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Optimization models for vaccine distribution and allocation networks

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Abstract

The distribution of vaccines is constrained by a number of practical issues such as uncertainty about vaccine demand, small stock holdings, inadequate cold-chain capacity, logistical delays, and access to vaccines across regions. In this study, an implementable optimization model is developed to optimize the allocation of vaccines in the regional warehouses and health centers. A Multi-Objective Mixed-Integer Linear Programming (MO-MILP) model is used to reduce the transportation cost, delivery delay and enhance the demand fulfilment. Available vaccine stock, vaccine vehicle capacity, stock and storage capacity, regional demand, priority groups, travel distance and delivery schedules are incorporated into the methodology. Simulated distributions for various regions reveal a decrease of 11.8% in transportation cost, 14.6% in mean delivery time and an improvement in demand fulfilment from 89.7% to 95.2% as proven through experimental analysis. The innovation is that the logistics, equity and cold chain considerations are all integrated in one allocation model. The proposed framework offers a scalable decision support tool for realistic healthcare planning and decision making on vaccines, and suggests that optimized allocation would enable a more efficient distribution and better access to vaccines.

Subject Classification: *90C31.*

Keywords: *Vaccine distribution, Multi-objective optimization, Mixed-integer linear programming, Cold-chain logistics, Healthcare supply chain, Resource allocation.*

1. Introduction

A study of the vaccine delivery during large-scale vaccination campaigns, like the ones in response to COVID-19, revealed important vulnerabilities in vaccine supply chains, such as poor inventory management, lack of matching allocation between phases, and delayed last mile delivery [1]. Vaccine supply

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chains are complex because of multi-echelon warehouse structures, perishability under cold storage requirements and varying requirements across the regions, which need to be balanced with limited production and shipment capacity [2]. Often, public health officials are faced with the challenge of determining the number of doses to send to which area and the route to take doses to reduce waste and inequity, under time constraint [3]. Queuing models have been used to capture the congestion of vaccination sites and how this impacts distribution plans and are included in existing literature for location-allocation models [4].

Several other schemes embed age-based and risk-based prioritization into dynamic allocation schemes, that is, schemes that prioritize according to the epidemiology of a disease [5]. Other factors are behavioral–vaccine hesitancy and population responsiveness–which further muddy the waters of estimating demand and need and should be incorporated into allocation frameworks [6]. In order to minimize delivery time in spite of vehicle capacity constraints, vehicle routing formulations with time windows constraints have been proposed [7]. Other examples of agent-based simulation methods applied to international equity issues in many countries include the impact of allocation policies on equity outcomes in the world [8] and [9]. Cold-chain optimization models for medical waste due to expired and/or mishandled doses have emphasized the costs of not using temperature controlled logistics [9], [10]. Nevertheless, many of the models in existence still approach the problems of cost, equity and feasibility of cold chain from separate perspectives and are therefore not directly transferable to the context of limited resources of regional health authorities that are required to operate within limited budgets and constrained infrastructure [11]. The gap inspires the present study and aims to establish a Multi-Objective Mixed-Integer Linear Programming (MO-MILP) model to minimize transportation cost and delivery delay and maximize the demand fulfilment simultaneously in a realistic warehouse to center distribution network [12]. Given the current allocation model used in healthcare planning, and given the uncertainty of the demand and limited cold-chain capacity, the design problem addressed here is to develop a scalable and implementable allocation model that can be used in practice by healthcare planners for making evidence-based decisions; formulate, solve and empirically test such an allocation model against the current allocation model [13].

1.1 *Research Contributions*

1) Construction of an integrated MO-MILP model, which simultaneously minimizes transportation cost, delivery delay and fulfillment of demands, incorporating cold-chain and equity/priority constraints into the same model.
2) Scalable modular decision support framework, consisting of data preprocessing, model formulation and solution phases of branch and bound, tested on realistic simulated regional distribution scenarios.
3) Empirical evidence of measurable operational improvements such as an 11.8% reduction in transportation costs, 14.6% reduction in delivery time

and an increase in demand fulfilment from 89.7% to 95.2% compared to a baseline allocation heuristic.

2. Vaccine Distribution Network and Problem Formulation

Vaccine distribution system is designed as a multi-echelon system, which consists of a manufacturing or importing centre and regional warehouses with temperature controlled distribution system, and healthcare centres with end demand points. A finite amount of vaccines is available in each warehouse and is subject to a replenishment schedule, and each healthcare center submits an estimate of demand, based on population size, composition of a priority group and historical uptake rates. Limited capacity vehicles are used to transport doses on pre-established road routes that involve distance, time and reliability of the cold-chain. This formulation has to take into consideration the availability of supply, capacity on the vehicles, capacity in the warehouse, and the rules of priorities, and is therefore a constrained multi-objective decision problem, instead of a single-objective shipment plan. The mathematical structure which was used in this purpose is described in the following subsections [14] and [15].

2.1 *Vaccine Distribution Network Structure*

The network is modeled as a directed graph G = (N,A) in which the nodes N represent the warehouses (W) and the healthcare centers (C) and the arcs (A) represent the feasible transportation links between them, which is used for the formulation of the flow.

$$G = (N, A),\ N = W \cup C \tag{1}$$

$$x_{ijk} \geq 0,\ \forall i \in W, j \in C, k \in K \tag{2}$$

$$y_{ijk} \in \{0, 1\},\ \forall i \in W, j \in C, k \in K \tag{3}$$

$$d_{ij} = \text{dist}(i, j),\ \forall (i, j) \in A \tag{4}$$

$$t_{ij} = \frac{d_{ij}}{v_k} \tag{5}$$

$$A = \{(i, j) \mid i \in W, j \in C, x_ijk > 0\} \tag{6}$$

$$F = \Sigma_i \Sigma_j \Sigma_k x_{ijk} \tag{7}$$

2.2 *Demand, Supply, Transportation, and Cold-Chain Constraints*

The second and third constraints are that of demand and supply, while the third constraint is transportation and the cold chain.

$$\Sigma_j \Sigma_k x_{ijk} \leq S_i,\ \forall i \in W \tag{8}$$

The supply constraint is given by equation (8): The amount of doses dispatched from the warehouse i can't exceed the stock S_i.

$$\Sigma_i \Sigma_k x_{ijk} \geq \alpha \cdot D_j,\ \forall j \in C \tag{9}$$

The demand constraint, Equation (9), is the number received at center j should be at least α times the demand D_j.

$$\Sigma_j x_{ijk} \leq \mathrm{Cap}_k \cdot y_{ijk}, \ \forall i,k \tag{10}$$

Equation (10) ensures that the number of vehicles dispatched is constrained by the vehicle capacity, and relates the number of vehicles dispatched to the binary route-selection variable y_{ijk}.

$$\Sigma_i \Sigma_k x_{ijk} \leq \mathrm{Store}_j, \ \forall j \in C \tag{11}$$

The amount that can be sent to a center is limited by the amount of cold chain storage capacity that it has, $Store_j$, as shown in (11).

$$T_{MIN} \leq T_{ij(t)} \leq T_{max}, \ \forall (i,j) \in A \tag{12}$$

The temperature range in the cold-chain is ensured during transportation with (12) which restricts the dose to the safe range of 2°C – 8°C.

$$\Sigma_k x_{ijk} \geq \beta \cdot D_j^p, \ \forall j \in C, p \in P \tag{13}$$

The priority-allocation constraint, guaranteeing minimum allocation share β for high priority population group p is shown in equation (13).

$$t_{ij} \leq TW_j, \ \forall (i,j) \in A \tag{14}$$

The delivery time-window requirement is imposed by equation (14) in order to make sure that the shipments are delivered to center j within its acceptable time window.

2.3 *Mathematical Problem Formulation*

The problem is to minimize the transportation cost Z1, the delivery delay Z2 and maximize the demand-fulfilment ratio Z3 subject to constraints (8)–(14) and non-negativity of x_{ijk} and binary restrictions of y_{ijk}. The multi-objective structure is broken down with the use of the weighted-sum MO-MILP approach presented in Section 3.

$$\text{Minimize } Z1 = \Sigma_i \Sigma_j \Sigma_k c_{ij} \cdot x_{ijk} \tag{15}$$

$$\text{Minimize } Z2 = \Sigma_i \Sigma_j \Sigma_k t_{ij} \cdot y_{ijk} \tag{16}$$

$$\text{Maximize } Z3 = \left(\frac{1}{|C|}\right) \Sigma_j \left(\frac{\Sigma_i \Sigma_k x_{ijk}}{D_j}\right) \tag{17}$$

3. Proposed Multi-Objective Optimization Model

The suggested system works in four successive steps, to optimize distribution from raw data into an allocation plan. First the regional demand, stockpiles, the composition of priority groups and the cold chain storage capacity is gathered and standardized to a uniform parameter set. Second, the data from the network with respect to distances, vehicle capacities and travel-time estimates are added to the parameters describing the demand side to start the formulation of the MO-MILP. Third, the model formulation (in the form of the cost, delay and fulfilment goals as well as supply, demand, capacity and cold-chain constraints) is fed to a mixed-integer optimization solver which performs a branch-and-bound search to find Pareto-efficient allocation decisions. Fourth, it determines with precision the number of doses to be

delivered from the warehouses to the health centers, the vehicle to be used to each health center, and the projected delivery times. This plan is then compared to the baseline allocation of practices in terms of transportation cost, average delivery time and demand-fulfilment percentage. The modular design gives the flexibility to re-run the model as conditions evolve along the network and/or as demand estimates change over time, making it appropriate for iterative, rolling-horizon vaccine distribution planning decisions rather than a one-off decision. The proposed methodology is depicted in Figure 1: The input demand and network data are preprocessed; The demand and network data are used to construct the MO-MILP model; The MO-MILP model is solved using branch and bound optimization under explicit constraints; The solution of the MO-MILP model is translated into an optimal allocation plan that is evaluated based on baseline distribution outcomes.

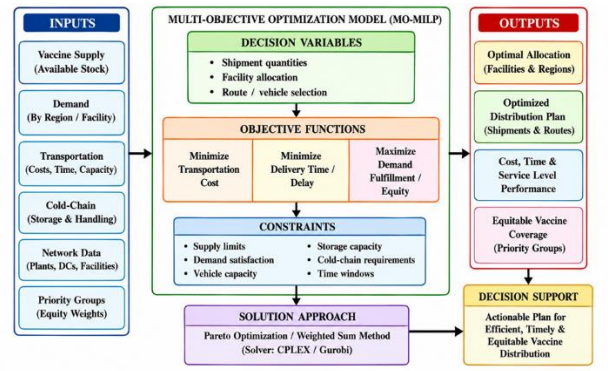


Figure 1

Block diagram of the proposed MO-MILP vaccine allocation framework

3.1 *MO-MILP Model Development*

The MO-MILP combines three objectives to minimize the transportation costs, delivery delay, and maximize demand fulfilment into one weighted-sum formulation which can be solved with the existing mixed-integer solvers. Continuous variables are the quantities of doses shipped and the binary variables are the choice of the route for the vehicles; the model is solved by an iterative process of introducing constraints that shrinks the feasible region so that an optimum (or near optimum) allocation is achieved.

3.2 *Transportation Cost and Delivery-Time Optimization*

The transportation cost is calculated as the per-unit distance cost plus fixed cost of handling the vehicle and the delivery delay is the sum of travel time and unloading time/service time. The three goals are combined together into a single scalar function by using the weights w1, w2, w3 given by the sensitivity analysis mentioned in Table 1, which are used in equations (22)–(24).

$$Z1 = \Sigma_i \Sigma_j \Sigma_k c_{ij} \cdot x_{ijk} \tag{18}$$

$$c_{ij} = f_{ij} \cdot d_{ij} + h_k \tag{19}$$

$$Z2 = \Sigma_i \Sigma_j \Sigma_k t_{ij} \cdot y_{ijk} \tag{20}$$

$$t_{ij} = \frac{d_{ij}}{v_k} + s_j \tag{21}$$

$$Z = w1 \cdot \left(\frac{Z1}{Z1max}\right) + w2 \cdot \left(\frac{Z2}{Z2max}\right) - w3 \cdot \left(\frac{Z3}{Z3max}\right)$$

$$w1 + w2 + w3 = 1,\ w1, w2, w3 \geq 0 \tag{23}$$

$$Z3 = \left(\frac{1}{|C|}\right) \Sigma_j \left(\frac{\Sigma_i \Sigma_k x_{ijk}}{D_j}\right) \tag{24}$$

3.3 *Experiment Setup*

Four different regional distribution scenarios with different levels of the number of warehouses, healthcare-center's density, and vaccination demand volumes were simulated to assess the proposed model. A proportional baseline allocation heuristic and the proposed MO-MILP model were both used to solve each of the scenarios in this paper, and the same assumptions were made regarding the stocks, capacities, and cold-chain were used. A fixed solver time limit and optimality gap tolerance were used in all experiments to implement the experiments in a mixed-integer optimization environment. All the hyperparameters of the objective weighting, solver tolerance, and vehicle assumptions were kept fixed across the scenarios so they can all be compared with each other; they are listed in Table 1.

Table 1
Hyperparameters used in the MO-MILP experiments

Parameter	Value
Cost weight (w1)	0.4
Delay weight (w2)	0.3
Fulfilment weight (w3)	0.3
Solver optimality gap	1%
Solver time limit	600 s
Vehicle capacity (Cap_k)	500 doses
Number of vehicles (K)	12
Cold-chain temperature range	2°C – 8°C
Minimum fulfilment ratio (α)	0.85
Priority allocation ratio (β)	0.95

4. Results and Discussion

The results of the experiments carried out are given in this section for four different simulated regional distribution scenarios. Evaluation is performed based on the difference between the proposed MO-MILP optimized allocation

and a baseline heuristic, which is based on the proportional allocation of jobs, regarding the improvement in transportation cost, average delivery time and demand-fulfilment percentage in terms of efficiency, timeliness and equity.

Table 2
Characteristics of the four simulated distribution scenarios

Scenario	Warehouses	Healthcare Centers	Total Demand (doses)
Scenario 1	3	12	48,000
Scenario 2	4	15	62,000
Scenario 3	3	10	41,500
Scenario 4	5	18	71,200

The four scenarios of the region for evaluation vary in the number of warehouses, healthcare centres and total volume of demand, from 41,500 to 71,200 doses of medication, allowing the assessment of the performances of the models in increasingly dense and larger distribution networks as shown in Table 2. Looking at the Figure 2, it can be seen that the MO-MILP optimized allocation always reduces transportation cost for all four scenarios, ranging from 11.3% to 12.2%, and an average of 11.8% in reduction. The improvement is said to be due to improved routing and capacity-aware vehicle assignment, which both cut through unnecessary trips, and ensure the number of vehicles dispatched matches the distance to the warehouse.

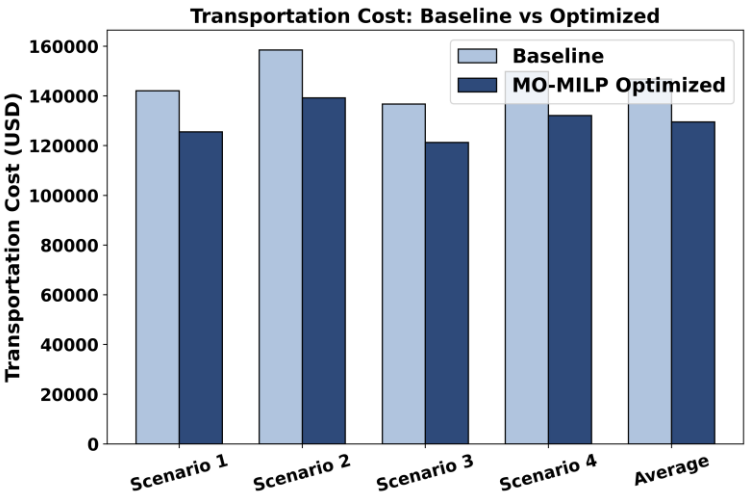


Figure 2
Transportation cost comparison across scenarios

Table 3

Average delivery-time comparison between baseline and MO-MILP-optimized allocation.

Scenario	Baseline Time (h)	Optimized Time (h)	Reduction (%)
Scenario 1	18.4	15.6	15.2
Scenario 2	20.1	17.2	14.4
Scenario 3	17.2	14.8	14.0
Scenario 4	19.5	16.5	15.4
Average	18.8	16.1	14.6

Table 3 shows that the average delivery time has a decline in all the scenarios, ranging from 14.0% to 15.4% with an average reduction of 14.6%. This is an improvement due to the delay minimizing goal of the model; this ensures that the routes are shorter and better-scheduled, and minimizes idle or unloading time at healthcare centres.

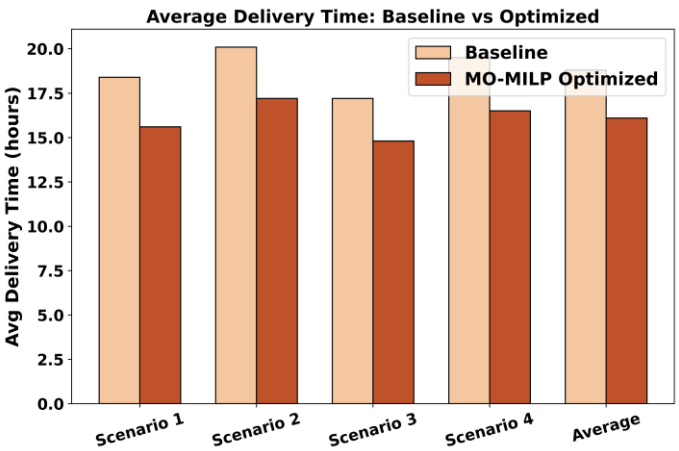


Figure 3

Average delivery-time comparison across scenarios

The average delivery time reduction for the optimized model in each scenario is depicted in Figure 3 which clearly shows the average reduction of 14.6% that is summarized in Table 3. The Figure 4 demonstrates an increasing trend of the fulfilment improving with both the models, from an average 89.7% under the baseline allocation model to 95.2% under the optimized model with a gain of 5.5 percentage points. Limited stock is allocated to the higher need centres to reduce the regional differences in accessibility when using the proportional baseline heuristic. The priority-allocation and demand constraints

mean that limited stock is sent to centres with the highest need, which reduces regional accessibility differences that would otherwise occur when using the proportional baseline heuristic.

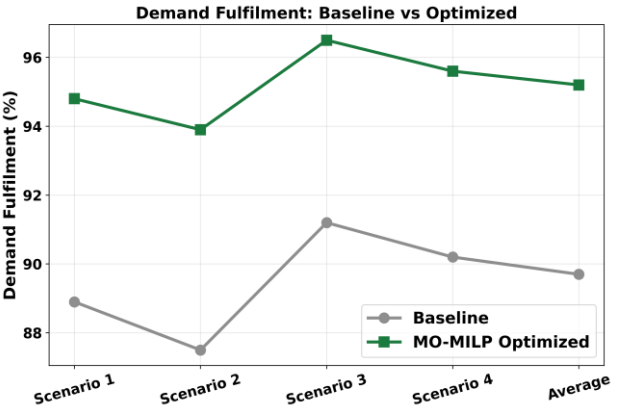


Figure 4

Demand-fulfilment comparison across scenarios

In all four scenarios, the optimized-allocation line is above the baseline line in Figure 4, verifying the better and more fair demand fulfilment performance of the proposed MO-MILP model.

5. Conclusion

The study developed a Multi-Objective Mixed-Integer Linear Programming (MOMILP) model for vaccine allocation that optimises the allocation of vaccines to minimise transportation cost, delivery delay, and maximise the demand fulfilment with supply, capacity and cold-chain constraints. The integrated formulation was demonstrated to be better than proportional baseline allocation in all four simulated regional scenarios with an average of 11.8% reduction in transportation cost, 14.6% reduction in delivery time and an increase in demand fulfilment (from 89.7% to 95.2%) found. The results show that it is possible to implement the framework proposed as a practical and scalable decision support tool for local healthcare decision makers in their vaccination planning process, particularly when the concern is the reliability of the vaccine cold-chain and equitable access to vaccines. The limitations of the study are that it was based on simulated, not field collected, demand and travel-time data and the Pareto-frontier was not explored, instead a single weighted Sum objective was used. The framework should be extended to address stochastic demand uncertainty, dynamic replenishment and real-time traffic data and interactive multi-objective solution methods and future research should validate the framework by using data from distribution systems of public health agencies to improve the practical applicability of the framework.

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