \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (11)$$

$$T_i^o \geq 0 \qquad \forall i\ ,o \qquad (12)$$

The objective function (1) finds the shortest time-feasible path from the source node to the destination while satisfying medical and operational constraints. Constraint (2) shows an organ outflow and ensures that each organ departs from the source node exactly once. It is critical to initiate a valid transport path. Constraint (3) demonstrates an organ inflow and guarantees that each organ arrives at its destination exactly once, ensuring completion of the transport. Constraint (4) presents a flow conservation constraint at all intermediate nodes, which ensures that organs passing through transshipment airports continue on a connected path. This prevents disjointed or looping paths that would be biologically invalid. Constraint (5) demonstrates time propagation with handling time and enforces temporal consistency: if a flight is selected, then the time of departure from node *i*, plus the flight duration and the handling time at node *j*, must not exceed the departure time of the next leg. Constraint (6) shows organ availability constraint at the source. Constraint (7) enforces the arrival deadline at the destination node. The term involving ε introduces a small buffer for arcs without ATC priority ($\pi = 0$). This parameter is calibrated as a minimal operational tolerance so that it only distinguishes priority conditions without significantly altering the feasible region of the model. Constraint (8) shows flight eligibility, and it means not all commercial flights can be used for organ transport due to medical, legal, or logistical constraints. Some flights may lack the required refrigeration facilities, may not allow human tissue cargo due to airline policy, or may not be coordinated with national transplant networks. To ensure feasibility, a binary parameter $\delta_{ij}^a \in \{0,1\}$ is used to indicate whether flight *a* from airport *i* to *j* is eligible. Constraints (9) and (10) presents two bounds for T_i. Constraints (١١) and (١٢) show the type of decision variables.

4.4 Robust Optimization Model

A robust organ transportation model extends traditional deterministic planning by explicitly accounting for uncertainty in flight schedules and transit times. Rather than relying on fixed travel durations, it incorporates multiple delay scenarios to simulate real-world disruptions such as late departures or extended layovers. Based on Mulvey et al. (1995) approach, the objective is to find routing strategies that remain feasible and effective across all considered scenarios, not just under ideal conditions. This approach improves reliability and resilience, especially for time-critical deliveries constrained by cold ischemia limits.

$$\text{Min } z = \sum_{s} p^s \left[\sum_{o}\sum_{i\in sink(o,i)} T_i^{o,s} + P\sum_{i}\sum_{j}\sum_{(i,j,a)\epsilon A}\sum_{o} x_{ij}^{a,o}\right] + \rho\sum_{s}\sum_{i}\sum_{j}\sum_{(i,j,a)\epsilon A}\sum_{o} dev_{ij}^{a,o,s} \qquad (13)$$

s.to:

$$\sum_{i\in source(o,i)} \sum_{j} \sum_{(i,j,a)\epsilon A} x_{ij}^{a,o,s} = 1 \qquad \forall\, o,s \qquad (14)$$

$$\sum_{i} \sum_{j\in sink(o,j)} \sum_{(i,j,a)\epsilon A} x_{ij}^{a,o,s} = 1 \qquad \forall\, o,s \qquad (15)$$

$$\sum_{i} \sum_{(i,j,a)\epsilon A} x_{ij}^{a,o} = \sum_{i} \sum_{(j,i,a)\epsilon A} x_{ji}^{a,o} \qquad \forall\, o, j \notin source\ (o,j)\ \&\ sink(o,j) \qquad (16)$$

$$T_j^{o,s} \geq T_i^{o,s} + d_{ij}^{a} + \tau_{ij} - M\left(1 - x_{ij}^{a,o,s}\right) \qquad \forall i,j,o,(i,j,a)\epsilon A \qquad (17)$$

$$\sum_{i\in source(o,i)} T_i^{o,s} \geq H_{available}^{o} \qquad \forall\, o,s \qquad (18)$$

$$\sum_{i\in sink(o,i)} T_i^{o,s} \leq H_{t_max}^{o} - \varepsilon \sum_{i} \sum_{j} \sum_{(i,j,a)\epsilon A} x_{ij}^{a,o,s}\left(1 - \pi_{ij}^{a}\right) \qquad \forall\, o,s \qquad (19)$$

$$x_{ij}^{a,o,s} \leq \delta_{ij}^{a} \qquad \forall\ i,j,o,s,(i,j,a)\epsilon A \qquad (20)$$

$$T_i^{o,s} \geq h_{ji}^{a,s} x_{ji}^{a,o} + d_{ji}^{a} + \tau_{ji} - M\left(1 - x_{ji}^{a,o,s}\right) \qquad \forall i,j,o,(j,i,a)\epsilon A \qquad (21)$$

$$T_i^{o,s} \leq h_{ij}^{a,s} + M\left(1 - x_{ij}^{a,o,s}\right) \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (22)$$

$$xavg_{ij}^{a,o} = \sum_{s\epsilon S} p^{s}\ x_{ij}^{aos} \qquad \forall\ i,j,o,s,(i,j,a)\epsilon A \qquad (23)$$

$$dev_{ij}^{aos} \geq x_{ij}^{aos} - xavg_{ij}^{a,o} \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (24)$$

$$dev_{ij}^{aos} \geq xavg_{ij}^{a,o} - x_{ij}^{aos} \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (25)$$

$$x_{ij}^{a,o,s}\epsilon\{0,1\} \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (26)$$

$$T_i^{o,s} \geq 0 \qquad \forall i,o,s \qquad (27)$$

$$xavg_{ij}^{a,o}\epsilon[0,1] \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (28)$$

$$dev_{ij}^{aos} \geq 0 \qquad \forall\ i,j,o,(i,j,a)\epsilon A \qquad (29)$$

To incorporate robustness into the model under uncertain flight conditions using the Mulvey approach, the objective function was extended with a penalty term weighted by the scalar parameter ρ, which captures the cost of inconsistency between scenario specific routing decisions and a common scenario-independent baseline. This baseline is expressed through an average decision variable that reflects a unified flight plan across all scenarios. By summing the absolute deviations of actual decisions from this average and penalizing them through ρ, the model promotes consistency and guards against reactive, scenario-specific divergence. This adjustment ensures that the final solution remains stable and implementable even when disruptions occur, aligning with the practical need to commit to a single plan in advance despite potential variations in flight conditions. By this description, Equation (13) shows the objective function which minimized the expected total arrival time across all organs and scenarios, while including two penalty terms: one penalizing longer path based on the number of flight segments used, and another penalizing instability. The descriptions of equations (14) to (22) are similar to the descriptions of equations (2) to (10) but for each scenario s. Equations (23) to (25) are for robust conditions. Constraint (23) explicitly defines the average decision variable as the probability-weighted mean of scenario-specific decisions. Constraints (24) and (25) model the absolute deviation between each scenario-specific decision and this average value. This formulation allows the model to penalize variability across scenarios and promotes stable routing decisions under uncertainty. Finally, equations (26) to (29) show the type of variables.

This modeling provides a flexible yet realistic decision-support tool for organ logistics. The deterministic model ensures basic feasibility under ideal conditions, while the robust extension handles real-world delays and enforces stability. Together, these models enable planners to balance speed, reliability, and feasibility across commercial air networks.

5. Model Implementation

This section describes the implementation of the proposed models, the experimental setup using synthetic flight data, and the results obtained from solving both deterministic and robust formulations. All input data used in the model—including flight schedules, network structure, and organ transport demands—were synthetically generated randomly. Although the experimental evaluation is based on synthetically generated flight schedules, the proposed optimization framework does not rely on any specific statistical assumptions about the underlying delay distributions and is therefore structurally applicable to real-world airline networks once operational data are provided. Sensitivity analyses are also presented to evaluate the influence of key parameters on solution performance.

The deterministic and robust models were implemented in GAMS and solved using the CPLEX solver via the NEOS Server. The transportation network was modeled as a directed graph, where nodes represent airports and arcs represent scheduled commercial flights. Each arc is uniquely defined by a triplet (i, j, a), denoting the origin node, destination node, and flight identifier. Four organ types were considered (heart, kidney, liver, and lung), each with unique cold ischemia time constraints, for modeling purposes, the heart was assigned a nominal CIT parameter of 240 minutes to represent the lower bound of its clinically reported viability window, allowing the formulation of a clear deadline constraint in the optimization model. while the kidney had a longer window of 1440 minutes. Handling time between connecting flights was fixed at 20 minutes. Three delay scenarios were created to simulate real-world uncertainty:

- Scenario 1: No delay (p = 0.4)
- Scenario 2: 30-minute delay (p = 0.3)
- Scenario 3: 45-minute delay (p = 0.3)

The objective function minimized the expected total arrival time, plus a penalty 30 for each additional flight segment used, and a robustness penalty ρ = 10 for deviation across scenarios

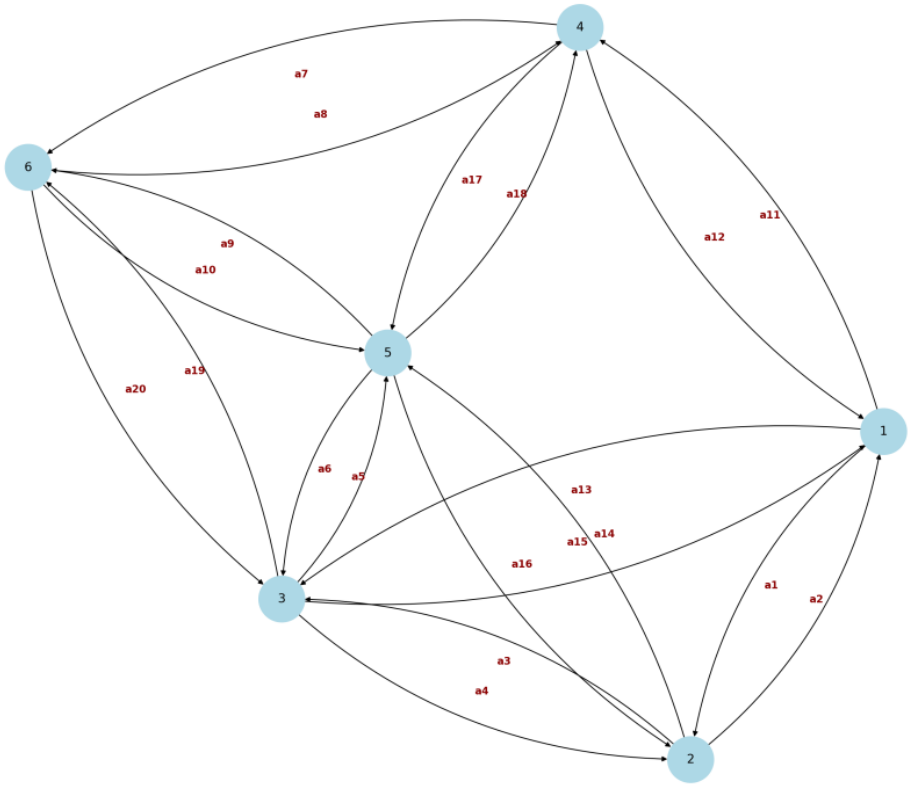


Fig 1. Flights Network

5.2 Sensitivity Analysis

Sensitivity analysis was conducted on P (penalty for routing complexity) in Figure 2, and τ (handling time between connections) in Figure 3. Both deterministic and robust models were tested to assess how performance responds to changes in these values.

5.2.1 Penalty Parameter (P)

The sensitivity analysis of parameter P explores how the model responds to changes in the time-equivalent penalty assigned to each additional flight segment. Since P influences the preference for simpler, more direct routes versus complex multi-leg connections, understanding its effect is crucial for tuning model behavior. By varying P across a defined range, we assess the trade-off between total transport time and routing complexity in both deterministic and robust formulations. This analysis helps reveal how heavily the model prioritizes directness over flexibility under different transport conditions.

The parameter P, set to 30 in the base case, was introduced in the objective function as a time-equivalent cost applied per flight segment. Its role is to discourage the use of fragmented, multi-leg routes by introducing a temporal penalty for each additional transfer. This helps prioritize faster and more direct routes where possible. In the deterministic model, reducing P lowered the impact of flight segment penalties, leading to the selection of longer but potentially more flexible paths. Conversely, increasing P resulted in the preference for more direct connections, which minimized the number of transfers and generally improved performance for organs with short cold ischemia time limits. The objective function's value changed noticeably with variations in P, demonstrating the model's sensitivity to how transfer complexity is valued.

In the robust model, the influence of P was present but less pronounced due to the inclusion of deviation penalties across scenarios. Even so, higher values of P continued to nudge the model toward simpler and more stable routing patterns, reducing exposure to delay-related risks.

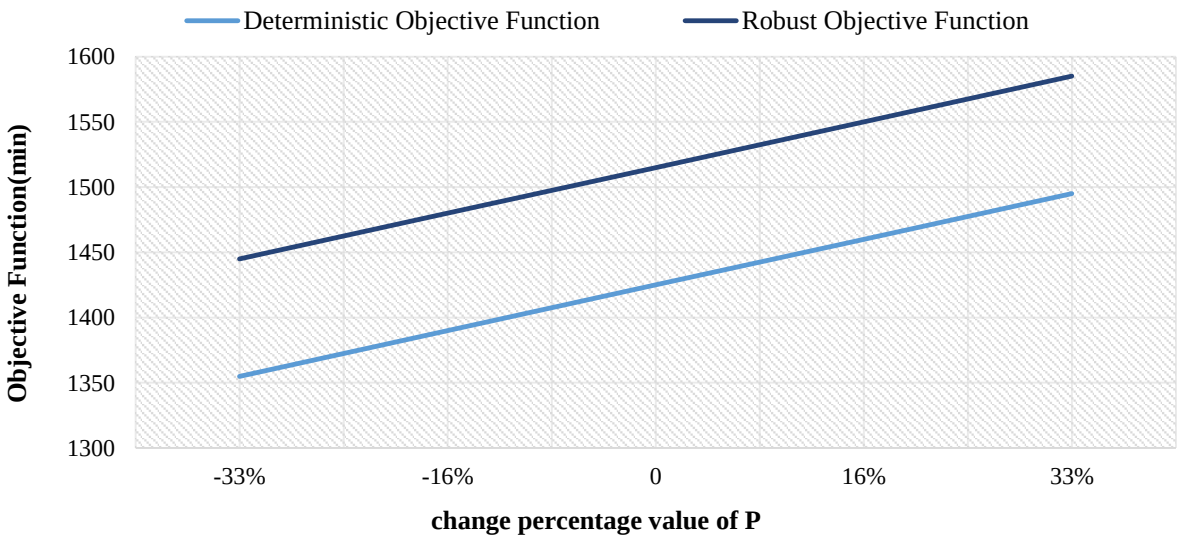


Figure 2. Sensitivity Analysis of Objective Function with Respect to the Parameter P in Deterministic and Robust Condition

5.2.2 Handling Time (τ)

The sensitivity analysis of the parameter τ examines the impact of varying the assumed transfer time required between connecting flights. This parameter plays a critical role in modeling real-world delays associated with loading, unloading, and handling organs at transit points. By adjusting τ, the analysis evaluates how tighter or looser assumptions about transfer durations influence overall feasibility and timing. This exploration helps quantify the

operational importance of minimizing transfer inefficiencies, especially for organs with shorter cold ischemia time limits.

Handling time τ, was fixed at 20 minutes in the base model. Sensitivity analysis tests explored how reducing or slightly increasing τ impacted feasibility and timing performance. In the deterministic setting, small reductions in τ (e.g., to 18 or 16 minutes) enhanced the model's flexibility, enabling feasible solutions for cases that were previously too tight-particularly for highly perishable organs like the heart. However, when τ was increased to 22 minutes, the cumulative delay rendered certain scenarios infeasible due to exceeding the organ's allowable cold ischemia time. The robust model showed greater tolerance to such increases, thanks to its conservative scenario planning. Still, performance degraded when τ grew beyond feasible bounds, reaffirming the importance of efficient handling processes in time-critical organ logistics.

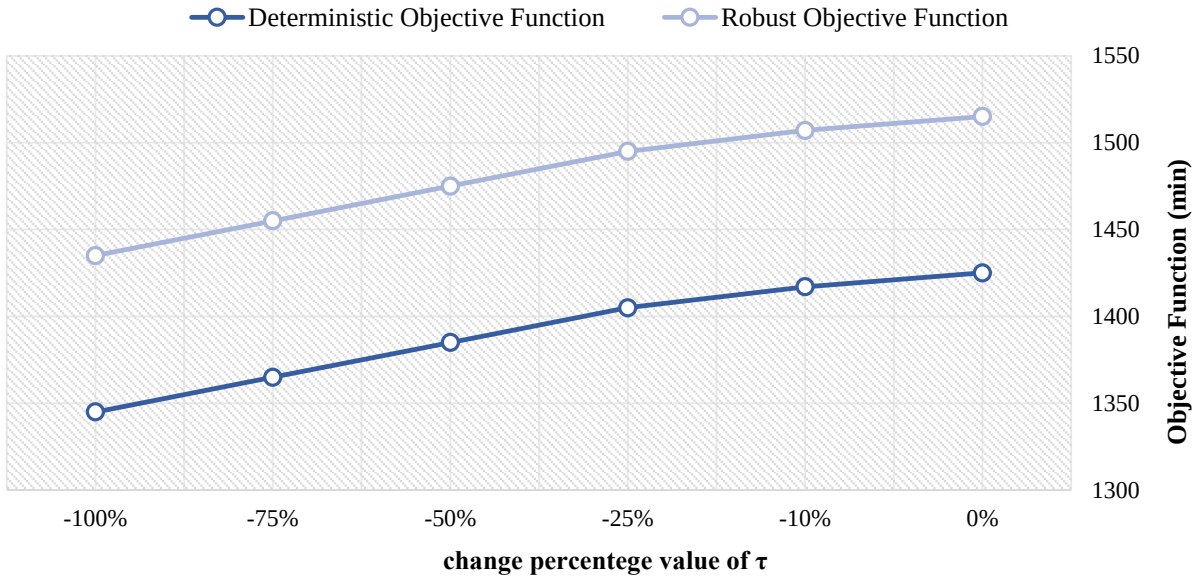


Figure 3. Sensitivity Analysis of Objective Function with Respect to the Parameter τ in Deterministic and Robust Condition

Comparative results show that the robust model consistently produced more reliable solutions, especially under delay scenarios, though at a higher computational cost. Deterministic solutions often failed to remain feasible when delays were introduced post-optimization.

Preliminary testing and data generation were conducted on a personal laptop equipped with an Intel Core i7 processor and 16GB of RAM, providing a baseline for evaluating scalability. Table 1 presents key performance metrics for each test case, including the number of nodes, number of organs, the resulting objective function values under deterministic and robust conditions, and the corresponding execution times. In the baseline experiments reported in Table 1, the organ handling time parameter (τ) was fixed at 20 minutes**,** representing the nominal duration required for loading, unloading, and transfer operations. This baseline value serves as the reference point for the sensitivity analysis shown in Figure 3. Across eight test cases, the model's objective function increased with the addition of nodes and organ types. This was expected, as a more complex network introduces additional decision variables and flight combinations, raising the potential routing time and increasing the need for handling and transshipment operations. For instance, in simpler cases with fewer organs or limited node interconnections, the objective function remained relatively low and solution time was minimal. As more organs were introduced-moving from three (e.g., heart, liver, kidney) to seven types (adding lung, pancreas, intestine, and stomach)-the objective value grew due to longer

cumulative transport times and a greater number of flight segments required. Similarly, adding nodes increased the solution space and therefore the number of viable routing options, which in turn raised computational time.

A clear distinction emerged between the deterministic and robust models. Under deterministic conditions (assuming fixed flight schedules), the model consistently found optimal solutions with minimal deviation. However, the robust model-which incorporated three uncertainty scenarios representing no delay, moderate delay (30 minutes), and severe delay (45 minutes)-resulted in significantly higher objective values. This increase reflects the additional penalty terms introduced in the robust objective function to ensure non-anticaptivity and route stability across the test cases. Moreover, the robust model exhibited notably longer execution times, particularly as the number of nodes or organ types increased. The computational burden rose sharply due to the expanded scenario set and the need to track multiple solution paths while enforcing consistency constraints. In some test instances, robust solution times were several times longer than their deterministic counterparts.

Table 1. Performance Comparison of Deterministic and Robust Models across Test Cases

Test Case	Number Of Nodes	Number Of Organs	Objective Function Deterministic	Objective Function Robust	Execution Time Deterministic	Execution Time Robust
1	6	3	1135	1202.5	0.04	0.054
2	6	4	1425	1515	0.046	0.056
3	8	4	1490	1530	0.051	0.068
4	8	5	2012	2080	0.051	0.079
5	10	5	2150	2162	0.053	0.09
6	10	6	2360	2445	0.054	0.098
7	12	6	2480	2575	0.058	0.162
8	12	7	2635	2807.5	0.061	0.183

The robust model achieved its goal of providing resilient transport plans across a range of possible disruptions. As reflected in Table 1, this protection results in higher objective values compared with the deterministic model, since the robust formulation deliberately selects routes with additional time buffers to ensure that the cold ischemia time constraints remain satisfied under potential flight delays within the considered uncertainty bounds. Although it required more computation time, the gain in feasibility and stability justified the added complexity. The deterministic model, while faster, proved vulnerable to even minor delays, particularly in cases involving highly perishable organs or long routes. Sensitivity analysis confirmed that parameters like τ and P greatly influence route feasibility, especially when flight schedules are dense or time windows are tight.

6. Conclusion and Future Work

This study developed and analyzed a mathematical framework for optimizing the transportation of transplantable organs through commercial flight networks under uncertainty. Given the strict time constraints imposed by cold ischemia time, and the unreliability of scheduled commercial flights, the problem was modeled as a resource-constrained shortest path problem and extended using robust optimization based on the Mulvey et al. (1995) framework.

Two model variants were implemented: a deterministic formulation for ideal planning scenarios, and a robust formulation designed to withstand real-world disruptions such as flight delays. The models accounted for important operational constraints, including flight eligibility, handling time at transfer points, and air traffic control prioritization.

Experimental results based on synthetic flight data demonstrated that while the deterministic model is faster to solve, it often fails under even modest delay conditions. In contrast, the robust

model consistently yielded feasible and resilient transport plans, especially for high-priority, time-sensitive organs like hearts and lungs. Sensitivity analysis confirmed that parameters such as routing penalties (P) and handling time (τ) have significant influence on model performance and feasibility.

The research contributes a practical and generalizable optimization tool that supports real-time organ transport decision-making in dynamic, uncertain environments. It bridges the gap between theoretical modeling and operational realism, offering value to healthcare planners, transplant coordinators, and policymakers.

While the proposed models provide a solid foundation, several limitations must be acknowledged:

- Synthetic data was used for testing; applying the model to real-world flight and organ registry data would improve validation.
- Static flight schedules were assumed. Real-time updates and rolling-horizon planning would increase responsiveness.
- Inter-organ coordination (e.g., transporting multiple organs on shared routes) was not considered but represents a relevant future extension.
- Environmental and cost-based objectives (e.g., CO_2 emissions, transport budget constraints) were outside the scope but are worth integrating.
- Large-scale implementation over national-level networks will likely require computational enhancements such as decomposition techniques, heuristic solution methods, or parallel computing to support real-time decision-making.

Future work could also involve incorporating machine learning for delay prediction, using multi-objective optimization to balance speed, cost, and fairness, and integrating real-time GPS or hospital capacity data to dynamically update plans. In addition, extending the model to cover multi-modal transport (e.g., ground-to-air-to-ground) would better reflect real transplant logistics.

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