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Assessing Centralized and Decentralized 3D Printing Manufacturing: A Comparative Study of Customer Demand Allocation and Delivery Distance Optimization in Egypt

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Abstract

3D printing (3DP) is a revolutionary manufacturing method that enables rapid prototyping, customization and local production of parts, hence reducing waste of resources. A new paradigm in the supply chain could be then realized by capitalizing on 3DP, that is: decentralized manufacturing, characterized by geographic dispersion and enhanced resilience to risks and disruptions, while also offering customers numerous benefits, including faster fulfilment of personalized orders. However, optimizing the allocation of customer demands is a complex challenge, especially in the context of decentralized 3DP shops operating under limited capacity constraints. By optimizing based on delivery distance, it is possible to reduce resource consumption and environmental impact while also shortening overall delivery time, thereby achieving better realization of the advantages of decentralized 3DP. This research firstly addresses the challenge of efficiently allocating customer demand to decentralized 3DP shops, optimizing delivery distances while considering capacity constraints by leveraging on mature Mixed Integer Linear Programming (MILP) based 3DP optimization techniques and innovative combination with Monte Carlo simulation. Furthermore, the study analyzes quantitatively and qualitatively the superior probability and difference in overall delivery distance between decentralized 3DP shops and hypothetical centralized 3DP hubs across various sub-scenarios with massive, randomized customer instances in the greater Cairo region in Egypt. Through this research, we aim to gain a comprehensive understanding on the advantages of decentralized 3DP on a much broader scale.

Keywords
Decentralized 3D printing, Demand allocation, Delivery distance optimization, Monte Carlo simulation and Sustainable 3DP logistics.

1. Introduction
3D printing, also known as Additive Manufacturing (AM), has evolved into a versatile and disruptive technology. This technology creates a 3D-printed object from a digital 3D model by adding materials layer-by-layer (Espino et al.

2023). This technology has found applications in various industries, from aerospace (Karkun et al. 2022) and healthcare (Whitaker. 2014) to consumer goods (Bogers et al. 2016), offering unprecedented possibilities for customization and rapid prototyping. Decentralized 3DP brings about a fresh approach to manufacturing. This approach is marked by spreading operations across different locations, bolstering resilience to potential risks (Choong et al. 2020). Additionally, it provides customers with various advantages, such as quicker delivery of personalized orders (Ben-Ner et al. 2017).

Within the realm of decentralized 3D printing, realizing its full potential hinges upon a central challenge: the precise allocation of customer demands to a web of decentralized 3DP shops. This allocation must masterfully harmonize the crucial objectives of optimizing delivery distances while gracefully accommodating the practical constraints associated with each shop's capacity. This challenge takes on a profound significance when considered within the context of greater Cairo region in Egypt (shown in Figure 1), where a plethora of decentralized 3DP shops, each with its unique capacity constraints, is strategically dispersed throughout the cityscape.

The foremost benefit of optimizing total delivery distances is the significant reduction in total delivery time. By intelligently routing customer demands to the decentralized 3DP shops, products can be delivered swiftly, meeting customer expectations for rapid order fulfillment. Beyond its impact on delivery times, the optimization of transportation routes also holds substantial environmental significance (Dekker et al. 2020). This tangible reduction in pollution emissions aligns closely with broader environmental protection goals, making a significant contribution to cleaner air and a healthier urban environment. In summary, this research is vital in addressing the pressing need for sustainable practices, particularly within the context of the greater Cairo region, where the unique challenges and opportunities of decentralized 3DP demand our attention and innovative solutions.

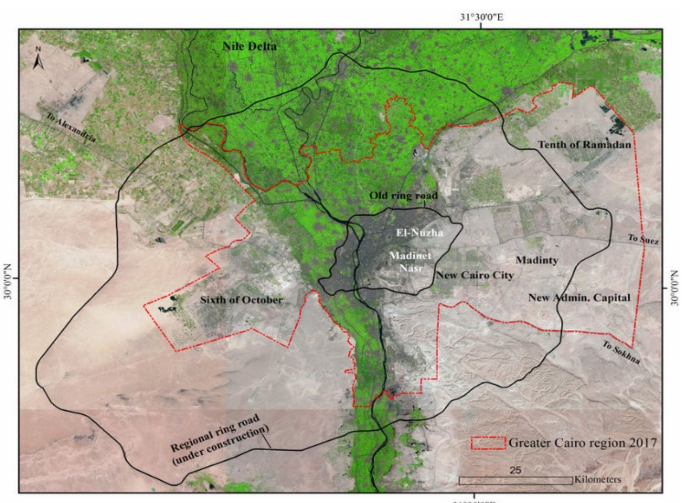


Figure 1. The greater Cairo region in 2017 (Salem. 2018)

1.1 Research Objectives

The paper centrally focuses on leveraging existing 3DP infrastructure for decentralized manufacturing in Cario area. It emphasizes the infeasibility of decentralized manufacturing without 3DP and capitalize on current real available distributed 3DP network.

Utilizing real-world 3D printing (3DP) data from Cairo, Egypt, and prioritizing customer satisfaction, this study innovatively combines Monte Carlo simulations with mature 3DP MILP-based demand allocation optimization techniques while integrating the Open-Source Routing Machine (OSRM) for precise shortest path distance calculations. Its primary aim is thus to analyze the probability and difference in the total delivery distances, comparing between customer allocation to decentralized 3DP shops and hypothetical centralized 3DP factories across various scenarios and massive randomized customer instances.

Furthermore, the proposed scenarios add another layer in providing a deeper understanding and analysis of when to use central hubs versus the decentralized network of 3DP facilities. Each scenario varies in demand range and number of customers, offering decision makers and stakeholders with comprehensive information in determining the circumstances of which choice would be more efficient as in cases of disruptions that affect demand and customer size change.

2. Literature Review

In the field of 3DP task allocation and scheduling, heuristic approaches and methods based on Mixed Integer Programming (MIP) are widely applied.

In the realm of heuristic methods, Cheng et al. (2018) proposed a bi-level programming approach to optimize collaborative manufacturing resources on a 3DP cloud service platform, effectively balancing customer and enterprise interests. Alicastro et al. (2021) introduced a reinforcement learning iterated local search algorithm for complex AM machine scheduling, providing efficient heuristic solutions with low computational expenses. Furthermore, Wang et al. (2023) introduced an Adaptive Large Neighborhood Search (ALNS) heuristic to minimize travel and service delay costs for vehicles equipped with 3D printers, particularly effective for instances with up to 200 customers.

Shifting to the realm of Mixed Integer Programming (MIP) methods, Chen et al. (2019) significantly contributed with an IoT system for 3D printing, reducing cycle times by 33% through efficient order management and workload balancing with Mixed Integer Quadratic Program (MIQP). Kucukkoc (2019) addressed AM machine scheduling, providing detailed solutions for various scenarios to optimize processing time-related performance measures, particularly to minimize make span, with MILP models. Furthermore, de Brito et al. (2019) optimized 3D printer deployment in spare part supply chains using MILP models, achieving cost-effective solutions. In contrast, Santander et al. (2020) explored the integration of plastic recycling and open-source 3D printing, using a MILP model to assess its economic and environmental feasibility in closed-loop supply chains. In a different domain, Demir et al. (2021) integrated logistics within 3DP production planning with a comprehensive MILP-based approach for optimizing both production and delivery schedules. Additionally, Alghamdy et al. (2023) introduced an MILP-based optimization model for 3D food printing job-scheduling, effectively improving deadline compliance. Lastly, Shahpasand et al. (2023) designed a specialized closed-loop supply chain for 3D-printed tires, demonstrating 51-61% greater economic efficiency and reduced carbon emissions through MILP-based optimization.

In the context of manufacturing and supply chains, the Monte Carlo simulation method stands out for its ability to address complex scenarios and uncertainties. Lee et al. (2013) utilized Petri nets and Monte Carlo simulation to model distributed manufacturing networks, evaluating quality risks and mitigation strategies. Khajavi et al. (2014), using the F-18 fighter jet's spare parts supply chain as a case, employs Monte Carlo simulation to investigate four scenarios with different supply chain configurations and AM machine specifications, indicated that, under current AM technology, centralized production is the preferred. However, as AM machines become more cost-effective, autonomous and have shorter production cycles, distributed production becomes a viable option. Franke et al. (2021) incorporated Monte Carlo simulation into production planning to assess plan robustness, especially in response to unforeseen events and short-notice orders. Poudel et al. (2023) compared decentralized and centralized approaches for multi-robot cooperative AM scheduling, demonstrating the decentralized approach's scalability and robustness with the help of Monte Carlo analysis.

Having explored the existing body of work in this field, it's now imperative to turn our attention to the current research gaps and the focal points that this study will address:

- **Regional emphasis in 3DP task allocation**: Despite the common use of the MILP method in 3DP task planning, a notable research gap is the limited exploration and application in emerging markets such as the greater Cairo region in Egypt. This research aims to fill this gap by applying real 3DP shop data and providing tailored insights into the specific challenges and opportunities in this dynamic area, enhancing our understanding of 3DP logistics in the Cairo region.
- **Monte Carlo and scenario simulation analysis for precision quantitative analysis**: This study pioneered the use of Monte Carlo simulation to generate extensive number of customer instances in various sub-scenarios, which considers the distribution of customers' geographical locations and demands, allowing for a comprehensive and accurate quantitative analysis of decentralized and centralized 3DP in terms of distribution distances, and determining the superiority and inferiority of both scenarios. The Monte Carlo

simulation thus adds complexity to the MILP method and reflects real world variability and unpredictability. While the sub-scenarios provide different demand and customer size combinations, which aids stakeholders in demand allocation and efficient use of 3DP decentralized networks vs central manufacturing hubs.

3. Methods

Methods and models for studying decentralized 3DP in the greater Cairo region are introduced in this part, focusing on data collection and preprocessing from local 3DP shops. A mathematical model of decentralized 3DP scenario is established and optimized. Additionally, hypothetical centralized 3DP scenario is modeled, and Monte Carlo simulations are conducted for comparative analysis.

3.1 Data Collection and Preprocessing of 3D Printing Shops in Greater Cairo Region

In the initial phase, data regarding the 3DP shops in the region needed to be collected. We thus capitalize on the data collected by (Abdelhalem. 2023) where geographical coordinates of these shops are gathered from Google Map and the capacity of each shop is determined through telephone interviews, supplemented with reasonable normalized estimation, we use the data represented in Table 1 and Figure 2 as the bases of this investigation.

Table 1. Location and capacity of 3DP shops in greater Cairo region (Abdelhalem. 2023)

Shop ID	Latitude (°)	Longitude (°)	Capacity (working hour/day)
Shop 0	30.0868804	31.029722	75
Shop 1	29.9699753	30.9405735	100
Shop 2	29.9949791	30.9627998	200
Shop 3	29.9522349	30.8898337	40
Shop 4	30.0444196	31.2357116	75
…	…	…	…
Shop 42	30.1382419	31.7034685	50
Shop 43	30.1936185	31.4699352	200
Shop 44	30.0815411	31.243058	40

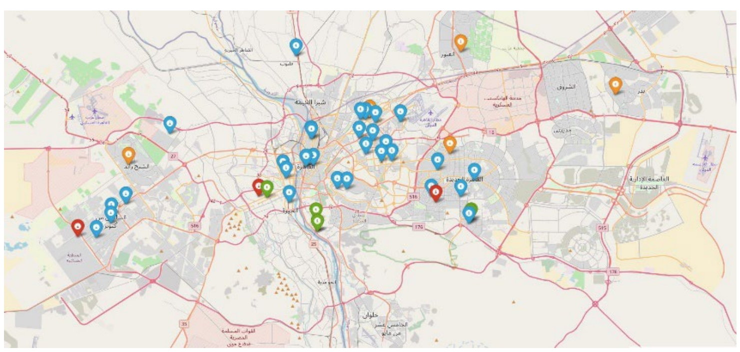


Figure 2. Geographic distribution of 3DP shops of greater Cairo region in OpenStreetMap (OpenStreetMap contributors. 2023)

The summary of the 3DP shops is listed as below:

- The number of 3DP shops is 45.
- The capacity C_i of 3DP shop i is distributed in this range: $C_i \in [40, 225]$.
- The total capacity C_{total} is 4610 working hours.

3.2 Mathematical Modeling of Decentralized 3D printing Scenario

The mathematical modeling process for this problem involves defining the key components, decision variables, objective function, and constraints. The aim is to find the optimal set of 3DP shops to fulfill demand of customers while optimizing the delivery distance. The parameters are listed below in Table 2.

Table 2. Parameters and variables in mathematical modeling of the decentralized 3DP scenario

Symbol	Meaning	Unit
M	Number of 3DP shops	/
N	Set of 3DP shops, indexed by i , $i = 0,1,2,3,\dots,M-1$.	/
Q	Number of customers	/
G	Set of customers and in this case, indexed by j, $j = 0,1,2,3,\dots,Q-1$.	/
C_i	Capacity of 3DP shop i, represents its ability to fulfill customer demand	working hour (integer)
D_j	Demand of customer j	working hour (integer)
D_{ij}	Demand assigned to 3DP shop i by customer j.	working hour (integer)
x_{ij}	Binary decision variables	/
d_{ij}	Shortest single-point delivery distance from 3DP shop i to customer j.	Kilometers (km)
TDD	Total Delivery Distance	Kilometers (km)

D_j , D_{ij} and C_i are defined using a common unit of measurement as working hour. This choice, rooted in the common industrial practice, intuitively represents 3D printer operating time and real-world customer demand in this 3D printing specific problem. Integer values align with practical 3D printing scenarios, where working hours are discrete units, simplifying modeling and problem-solving. Maintaining equal-sized working hours for capacity and demand enables direct comparison and evaluation in a unified unit, streamlining problem formulation and analysis. Binary decision variables x_{ij} indicates whether 3DP shop i is selected ($x_{ij} = 1$) or not ($x_{ij} = 0$) by customer j. If D_{ij} is non-zero, the corresponding x_{ij} is set to 1, indicating the shop selection. The assignment of x_{ij} is employed for the convenient calculation of TDD. When the shop is selected, entire single-point distance d_{ij} must be included in the total objective function calculation, multiplied by a coefficient of 1 (i.e. corresponding x_{ij}). The model thus integrates integer and continuous variables and thus is a Mixed Integer Linear Programming.

Considering the characteristics of decentralized 3D printing scenario and customer satisfaction, the constraints are listed below in equation (1) and (2):

- Consideration of customer satisfaction, ensure that each customer's demand is 100% satisfied.
  For every customer j :

$$\sum_{i=0}^{M-1} D_{ij} \cdot x_{ij} = D_j \tag{1}$$

- Due to the limited capacity of the decentralized 3DP stores, their capacity need to be ensured not to be exceeded. For every 3DP shop i :

$$\sum_{j=0}^{Q-1} D_{ij} \cdot x_{ij} \leqslant C_i \tag{2}$$

The objective function is to optimize the Total Delivery Distance (TDD) in equation (3):

$$TDD = \sum_{j=0}^{Q-1} \sum_{i=0}^{M-1} d_{ij} \cdot x_{ij} \tag{3}$$

The meaning of equation (3) is: First, calculate the distance from one customer to their chosen printing shops and then sum the required delivery distances for individual customers. This objective function TDD as the object to be optimized. Due to 3DP, customers typically transmit design files to print shops online, so only the one-way delivery distance from the shop to the customer after production is considered. Considering real-word situation, the shortest single-point delivery distance d_{ij} is calculated using the shortest driving distance from Open-Source Routing Machine (OSRM) API (Luxen et al. 2011) from OpenStreetMap (OpenStreetMap contributors. 2023).

The assumption essential for problem solvability: Total demand is not larger than total capacity (cf. equation (4)).

$$\sum_{i=0}^{M-1} C_i \geqslant \sum_{j=0}^{Q-1} D_j \tag{4}$$

3.3 Optimization based on CBC Solver in PuLP of Decentralized 3D Printing Scenario

The PuLP library (Mitchell et al. 2011) in Python is chosen to be imported as an optimization tool in this MILP problem. The CBC (Coin-OR Branch and Cut) solver is selected for the conduction of optimization of the MILP problem. CBC is an open-source optimization solver that is part of the COIN-OR project. It is designed for solving MILP problems. CBC combines branch-and-bound with cutting-plane methods to efficiently find optimal solutions to complex optimization problems, making it a valuable tool in operations research and mathematical optimization (Matthew et al. 2020).

CBC optimization process involves reading the problem's input file in MPS (Mathematical Programming System) format, initializing the problem, obtaining an initial solution, and evaluating integer infeasibility. Main optimization iterations follow, employing various algorithms like branching and cut generation. Mini branch and bound iterations further enhance the solution. CBC continues optimization attempts until no better solutions are found, eventually providing a final integer solution. Statistical information, including iteration count and CPU time, is reported. Key algorithms include initial relaxation linear programming solve, branching, cutting plane method, and pruning to improve solution quality. The result from optimization process is the optimized total delivery distance $TDD_{optimized}^{decen}$ in the decentralized 3DP scenario.

3.4 Modeling of Hypothetical Centralized 3D Printing Factory Scenario

Firstly, the selection of locations for centralized 3DP manufacturing facilities is considered, considering the practical circumstances in the Cairo region. Two centralized 3DP facilities are situated at (cf. Figure 3):

- Location A - (29.927122°, 30.887749°) in 6th of October City
- Location B – (30.152666°, 31.402938°) in Craftsmen City.

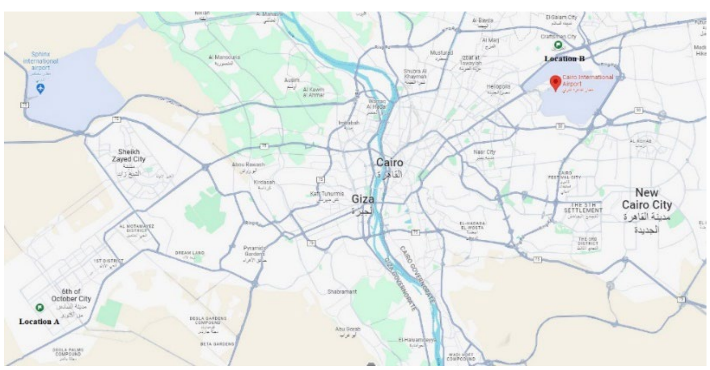


Figure 3. Location A and B in greater Cairo region (Google Map 2023)

The decision to assume facilities in these two specific areas is also underpinned by various factors. Location A is positioned at the heart of an industrial zone, where numerous automotive manufacturing industries are concentrated. Location B is surrounded by a substantial presence of manufacturing industries as well as being a hub for craftsmen. The presence of a thriving industrial sector indicates a robust demand for 3DP services, underlining the strategic importance of these locations. Both Location A and Location B have excellent road infrastructure, with the added advantage that Location B is situated next to an airport. This accessibility is crucial for ensuring timely delivery of 3D-printed items to meet market demands.

The mathematical modeling for the centralized 3DP facilities scenario is as follows:

- Assumption: The production capacity of a single facility exceeds total demand of the customers D_{total}. i.e.:

$$C_A > D_{total} \wedge C_B > D_{total} \tag{5}$$

Here C_A and C_B is the production capacity of the central manufacturing facility A and B, respectively. The assumption that the production capacity is more than demand is rooted in the idea that these hypothetical production facilities can thus be later assumed as large 3dP hubs or any other type of mass production facilities.

- Minimum total delivery distance of the centralized scenario $TDD_{\min}^{cen}$:

$$TDD_{\min}^{cen} = \sum_{j=0}^{Q-1} \min\left(d_{Aj}, d_{Bj}\right) \tag{6}$$

The purpose of equation (6) is to calculate the minimum total delivery distance for the centralized scenario. It compares the shortest single point delivery distances d_{Aj} and d_{Bj} between positions A and B for each customer j and selecting the shorter of the two distances, then adds up all the shortest distances.

3.5 Monte Carlo Simulation for Comparative Statistical Analysis between Hypothetical Centralized and Decentralized 3D Printing Factory Scenario

Monte Carlo simulations are used here to model different situations and evaluate their performance, focusing on total delivery distance. The simulations assume uniform distributions for variables of customer locations and demands. Through repetitive simulations, a diverse range of real-world situations is considered, providing insights into the logistics performance of decentralized and centralized 3DP models. Initially, the model's validity and computational performance was initially assessed by running a small data sample. The specific steps are shown in Figure 4 and explained as follows:

1. Initialization: The process begins by initializing the Monte Carlo simulation. This involves defining the number of iterations for the simulation loop L. In this paper, $L = 10000$.
2. Random generation of customer data: In each iteration, customer locations and their respective demand values are randomly generated following a uniform distribution.
3. TDD calculation: The core of the Monte Carlo simulation lies in the calculation of the Total Delivery Distance (TDD) under the conditions of the MILP model. During each iteration, $TDD_{optimized}^{decen}$ and $TDD_{\min}^{cen}$ are calculated.
4. Data recording: For each iteration, the results of $TDD_{optimized}^{decen}$ and $TDD_{\min}^{cen}$ are recorded.
5. Data output: Once all iterations are complete, the recorded TDD values are output.
6. These steps are implemented and applied across the proposed sub-scenarios in the following section and represented in Table 3.

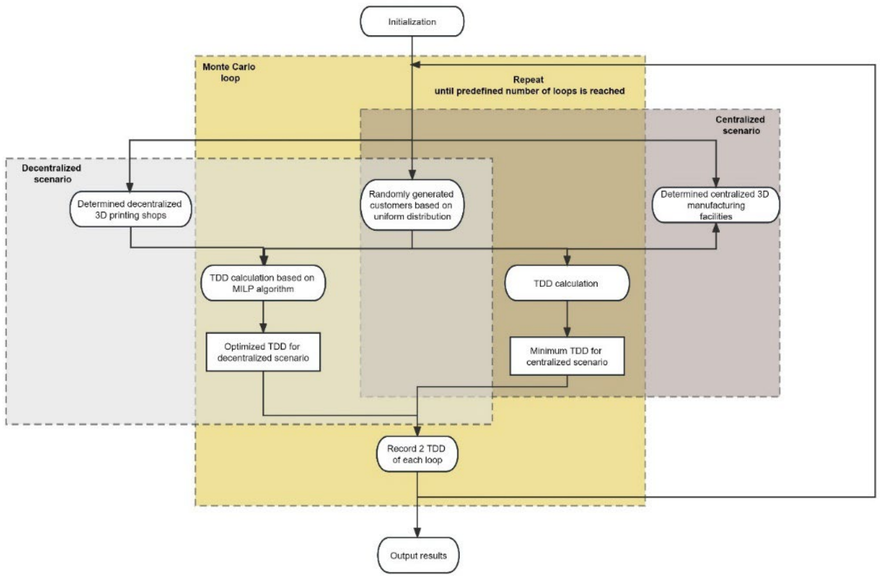


Figure 4. Monte Carlo simulation algorithm flowchart for comparison of centralized and decentralized scenario

4. Results and Discussion

The outcomes of applying the MILP-based generalized method to real-world conditions in greater Cairo region in Egypt are presented in this section. Additionally, the results of the qualitative and quantitative assessments of delivery distance of de- and centralized scenarios from Monte Carlo simulations, will also be showcased and analyzed. Bearing in mind the real situation, customers are randomly distributed within the following geographical boundaries:

- Minimum Latitude: 29.87000000° - Maximum Latitude: 30.25000000°
- Minimum Longitude: 30.830000° - Maximum Longitude: 31.8100000°

In addition to this:

- CBC MILP solver version is: 2.10.3.
- No time limit set for CBC MILP solver.

These sub-scenarios in Table 3 are designed to validate the performance of the algorithm and for qualitative and quantitative analysis based on Monte Carlo simulation.

Table 3. Parameters of Sub-scenarios

Sub-scenarios	Customer demand range (working hour/day)	Number of customers
Sub-scenario 1: Large number of customers - Low individual demand	1 - 39	100
Sub-scenario 2: Medium number of customers - Medium individual demand	40 - 225	30
Sub-scenario 3: Low number of customers - Large individual demand	226 - 500	10
Sub-scenario 4: Sparse number of customers - Intensive individual demand	501 -1000	6

4.1 Result of Generalized Demand Allocation Method

The focus of this section is to demonstrate the store-customer allocation in the Cairo area and to validate the effectiveness of the algorithm, thus laying the groundwork for the use of Monte Carlo simulation in conjunction with this algorithm in the following section (Table 4).

Table 4. Example of customer demand and location of sub-scenario 2 in greater Cairo region

Customer	Location (°)	Demand (working hour/day)	Customer	Location (°)	Demand (working hour/day)
Customer 0	(30.1908803,31.5727953)	178	Customer 15	(30.0512637,31.6780037)	88
Customer 1	(30.0298172,31.0837384)	92	Customer 16	(29.9689871,31.6189273)	87
Customer 2	(30.0642844,31.2268355)	194	Customer 17	(30.0785057,30.8437609)	48
Customer 3	(30.1678435,31.1272465)	180	Customer 18	(30.1434878,31.2208471)	196
Customer 4	(30.0511068,31.4017144)	190	Customer 19	(30.1834411,31.4847901)	208
Customer 5	(30.2150829,31.3245931)	113	Customer 20	(29.8704343,31.3137063)	106
Customer 6	(29.9770984,31.5706881)	153	Customer 21	(30.1996891,31.0690327)	161
Customer 7	(30.1049802,31.0754962)	63	Customer 22	(29.9935777,31.6830618)	57
Customer 8	(30.2157036,31.7931298)	192	Customer 23	(29.9426055,31.3861605)	62
Customer 9	(30.1778825,31.7141226)	138	Customer 24	(29.9606741,31.7781894)	213
Customer 10	(29.9878561,31.5452351)	121	Customer 25	(30.1752082,31.2690102)	73
Customer 11	(30.2115585,31.5003043)	187	Customer 26	(29.9005694,31.1436535)	78
Customer 12	(30.0494142,30.9286872)	101	Customer 27	(30.0630174,31.7441771)	49
Customer 13	(30.0349853,31.4286692)	114	Customer 28	(29.9114420,31.3702419)	60
Customer 14	(30.2169442,31.7772742)	87	Customer 29	(30.1384933,31.3664921)	219

Table 5. Example of the result of shop-customer assignment of sub-scenario 2 in greater Cairo region

Print Shop	Capacity (working hour/day)	Occupancy Rate	Contributions from Customers	Print Shop	Capacity (working hour/day)	Occupancy Rate	Contributions from Customers
Shop 0	75	100.00%	[(7, 63), (21, 12)]	Shop 23	75	100.00%	[(29, 75)]
Shop 1	100	0.00%	[]	Shop 24	50	100.00%	[(5, 46), (29, 4)]
Shop 2	200	49.50%	[(12, 99)]	Shop 25	175	100.00%	[(8, 175)]
Shop 3	40	0.00%	[]	Shop 26	200	84.00%	[(8, 17), (19, 151)]
Shop 4	75	100.00%	[(2, 75)]	Shop 27	100	100.00%	[(18, 64), (29, 36)]
Shop 5	50	0.00%	[]	Shop 28	175	100.00%	[(0, 175)]
Shop 6	90	100.00%	[(1, 90)]	Shop 29	90	100.00%	[(9, 85), (15, 5)]
Shop 7	100	100.00%	[(6, 31), (23, 62), (24, 7)]	Shop 30	100	0.00%	[]
Shop 8	40	100.00%	[(15, 40)]	Shop 31	90	73.33%	[(20, 66)]
Shop 9	200	100.00%	[(24, 200)]	Shop 32	100	100.00%	[(20, 40), (28, 60)]
Shop 10	90	100.00%	[(3, 90)]	Shop 33	40	0.00%	[]
Shop 11	40	100.00%	[(18, 40)]	Shop 34	200	100.00%	[(1, 2), (21, 120), (26, 78)]
Shop 12	200	100.00%	[(10, 53), (15, 3), (16, 87), (22, 57)]	Shop 35	100	100.00%	[(2, 48), (18, 52)]
Shop 13	50	100.00%	[(12, 2), (17, 48)]	Shop 36	90	100.00%	[(3, 61), (21, 29)]
Shop 14	50	100.00%	[(25, 50)]	Shop 37	100	100.00%	[(2, 71), (3, 29)]
Shop 15	225	0.00%	[]	Shop 38	100	100.00%	[(6, 32), (10, 68)]
Shop 16	90	100.00%	[(0, 3), (11, 30), (19, 57)]	Shop 39	40	100.00%	[(15, 40)]
Shop 17	50	0.00%	[]	Shop 40	100	100.00%	[(4, 94), (24, 6)]
Shop 18	100	100.00%	[(13, 100)]	Shop 41	90	100.00%	[(5, 67), (25, 23)]
Shop 19	90	100.00%	[(6, 90)]	Shop 42	50	100.00%	[(14, 1), (27, 49)]
Shop 20	40	0.00%	[]	Shop 43	200	100.00%	[(9, 53), (11, 61), (14, 86)]
Shop 21	200	100.00%	[(11, 96), (29, 104)]	Shop 44	40	100.00%	[(18, 40)]
Shop 22	110	100.00%	[(4, 96), (13, 14)]				

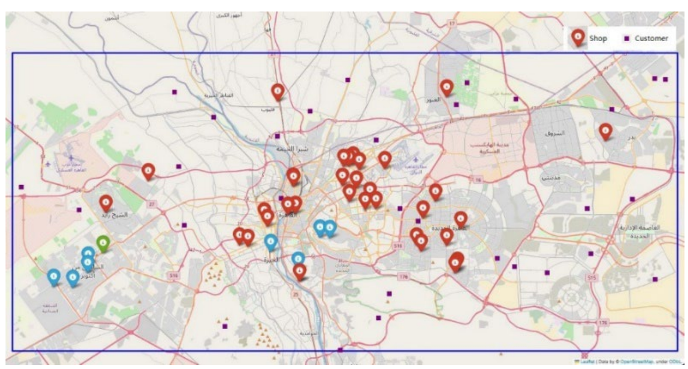


Figure 5. Example of sub-scenario 2 in greater Cairo region in OpenStreetMap (OpenStreetMap contributors. 2023)

Considering space limitations, only the example output of the sub-scenario 2 is presented. In the example, D_{total} is 3808 working hours, which is 82.60% of C_{total}. TDD is 723.226km (cf. Figure 5, Table 4 and 5). This case illustrates that, when the total customer demand is below the overall 3DP capacity, each customer's needs can be fully satisfied at a 100% rate. As indicated in Table 5, a 3DP shop can serve multiple clients, such as Shop 0, which took 63 and 12 working hours from Customer 7 and 21, respectively. Moreover, a single customer's demand can be optimized and distributed across various printing shops, as seen with Customer 0, whose demand was assigned to Shop 16 and 28. Achieving complete customer satisfaction can significantly enhance overall satisfaction with the 3D printing shop.

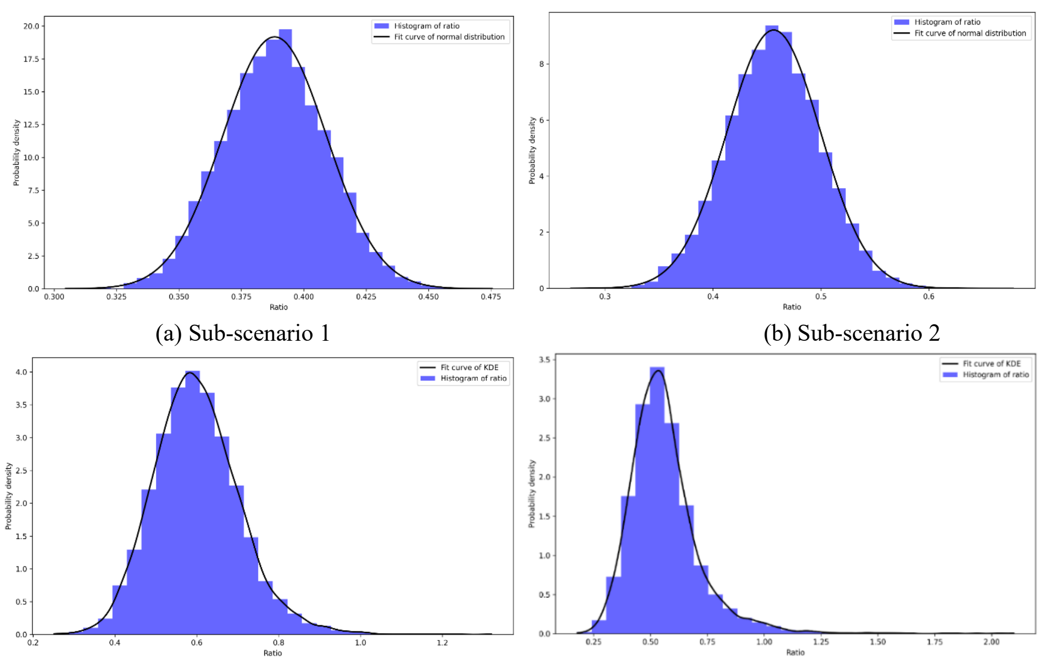
4.2 Result and Analysis of Comparative Statistical Analysis between Decentralized and Centralized Scenario based on Monte Carlo Simulation

The focus of this section is to provide result and comprehensive quantitative and qualitative analysis between decentralized and centralized 3DP scenario in term of total delivery distance from massive random customer situations between various sub-scenarios, which are derived from the application of Monte Carlo simulation.

The target subject of the analysis is the distribution of the ratio r (cf. equation (7)) and $\overline{TDD}_{save}$ (cf. equation(8)):

$$r = \frac{TDD_{optimized}^{decen}}{TDD_{min}^{cen}} \tag{7}$$

The results of distribution of the ratio r are shown in Figure 6(a)(b)(c)(d). The p-value from the Shapiro-Wilk test (Shapiro et al. 1965) is compared to the significance level (alpha), set at 0.05. If $p <$ alpha, indicating a deviation of ratio r from normal distribution, Kernel Density Estimation (KDE) (Parzen. 1962) is applied. If r conforms to normality criteria, fitting is performed using the normal distribution's probability density function (Patel et al. 1996).



(a) Sub-scenario 1

(b) Sub-scenario 2

(c) Sub-scenario 3

(d) Sub-scenario 4

Figure 6. Distribution of ratio in 4 sub-scenarios in greater Cairo region

The result of key parameters from Monte Carlo simulation is shown in Table 6:

Table 6. Results of key parameters from Monte Carlo simulation in 4 sub-scenarios in greater Cairo region.

Key parameters	Sub-scenario 1	Sub-scenario 2	Sub-scenario 3	Sub-scenario 4
$\overline{TDD}_{save}$	$1356.94km$	$361.61km$	$89.32km$	$58.71km$
Percentage of cases where $TDD_{optimized}^{decen} > TDD_{\min}^{cen}$	0.00%	0.00%	0.19%	1.76%
Minimum ratio $r_{\min}$	31.23%	28.72%	25.16%	17.79%
Mean ratio $\bar{r}$	38.83%	45.63%	60.06%	56.10%
Maximum ratio $r_{\max}$	46.77%	65.93%	132.00%	209.73%
10th percentile of ratio r_{10}	36.13%	40.11%	47.20%	39.89%
90th percentile of ratio r_{90}	41.51%	51.19%	73.21%	74.19%

Here is the definition of the parameters: $\overline{TDD}^{decen}_{optimized}$ is mean value of $TDD^{decen}_{optimized}$. $\overline{TDD}^{cen}_{\min}$ is mean value of $TDD^{cen}_{\min}$. $\overline{TDD}_{save}$ is mean value of saving total delivery distance between decentralized and centralized scenario.

$$\overline{TDD}_{save} = \overline{TDD}^{cen}_{\min} - \overline{TDD}^{decen}_{optimized} \tag{8}$$

Analyzing Table 6, several noteworthy quantitative results exist:

- In sub-scenario 1, it showcases an average delivery distance reduction of 61.17%, offering substantial savings of approximately 1356.94 km on average.
- In sub-scenario 2, the decentralized system also demonstrates remarkable performance, achieving an average distance reduction of 54.37%. Even in the worst-case situation, the decentralized approach covers 65.93% of the distance required in a centralized system.
- In sub-scenario 3 and 4, the decentralized system remains advantageous. Even in worst-case sub scenario 4, where decentralized distance is 109.73% greater, still saves an average delivery distance of 58.71km.

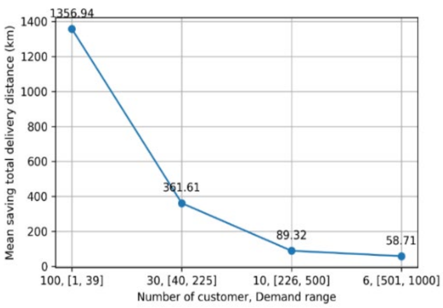


Figure 5. Summary of mean saving total delivery distance in 4 sub-scenarios in Cairo region

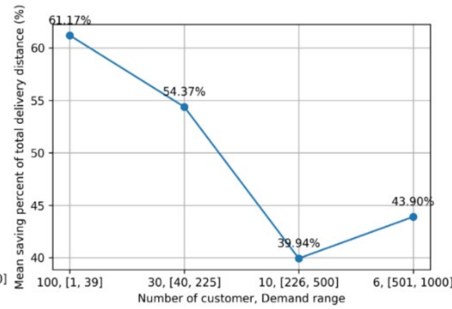


Figure 8. Summary of mean saving percent of total delivery distance in 4 sub-scenarios in Cairo region

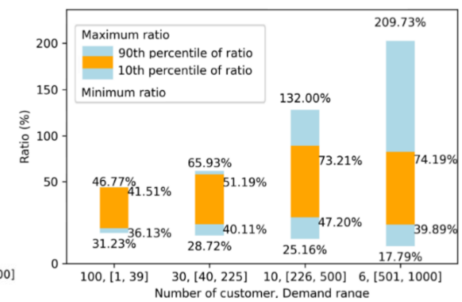


Figure 9. Summary of ratio in 4 sub-scenarios in greater Cairo region

As Figure 7, 8, 9 shown above, the following qualitative conclusions can be drawn based quantitative data:

- For situations with low individual demand but a large number of customers (decentralized customer distributed situation), decentralized 3DP shops perform the best, as supported by the data in sub-scenario 1.
- As demand increases and the number of customers decreases, the mean value of saving total delivery distance between decentralized and centralized scenario decreases and saving ratio indicates a downward trend in general.
- Decentralized 3DP is effective in reducing delivery distances in the majority of cases when compared to central printing factories.
- In extreme cases where customers are concentrated, such as in scenarios with high demand but few customers, central 3DP factories have an advantage in terms of total delivery distance.
- In scenarios with centralized customer distribution, particular attention must be given to each individual case. This is because the range of variability of the ratio can be substantial, resulting in extreme differences in total delivery distances between centralized and decentralized scenario under similar circumstances.

In summary, the utilization of Monte Carlo simulations and the focus on the region set the stage for uncovering practical and innovative solutions to optimize logistic networks and enhance the efficiency of 3DP logistics. Besides that, the robustness of the MILP-based algorithm has also been demonstrated in a large number of Monte Carlo simulations, as infeasible situations are not encountered. While the 4 sub-scenarios offer a viewing lens for decision makers to understand when to use the centralized hubs for manufacturing in contrast to capitalizing on the current decentralized network of available 3DPs.

5. Conclusion

In conclusion, this paper capitalizes on the idea that 3D printing (3DP) can offer decentralized manufacturing, which is particularly beneficial for emerging countries and urban city logistics planning. This concept is explored by employing a mature Mixed Integer Linear Programming (MILP) model to optimize delivery distances for customer demand allocation to real decentralized 3DP shops across Cairo, providing a real case study. This allocation is then compared to the allocation of each customer to the nearest of two hubs, utilizing Monte Carlo simulation to simulate real-world variability and disruptions in customer locations and demand size.

Taking into consideration the shortest distances traveled, calculated by the Open-Source Routing Machine (OSRM), for a realistic logistics study, this approach incorporates real geographical conditions and the road network in Cairo, Egypt. Furthermore, four sub-scenarios are proposed to offer a deeper view and statistical analysis, providing information that helps policymakers and stakeholders decide when to use the current network of 3DP in contrast to manufacturing in central hubs. Thus, the study enriches the theory and knowledge through this combination of tools and its application to the real case of Cairo.

The results, demonstrated through extensive testing and optimal solution, show a significant leaning towards decentralized manufacturing in the case of Cairo, hence achieving a substantial reduction in delivery distances. This reduction is especially pronounced in scenarios with a large customer base and low individual demand. Only in a very small percentage of the cases, where the number of customers is really low but individual demand is quite high (ranging between 500 to 1000 hours of demand), resembling an extreme case (for example, cases of supply chain disruptions, where the customers are institutions requiring massively produced parts), and while on average it is still better to use the 3DP network, stakeholders should take extra care for each individual case, as the tests show the decision can flip towards centralized manufacturing the more the number of customer decline and individual demand surge.

Our findings also bear significant practical implications, especially for the rapidly flourishing 3DP industry in Egypt. With the current state of 3DP facilities and relevant capacities, we expect a future where local manufacturing through nearby shops combined with last-mile delivery logistics is very promising. This study also serves as a guide for local businesses and policymakers to optimize and utilize, as well as foster the 3DP industry as it contributes to the local industry ecosystem and serves as a cushion for supply chain disruptions. Moreover, it contributes to environmental sustainability through reduced travel distance and the associated carbon footprint.

However, limitations exist, such as region-specific conclusions, idealized parameters, and insufficient consideration of 3DP specific variables and constraints as scheduling tasks, types of 3DP material and technology used. A hybrid system could also be devised to shift customers demand allocation to hubs when the 3DP facilities' capacity is reached, altering between two systems. A more nuanced customer demand could thus be modeled as well. We also recommend the expansion of the model to include other variables such as carbon footprint, transportation costs, constraining the hub's capacity, and proposing other hub locations.

Finally, we suggest the replicability of our study by capitalizing on alternate algorithms on the same data set from Cairo, Egypt. Additionally, apply the established model and analysis parameters to different cities and datasets to enhance the findings as well as reaching a more generalized conclusion.

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