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Optimizing India’s Medical Oxygen Supply Chain for Pandemics

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Abstract. The pandemic situation like COVID-19 worsened the medical situation in India, and the crisis of medical oxygen availability at hospitals in different parts of India has also been a deep concern. In this study, we analyzed the supply chain of medical oxygen from manufacturing units to the needy capital cities of states. A two-mode optimization model has been developed for better planning of transportation and supply of medical oxygen. Various industrial units with a liquid oxygen production facility have been considered as sources while road and rail routes have been considered as modes of transportation. Finally, the oxygen cylinders/tankers are transported by road to hospitals. The mathematical model tries to optimize the route and transport medium, considering various constraints. This paper identifies the challenges in Indian contexts and tries to address them by an optimal, cost-effective, and efficient planning for medical oxygen transportation.

1 Introduction

In India, during the second wave of the COVID-19, the demand for medical oxygen surged many times more than previous requirements. To meet the urgent needs for oxygen, even the other alternative sources such as oxygen concentrators and small capacity oxygen refilling centers were not sufficient. Shortages caused many casualties all around the country. A huge amount of oxygen is generated almost in every big steel plant and can be used as a substitute for liquid medical oxygen [1]. In such a crisis, industries emerged as an instant oxygen sourcing point for hospitals. Logistics management of liquid oxygen had a few challenges like the number of cryogenic tankers required, transportation mode selection, timely delivery, which is dependent on transportation mode selection, factory selection, quantities to be delivered to cities, return of empty tankers, and route plan for forward, reverse or closed-loop logistics. The available mode for transportation is the road, rail with Roll-on-Roll-off (RORO) transportation wherein cryogenic tankers are dispatched through rail, as it provides faster delivery with no hassle of traffic. The uncertainty and risks in the supply of liquid oxygen are many, such as fluctuating oxygen, which renders existing medical oxygen production facilities incapable of coping with these surges of oxygen Further, hospitals have limited storing capacity, and supply also depends on the industry's operation [2].

2 Literature Background

Sudden high demand of liquid medical oxygen can be generated during pandamics. The challenges faced with distribution of these medical oxygen are very new and require studies ahead to serve patients in a better way. Some of the relevant studies in the medical and healthcare domain are reviewed below to establish the research issues addressed in the present work.

To minimize the total distance covered between various points, a study by [3] was conducted on the salesman travel problem to distribute medicines in hospitals with the help of MILP. The complexity of the network increases with the introduction of additional supply and demand centers, and finding assignments with minimal cost is targeted [4]. The study by [5] found out the structure of the supply chain, degree of decision, methodology for model, objective, common information, constraints, originality, and use in designing of supply chain systems. The advanced version of the vehicle routing decision issues in a dynamic environment with a specific time window has been studied by [6]. The multi-plant and multi-customer issues have been studied to maximize profit by a mixed-binary Integer Programming model that integrates the enabled localities, manufacturing, and supply tasks within a supply chain [7]. To serve commodities in emergency conditions to reduce delivery time, four segments of spatial parting models in transport systems with distance, steering, convenience, and journey period are announced with the help of data-driven and machine learning optimization in a study by [8]. [9] considered various demand patterns with different sensitivity to lead time by two MILPs. In another study by [10], a heuristic approach was followed in a two-phase solution approach by clustering the facility and minimizing computation time. Route decision has been carried out using the ant colony optimization heuristic approach, in a study by [11] where fixed costs are involved in route selection. A clustering technique has been suggested by [12] to mitigate supply chain disruption and protect from vulnerability. In another study, a two-stage stochastic programming model was formulated to find blood supply in uncertain demand conditions [13]. In an emergency supply chain compromising decision criteria have been suggested based on min-max regret criteria by [14].

In a study by [15], when more than two facilities are closer, a polynomial-time algorithm is used to find an optimization solution otherwise np-hard approximation algorithm is used. The uncertainty of a supply chain network with flexibility is studied with the scenario-based approach by [16].

A comparative study on supply chain network design is carried out. The closed-loop supply chain study with MILP and semidefinite model has been studied by [17]. Supply chain under uncertainty with a bi-objective possibilistic mixed-integer programming model that integrates forward, and reverses supply networks has been studied by [18]. A metaheuristic approach for two-stage transportation fixed cost with a linear programming model was employed. Another study adopted an evolutionary approach for two-stage fixed cost in transshipment problems [19]. In a study of the closed-loop supply chain, concerns are addressed for deep uncertainty and dynamic support by an abductive approach [20]. Another study minimized the cost of homogenous commodity transportation by many links with a comparison of relative referencing by two LP methods. [21] used the Monalisa approximation method for optimal solution (MAMOS) for transportation problems. Triangular cost, supplies, and demands were studied as fully intuitionistic fuzzy transportation problems by [22]. In another study by [23], tactical and strategical decisions are studied to improve the value of the supply chain.

Mixed-integer programming-based studies have been done to reduce the time of inbound logistics by using the proper assignment of trucks [24]. A two-stage routing problem is converted into a single-stage counterpart and calculation is done for the value of transshipment [25]. Most of the reported studies have targeted single route optimization problems, but our study focuses on transportation with the option of two modes with many uncertainties. In the medical oxygen context of this study, supply is to be done using "LNG cryogenic tankers" in which the truck is equipped with a cooling system to maintain oxygen in a liquid phase. The proposed model is useful for the distribution of liquid medical oxygen in a crisis period when demand shoots up and there may be a requirement to supply from far most points of the country. There are many studies done on heuristic, qualitative, clustering, and other mathematical models for facility and city selection. But utilization of the option of two transportation RoRo and road mode is still a lacuna in existing research. As supply chain optimization concepts have been discussed extensively in research but a model where a selection of road v/s RoRo mode is dependent on various factors like factory production capacity, city demand, time, and cost in an emergent situation is the novelty of present work.

3 Model Description

In the proposed model, a set of oxygen plants (F1, F2, F3, F4 & F5) is available which is across various locations and they need to cater to various cities (Ct1, Ct2, Ct3, Ct4, Ct5, Ct6, Ct7, Ct8) so that oxygen demand is met. There are two sets of transportation modes available, Road & Railway, and both have their own sets of capacity constraints and price variations that impact the final selection decision.

Decision variables that need to be determined are the quantity of oxygen transported between 'I'-Facility to 'J' locations, and the distribution between modes of transport based on the constraints. There are constraints of the distance between location & facility in the selection of mode of transport, as distance needs to be a minimum of 250 km for selection of train mode, as well as there is minimum & maximum limiting constraint in transportation. In this MILP model, our objective is the reduction of cost, to make sufficient oxygen available to states at the minimum price.

Formulation of Objective function:

F_i= Various factory setup

C_j= Various demand centres

T_n= Various Transportation Modes

FC=Fixed cost for use of train for transportation.

D_j = Demand from cities

S_i= Supply capacity of factory

TQ_{ij}= Total volume moved from plant i to city j

TC_{ijn}= Cost of transportation from plant i to city j by n

Q_{ijn}= Quantity shifted from plant i to city j by n

DV_{ijn}= Decision variable to select transportation (0 – Non-Selection & 1 – Selection) from from plant i to city j by n

U_{ijn}= Units of particular transportation mode used to shift quantity Q from plant to city.

M = 10^5 A big enough number to satisfy the selection condition

Objective Function:

$$F_{Min} = \sum_{n \in N} \sum TC_{i,j,n} * Q_{i,j,n} + \sum U_{i,j,n} * FC \quad \forall\, i \in I, \quad j \in J, \quad n \in N$$

Subject to Demand

$$\sum_{j \in J} TQ_{i,j} \geq D_j \quad \forall\, i \in I, \quad j \in J$$

This constraint confirms that the cumulative volume supplied from plant i to city j should fulfill the complete demand of city j.

Supply from Facility

$$\sum_{j \in J} TQ_{i,j} \leq S_i \quad \forall\, i \in I, \quad j \in J$$

This constraint makes sure that all supplies from the factory i should surpass the production capacity of the particular factory.

Constraints for Transport mode selection (i.e., Select train mode only if the distance is ≥ 250 KM)

$$Q_{i,j,n} \leq DV_{i,j,n} * M \qquad \forall\, i \in I, j \in j, n = 1 \ (mode\ selection)$$

This inequality is to ensure non-selection of the train below the 250 km range of supply. Truck Capacity: Minimum: 10 MT & Maximum: 15 MT. Train Capacity: Minimum: 60 MT & Maximum: 105 MT.

The case analysis that we have considered in this research is based on the current COVID-19 scenario. Since the emergence of the COVID-19 pandemic, the oxygen demand has raised exponentially to support the infected patients. India has more than 8000 MT of oxygen production capacity whereas demand is around 6000 MT in this pandemic situation. In this hour of crisis, various industries have come forward to support the government as well as hospitals and diverted their oxygen to medical centers for a larger purpose.

4 Numerical Results

The following are our supply network distances matrix between factories and demand centers.

Table 1. Distance between Cities and Factories by Road

	Ct1	**Ct2**	**Ct3**	**Ct4**	**Ct5**	**Ct6**	**Ct7**	**Ct8**
F1	264	817	721	384	936	294	731	324
F2	668	675	584	656	800	815	185	405
F3	277	506	965	114	521	652	242	956
F4	374	751	550	288	138	295	155	269
F5	914	313	662	308	285	861	581	851

Table 2. Distance between Cities and Factories by Rail

	Ct1	**Ct2**	**Ct3**	**Ct4**	**Ct5**	**Ct6**	**Ct7**	**Ct8**
F1	242	792	775	397	843	292	801	296
F2	655	611	627	660	756	872	198	406
F3	292	542	891	105	543	596	234	945
F4	350	705	539	267	129	293	159	247
F5	891	289	650	329	290	947	629	894

The purpose of this model is to optimize the transportation charge and the selection of the transportation mode is directly dependent on cost. Following is the cost matrix for the supply of unit weight of oxygen between a particular supply center and to a specific demand center.

Table 3. Cost Matrix For Transportation of Oxygen by Rail

	Ct1	**Ct2**	**Ct3**	**Ct4**	**Ct5**	**Ct6**	**Ct7**	**Ct8**
F1	924	2860	2524	1344	3276	1029	2559	1134
F2	2338	2363	2044	2296	2800	2853	648	1418
F3	970	1771	3378	399	1824	2282	847	3346
F4	1309	2629	1925	1008	483	1033	543	942
F5	3199	1096	2317	1078	998	3014	2034	2979

Below is the cost matrix for transportation of oxygen through rail mode. Cost is calculated at Rs. 2 per kilometer and per unit weight of liquid medical oxygen. Also, a discount of 5% is assumed for distance above 500 kilometres.

Table 4. Cost Matrix For Transportation of Oxygen by Rail

	Ct1	**Ct2**	**Ct3**	**Ct4**	**Ct5**	**Ct6**	**Ct7**	**Ct8**
F1	484	1505	1473	794	1602	584	1522	592
F2	1245	1161	1191	1254	1436	1657	396	812
F3	584	1030	1693	210	1032	1132	468	1796
F4	700	1340	1024	534	258	586	318	494
F5	1693	578	1235	658	580	1799	1195	1699

The following constraints were considered while modeling the formulation. The assumed capacities were 105 by rail and 15 by trucks. Further, the minimum load for rail were 60 units.

Table 5. Table of Constraints

Constraints		Parameter	Remarks
Fixed Charge for train utilization	=	1000	Rs.
TRuck capacity (min)	=	10	MT
Truck capacity (max)	=	15	MT
Train capacity (min)	=	60	MT
Train capacity (max)	<=	105	due to less availability of tankers
Minimum distance for train	>=	250	km
Available Tankers	=	440	Nos
Demand	<=	Supply	maximize the demand fulfillment

The big-M method was used to select trains in a particular route based on the distance between the locations. A fixed charge was considered per rack of a train and a matrix was created based on the route selected for train transportation.

Table 6. Fixed Charge for Differenr Routes by Rail

	Ct1	**Ct2**	**Ct3**	**Ct4**	**Ct5**	**Ct6**	**Ct7**	**Ct8**
F1	0	0	0	0	0	1000	0	7000
F2	0	0	5000	0	0	0	0	0
F3	4000	0	0	0	0	0	0	0
F4	0	0	3000	0	0	5000	0	0
F5	0	2000	0	2000	2000	0	0	0

Based on the decision variable the final demand-supply matrix is populated as below which specifies which factory will supply to which demand center in what quantity. Further drilling down we will find the specific quantity that will be supplied to a particular demand center by the selected mode of transport.

Table 7. Supply Allocation by Truck

	Ct1	**Ct2**	**Ct3**	**Ct4**	**Ct5**	**Ct6**	**Ct7**	**Ct8**
F1	0	0	0	0	0	61	0	11
F2	0	0	47	0	0	1	145	0
F3	50	0	1	220	0	0	1	0
F4	0	0	1	0	1	30	0	0
F5	0	0	0	45	22	0	0	0

Table 8. Supply Allocation by Rail

	Ct1	**Ct2**	**Ct3**	**Ct4**	**Ct5**	**Ct6**	**Ct7**	**Ct8**
F1	0	0	0	0	0	105	0	735

F2	0	0	525	0	0	0	0	0
F3	420	0	0	0	0	0	0	0
F4	0	0	306	0	0	525	0	0
F5	0	199	0	210	210	0	0	0

This MILP model has been formulated and computed in MS-Excel 2013 using solver. After applying MILP methodology in the given problem set, the following results are reported.

• The factory F4 is located in a very strategic position where all its capacity has been consumed whereas other factories are not fully utilized.

• Supply to some of the demand-supply pairs like F2-C3 and F3-C1 is using both the transportation modes simultaneously. Because of constraints given for the minimum quantity that can be supplied by train, the remaining quantity is being supplied by trucks.

• The constraints drive the initial selection based on cost & distance parameters, but the frequency of mode or multimode is based on the capacity of mode.

• This will help in the optimization of resources and efficient and uninterrupted supply from facilities to the demand center.

5 Concluding Remarks

The present research work formulated a mixed-integer linear programming model to assist the effective supply of medical oxygen using a combination of rail and road transport during pandemic like exigencies. The study used the RORO network to optimize the cost and ensure the oxygen reaches the needy in times of emergency. The contribution of the study is twofold. It addresses the problem of medical oxygen supply during the crises including pandamic situations and effectively uses both rail and road transportation for the same. Second, the research opens up avenues for future works that may incorporate similar emergency supplies to manage the medical supply chains in an effective manner. The model can be used for better and cost effective transportation planning so as to properly manage the critical demand of any medical or other supplies from its factory locations. The model can also be used for finalizing the location of future factories according to varying demand of different medical and other supplies.

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