Optimizing a Multi-Level Logistics Network: Exploring the Location and Assignment of 3D Printed Orthotic Facilities

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Abstract: Proper distribution and location decisions have a direct impact on the accessibility of health care services and customer satisfaction. The purpose of this study is to explore the Capacitated Location and Routing Problem (CLRP) in health care, using a real case study from a non-governmental organization (NGO). At the strategic level, the study focuses on determining the most rational options for facility location and assignment. At the operational level, the research concentrates on optimizing routes between these facilities and creating production schedules for the production centers. Currently, a preliminary mixed integer linear programming model has been developed to address the Capacitated Facility Location Problem (CFLP), laying the groundwork for more complex systems.

1 INTRODUCTION

Global health spending has more than doubled in real terms over the past two decades and reached \$9.8 trillion in 2021, equivalent to 10.3% of global GDP (WHO, 2023). Despite the magnitude of this investment, access to health resources remains unequal across countries, particularly in low- and lower-middle-income countries. The WHO estimates that approximately 100 million people worldwide need orthotic devices, but only 10 percent have access to them (WHO, 2021). A study by the International Society for Prosthetics and Orthotics found that logistical factors can add up to 20 percent to the cost of orthotics in developing countries.

In this context, we are collaborating with an NGO to design a logistics network to supply orthotics made from recycled material to the disabled. Priority targets are developing countries. In 2017, the organization initiated the utilization of 3D printing technology in its orthotics business. However, this method of production necessitates the use of filaments crafted from plastic, which are currently produced in Europe. This creates logistical challenges, especially at border crossings, so the fundamental principle is that resources and production should be local. The production centers will make filaments from a variety of locally recycled thermoplastic waste, including plastic bottles and plastic chairs. This practice will simultaneously address two key environmental concerns: the conversion of plastic waste into a medical resource and the reduction of environmental pollution. Furthermore, even if these orthotics made from recycled materials are irreparably damaged or aging after a period of use, they can still be recycled and converted into filament again, as shown in Figure 1. This recycling model contributes significantly to the sustainable use of resources.

In order to reinforce this concept and enhance the efficacy of the supply chain, it is essential to devise a detailed logistics network.

In fact, the efficient distribution of medical devices requires decisions about the location of inventory and production facilities, as well as the means of delivery and distribution. In this problem, the decision maker will make three types of decisions:

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1) a decision on the location of the raw material warehouse (RW), the production center (PC), and the logistics center (LC); 2) a decision on the assignment among RW, PC, LC, and demand points (DP); and 3) a decision on distribution scheduling. In the article, we refer to the end of the supply chain as the "Demand point". In reality, this is not a single customer, but rather a refugee camp where all those in need of orthotics are gathered.

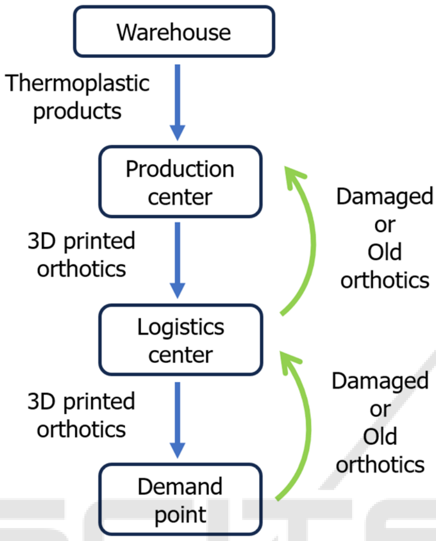

Figure 1: The concept of production and recycling.

To achieve this, we consider the facility location problem (FLP) and the vehicle routing problem (VRP) together, resulting in a location routing problem (LRP) to balance customer satisfaction and cost efficiency.

Although optimization methods for CLRP have been extensively studied in previous research, few health care studies have proposed methods for integrating these decisions. Existing models often do not sufficiently account for the quality and timeliness requirements specific to health care services. For example, by studying a real-world case study, a dynamic location-inventory-routing (LIR) model was proposed for the last-mile distribution of emergency supplies after a disaster. The model considers the equity of material distribution while minimizing the weighted sum of distribution cost and equity cost (Wang and Nie, 2023). The LRP for medical waste has been studied with the goal of minimizing total cost and emissions due to random travel time (Nikzamir and Baradaran, 2020).

The objective of this study is to enhance the CLRP model to more accurately reflect the influence of vehicle conditions, road conditions, and inventory decisions on the overall design of the logistics network. Given that goods are products with non-periodic demand, such as orthotics, this study will investigate the impact of this characteristic on location decisions. Furthermore, the potential for assigning DPs to more proximate PCs will be explored. By integrating these factors, we aim to construct a more refined and practical model that considers logistical efficiency while accounting for the specificity of customer needs, thereby providing a more reasonable solution.

The current research program is focused on strategic choice decisions involving the study of the location of production and logistics facilities, taking into account capacity constraints, as well as allocation planning, which is known as the Multi Echelon Capacitated Facility Location (MECFLP). In order to address this complex problem, several levels must be taken into account, (1) the collection of materials, (2) the production of medical devices, and (3) the delivery of these devices via logistics centers.

2 LITERATURE REVIEW

The design of an efficient supply chain is a crucial factor in strategic business decisions. In addition, decisions regarding the location of facilities must take into account a number of potential uncertainties.

Firstly, uncertainty in market demand is a key factor; market demand may fluctuate due to seasonality or unexpected events. The study of (Lee et al., 1997) points out that demand fluctuations are an important cause of supply chain volatility. In addition, uncertainty in the economic environment can also affect facility location decisions, especially exchange rate fluctuations and inflation (Chopra and Meindl, 2001). Economic recession or rapid growth can affect market demand and business profitability thus leading companies to reevaluate their supply chain strategies.

Uncertainty in the political and regulatory environment can have a significant impact on facility siting decisions (Bloom et al., 2007). Changes in government policies and regulations, such as tax policies, environmental regulations and trade policies, can affect a business's operating costs and compliance.

Problems at any link in the supply chain can have a domino effect throughout the chain (Christopher, 2016). The availability of resources at the front end of the supply chain is equally important in location decisions. Supplies of key raw materials can be disrupted or reduced due to geopolitics, natural disasters, etc., and uncertainty in energy prices and supply can affect production costs and operational stability. The outbreak of COVID-19 in 2020 caused massive disruptions in global supply chains, with many companies facing significant operational challenges due to raw material shortages (Ivanov and Das, 2020).

Furthermore, the location or capacity of facilities cannot be easily altered in the short term due to the high installation and maintenance costs involved. This is why the FLP, proposed by (Weber, 1929), remains one of the most popular investigations among many research projects.

An extension of the single-echelon FLP problem (OE-FLP), the two-echelon (2E-FLP) and multi-echelon FLP problem (ME-FLP) involves several supply chain stages, each of which must decide which facilities to open and how to allocate products or services between them in order to minimize total cost. Three corresponding mixed linear programming models have been proposed by (Wu et al., 2017) and they developed a Lagrangian relaxation method to solve three two-echelon FLP (2E-FLP) problems with different foci. The two-echelon FLP (2E-FLP) was combined with the application of drones to obtain the worst-case solution with the minimum total cost. This was achieved using the column constraint generation method and the Benders decomposition method (Zhu et al., 2022). An iterative heuristic has been proposed by (Tancrez et al., 2012) to solve the FLP problem and inventory management decisions in a three-tier supply network.

All of the aforementioned studies have a single objective. However, in the context of actual supply chain design, it is often necessary to balance various factors, including delivery time, total cost, and customer satisfaction. This is an FLP problem with multiple objectives (MO-FLP). For instance, FLP with two-step capacity (2E-CFLP) has been investigated in the context of plasma banks and blood collection stations. A multi-objective mixed linear programming model has been developed to consider the total transport time and total cost of the supply chain network (Vijaya et al., 2021). The 2E-FLP of health care facilities was studied by (Zhang et al., 2022), who determined the location, number, and coverage of health care facilities in this network, while taking into account total cost minimization. A recent study by (Wichapa et al., 2018) examined the FLP of infectious waste disposal. To address this ME-FLP problem, a combination of fuzzy hierarchical analysis and goal-based planning methods was employed, taking into account environmental, social, and geological factors.

Other variants of the FLP problem exist, such as the addition of constraints like maximum distance, customer incompatibility, and facilities size selection. Further details can be found in the literature reviews of (Melo et al., 2010) and (Farahani et al., 2015).

To the best of our knowledge, the ME-CFLP model, as stated in this paper has never been studied before. Although 2E-CFLP, which is similar to this model, has appeared in previous studies (Biajoli et al., 2019) (Souto et al., 2021), the study of ME-CFLP in a medical context helps to fill the research gap in this area. At the same time, the collaboration with NGO allows us to test the validity of the model using real data, which is undoubtedly of great interest. The model presented in this paper can be regarded as a simplified version of a more complex problem. However, it provides a solid foundation for the development of a more comprehensive model. The outcomes obtained by solving the model using Gurobi can be utilized to assess the efficacy of algorithms developed in the future.

3 PROBLEM FORMULATION

The article's model concerns a distribution network for recyclable plastic orthotics. As previously mentioned, the model includes different types of installations. These facilities have a range of potential site locations within one or more countries in Africa. We will combine a logistics network through warehouses, production centers, and distribution centers located in various locations to distribute orthotics from the production centers to customers in the least costly manner. Considering the fact that in reality the orthotics are 3D printed and made from plastics that are readily available locally. However, a single 3D printer requires a minimum of 15 hours to produce a single orthotic. Therefore, it is assumed that RW always has sufficient capacity, whereas PC and LC are subject to capacity constraints. All upstream plants can serve multiple downstream plants, but a DP can only be served by a single LC, as illustrated in Figure 2. The number of opened RWs depends on the cost of transportation per unit distance and the fixed cost of opening an RW. Since the capacity of RWs is assumed to be always sufficient, as mentioned earlier, a large difference between the values of the cost of transportation per unit distance and the fixed cost of opening an RW would result in either all PCs being allocated to only one RW or a large number of RWs being opened, both of which are inconsistent with the real situation. Therefore, to be realistic, we set the value of the cost of transportation per unit distance to be slightly larger than the fixed cost of opening an RW and limit the opening of up to 4 RWs.

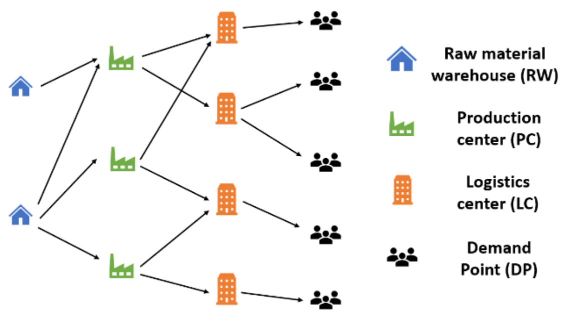

Figure 2: Distribution network for orthotics.

3.1 Notations and Definitions

Set

I : Set of production centers

U : Set of logistics centers

J : Set of demand points

E : Set of raw material warehouse

V : Set of nodes, $V = I \cup U \cup J \cup E$

Parameters

C_i : Fixed cost of opening a production center $i \in I$

C_u : Fixed cost of opening a logistics center $u \in U$

C_e : Fixed cost of opening a raw material warehouse $e \in E$

C_t : Transport cost per unit distance

D_j : Demand quantity for orthotics from demand point $j \in J$

Q_u : Maximum storage capacity of the logistics center $u \in U$

Q_i : Maximum production capacity of the production center $i \in I$

L_{ab} : Distance between two points a$\in V$ and b$\in V$

M : A big number

Variables

y_i : Binary variable indicating whether a production center $i \in I$ is open (1) or close (0)

y_u : Binary variable indicating whether a logistics center $u \in U$ is open (1) or close (0)

y_e : Binary variable indicating whether a raw material warehouse $e \in E$ is open (1) or close (0)

z_{uj} = 1 indicating whether a demand point $j \in J$ is assigned to a logistics center $u \in U$, 0 otherwise

z_{iu} = 1 indicating whether a logistics center $u \in U$ is assigned to a production center $i \in I$, 0 otherwise

z_{ei} = 1 indicating whether a production center $i \in I$ is assigned to a raw material warehouse $e \in E$, 0 otherwise

x_{ei} : A real variable indicating the quantity of products transported from the warehouse $e \in E$ to the production center $i \in I$.

x_{iu} : A real variable indicating the quantity of products transported from the production center $i \in I$ to logistics center $u \in U$.

3.2 Modeling

Then, the ME-CFLP can be formulated as follows:

$$\begin{aligned} Min\ Z = & \sum_{i\in I}(y_i \cdot C_i) + \sum_{u\in U}(y_u \cdot C_u) \\ & + \sum_{e\in E}(y_e \cdot C_e) + \sum_{u\in U}\sum_{j\in J}(L_{uj} \cdot z_{uj} \cdot C_t) \\ & + \sum_{i\in I}\sum_{u\in U}(L_{iu} \cdot z_{iu} \cdot C_t) \\ & + \sum_{e\in E}\sum_{i\in I}(L_{ei} \cdot z_{ei} \cdot C_t) \end{aligned} \tag{1}$$

Subject to

$$\sum_{u\in U} z_{uj} = 1, \forall j \in J \tag{2}$$

$$z_{uj} \le y_u, \forall j \in J, \forall u \in U \tag{3}$$

$$z_{iu} \le y_i,\ z_{iu} \le y_u,\ \forall u \in U, \forall i \in I \tag{4}$$

$$z_{ei} \le y_e,\ z_{ei} \le y_i,\ \forall i \in I, \forall e \in E \tag{5}$$

$$\sum_{j\in J} z_{uj} \cdot D_j \le Q_u \cdot y_u, \forall u \in U \tag{6}$$

$$\sum_{u\in U} x_{iu} \le Q_i \cdot y_i, \forall i \in I \tag{7}$$

$$\sum_{i\in I} x_{ei} \le Q_e \cdot y_e, \forall e \in E \tag{8}$$

$$\sum_{j\in J} D_j \cdot z_{uj} = \sum_{i\in I} x_{iu}, \forall u \in U \tag{9}$$

$$\sum_{u\in U} x_{iu} = \sum_{e\in E} x_{ei}, \forall i \in I \tag{10}$$

$$x_{iu} \le z_{iu} \cdot M, \forall i \in I, \forall u \in U \tag{11}$$

$$x_{ei} \le z_{ei} \cdot M, \forall i \in I, \forall e \in E \tag{12}$$

$$D_j \cdot z_{uj} \le z_{uj} \cdot M, \forall j \in J, \forall u \in U \tag{13}$$

$$\sum_{e\in E} y_e \le 4 \tag{14}$$

The objective function (1) minimizes the total costs in a multi-stage supply chain, including the fixed costs of opening the facility and the distance-dependent transportation cost.

Constraint (2) represents the assignment of each DP to only one LC. Constraints (3)-(5) ensure that services can only be provided by open facilities. Constraints (6)-(8) are the storage capacity constraint of the RW, the production volume constraint of the PC, and the maximum supply constraint of the LC, respectively. Constraints (9)-(10) are flow distribution constraints. They state that all raw materials from the RW are transported to the PC, all products produced by the PC are transported to the LC, and all products within the LC are transported to the DP. Constraints (11)-(13) are linear constraints representing the relationship between the transportation quantity x and the assignment relation z, where M is a very large constant. Constraint (14) represents a limitation on the maximum number of RW that can be opened.

4 EXPERIMENTAL RESULTS

4.1 Parameter Settings

We solve the model with the commercial solver, Gurobi, on a server equipped with a CPU model: AMD EPYC 7702 64-Core processor.

In this experiment, we randomly generate coordinate points within a 500x500 matrix. The experiment is divided into three categories, each containing a different number of PC and LC. Category 1 is a relatively small dataset covering 20 RWs, 20 PCs, and 20 LCs, Category 2 expands the scope to a medium size of 20 RWs, 50 PCs, and 50 LCs, and Category 3 explores large-scale problems, i.e., 20 RWs, 50 PCs, and 100 LCs. In each category, we tested 10, 15, 20 and 25 DPs, generating a total of 12 datasets. Each dataset contains 10 instances. The demand for each DP is randomly generated in the range of 5 to 25.

4.2 Results Analysis

From the data presented in the four tables, it can be observed that the average computation time for category 1 is considerably lower than that for categories 2 and 3. As the number of DPs increases, the computation time for each category also increases significantly. In particular, when there are 25 DPs, the model execution time for categories 1 and 2 grows rapidly and is approximately four and a half times longer than the execution time when there are 20 DPs. For category 2, the solution time begins to increase significantly at 20 DPs.

While the computation time for category 2 has been between that of category 1 and category 3, the gap between the computation time for category 2 and category 3 continues to widen as the number of DPs increases. The experimental results indicate that the computational complexity increases significantly with the expansion of the search space. Even a modest increase of five DPs at a time has a significant impact on the complexity of the problem, as do the other three dimensions (RW, PC, and LC). The interactions between variables (e.g. the connection between the production center and the logistics center) become more complex as the number of facilities and the number of demand points increase. This not only increases the number of combinations that need to be considered in the solution process, but also increases the difficulty of finding a globally optimal solution. Similarly, the expansion of constraints directly impacts the difficulty of the algorithm's solution, especially reflected in category 3, where the growth in the number of constraints requires greater memory and processing time.

Table 1: Computational results for instances with 10 DP.

Category	Av. time (s)	Variables	Constraints
1	4.68	1860	2110
2	24.93	7620	6730
3	61.78	13170	15830

Table 2: Computational results for instances with 15 DP.

Category	Av. time (s)	Variables	Constraints
1	11.06	1960	2315
2	82.30	7870	7235
3	280.51	13670	16585

Table 3: Computational results for instances with 20 DP.

Category	Av. time (s)	Variables	Constraints
1	24.38	2060	2520
2	209.02	8120	7740
3	965.55	14170	17340

Table 4: Computational results for instances with 25 DP.

Category	Av. time (s)	Variables	Constraints
1	112.47	2160	2725
2	721.02	8370	8245
3	1567.31	14670	18095

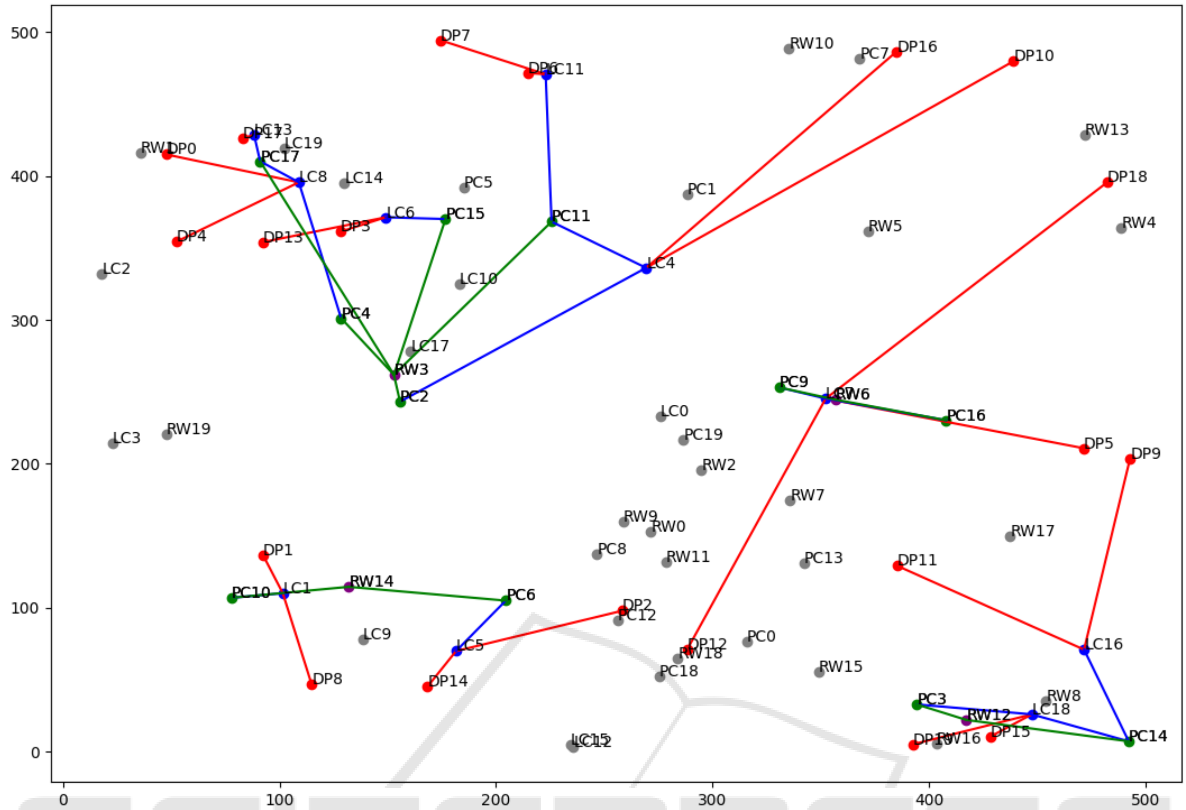

Figure 3: Optimal plan for Category 1 example 20dp_data8.

Figure 3 shows the optimal plan for category 1 example 20dp_data8. We can observe that the red points DP2, DP14 are assigned to the blue point LC5, which is assigned to the green point PC6, itself assigned to the purple point RW14, and so on. The grey nodes indicate that the facilities concerned are not activated.

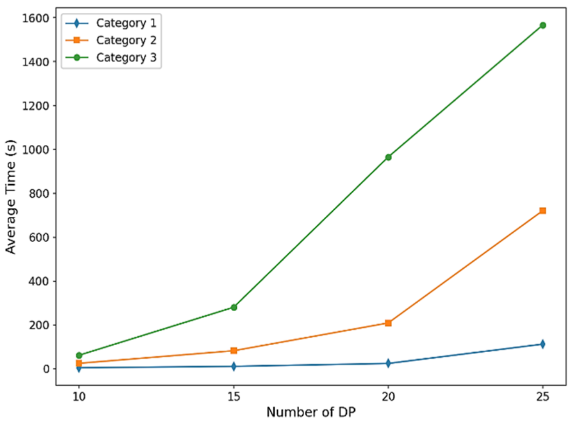

Figure 4: Computational results for different DP.

Figure 4 illustrates that the computational efficiency of utilizing Gurobi to resolve small-scale datasets, such as those belonging to category 1, is relatively high. When horizontally comparing the solution times of category 2 and category 3, it becomes evident that the complexity of the medium-sized problem gradually approaches that of the large-sized problem as the number of DPs increases. The computation time of category 3 increases exponentially with the increase in the number of DPs, indicating that large-scale datasets are very demanding in terms of computational resources.

5 CONCLUSION

The primary focus of this research is the investigation of the Capacitated Location Routing Problem (CLRP) within the context of health care, with a specific emphasis on the optimization of the distribution of orthotics manufactured from recycled plastic. The model developed in this study will efficiently utilize local resources and production capacity, thereby reducing the carbon footprint associated with long-distance transportation and streamlining the supply chain.

The study commences with an in-depth analysis of the Multi-Echelon Capacitated Facility Location Problem (ME-CFLP), which serves as the foundation for our exploration. In this initial phase, we develop an initial approach aimed at efficiently integrating and coordinating location and assignment decisions in health care systems. In order to assess the stability and applicability of our proposed model, we are conducting tests using randomly generated datasets. These tests provide a reliable validation of the accuracy and computation time of our analytical model under different configurations. For instance, we modified the demand, adjusted the capacity constraints of the facilities, and observed how the model adapted to these changes and how these adjustments affected the overall cost. The computational complexity of an optimization problem is typically proximal to the number of variables and constraints in the model. The problem was subsequently demonstrated to be NP-hard through testing.

The objective of future research is to refine the capacity parameters of the production center (PC) and the logistics center (LC). The application of advanced hyper-parameter tuning techniques will permit the automatic adjustment of model parameters according to different data sizes and distributions, thereby enhancing the robustness and flexibility of the system in various logistics situations. The next step in the research will be to apply techniques such as cluster analysis to optimize the distribution relationship between demand points (DPs) and logistics centers (LCs). In order to enhance the realism of the model and facilitate its adaptation to specific operational contexts, particularly in less accessible areas, the incorporation of more precise constraints, such as maximum travel distance and road conditions, will be considered. As the complexity of the problem increases and the exploration space grows, we also consider proposing a proto-heuristic algorithm to solve the model. Furthermore, the model is validated with real-world data to ensure that the developed solution effectively meets the local needs, while incorporating user feedback to continuously improve the model's performance.

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