International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 11 | Nov - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

A Comparative Study of Exact and Approximate Optimization Techniques in Designing a Multi-Objective Mixed Integer Linear Programming Sustainable Closed Loop Supply Chain Network Design

P.Vivek[1], Dr.Nilesh Ware[2]

[1]Department of Defence Technology and Management, Defence Institute of Advanced Technology, Pune
[2] Department of Defence Technology and Management, Defence Institute of Advanced Technology, Pune

---

Abstract –This paper proposes a novel methodology for understanding the performance of exact and approximate optimization techniques used for designing and optimizing a closed loop supply chain design. A multi-objective mixed integer linear programming model has been proposed with the aim of minimizing cost and emissions simultaneously. The model was solved under fixed test conditions using the ϵ-constraint method and the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The results indicate a significant performance difference between the two approaches. While the ϵ-constraint method is constrained by a limited search space, NSGA-II successfully identifies optimal Pareto-front solutions tailored to specific optimization goals. Although these solutions may involve higher implementation costs, NSGA-II significantly speeds up solving the multi-objective optimization network and offers decision-makers a diverse set of alternative solutions. Furthermore, the Pareto trade-off points generated by NSGA-II consistently yield lower emissions compared to those obtained via the ϵ-constraint method.

Key Words: Multi-objective optimization, closed loop supply chain, linear programming, epsilon constraint, NSGA-II, metaheuristics, sustainability.

1.INTRODUCTION

Global institutions are increasingly moving towards designing supply chains that can withstand the impending uncertainty in supplying raw materials for manufacturers. Critical suppliers are finding it difficult to source and ship to customers across the globe in the present scenarios. Supply chain managers are now focusing more on the design of closed loop supply chain networks which can reduce the cost of production and the carbon footprint associated with it. Reverse logistics is a key component of the closed loop supply chain design. The items returned can be either reusable, repaired, recycled or remanufactured. Reusing involves sending back bottles, containers etc. back into the supply chain. Certain electric items like electric equipment can be refurbished. Steel, paper and glass can be recycled. Internal components can be disassembled which can be used for remanufacturing (Ren Y. et al., 2025). But its very difficult to design Closed Loop Supply Chain (CLSC) networks due to lack of adequate incentives. (Li B. et al., 2023) shows that there is a lack of motivation amongst participating members such as manufacturers and recyclers because the profit margin is around 3-5%. In our study we have proposed a closed loop supply chain network design consisting of suppliers, manufacturers, distribution/collection centers and recycling centers. The multi-objective optimization model was designed and solved using ε-constraint method and Non-dominated Sorting Genetic Algorithm (NSGA-II).

The input parameters were assumed to be deterministic. The main aim of this study was to compare the performance of the two optimization techniques in designing a closed loop supply chain. The results indicate a statistical difference between the exact and approximate methods which is mainly attributed to the ability of exact solvers to execute complete search routines to arrive at exact mathematical bounds, whereas population-based algorithms like NSGA-II explore stochastic trade-off frontiers.

2. LITERARTURE REVIEW

Designing sustainable supply chains is now one of the most sought-after objectives for managers struggling with scarce resources for manufacturing and planning activities. From a managerial standpoint, prior studies demonstrate that supply chain integration significantly improves business and operational performance. As a result, firms persistently pursue effective solutions to strengthen coordination among organizational units(Dastani et al., 2022). Major publications in the past five years indicate publications focusing on sustainable production and engineering Fig.1. This is more evident in the wake of pandemic with supply chains getting disrupted at an unprecedented level. Study also indicated that researchers preferred the use of epsilon constraint method under exact methods and Genetic Algorithm (GA) / Non-dominated Sorting Genetic Algorithm (NSGA-II) for approximate methods Fig.2. Results of the citation cluster Fig.3 indicate that rapid advancements are being made by authors like (Upadhyay et al., 2021) who have reviewed the usage of blockchain technology in designing closed loop supply chain designs to reduce the ecological footprint.

(Nandi et al., 2021) studied the resilience and agility of circular supply chains during the pandemic.

To overcome the problem of choosing suppliers under uncertainty (Govindan et al., 2020) proposed a multi-objective mixed integer linear programming model for a closed loop supply chain design. The size of the clusters is directly proportional to the citations. Fig.4 shows the co-occurrence of keywords indicates the strength of association between the topics. 'Supply chain' is the dominant cluster followed by 'sustainable development' and 'multi-objective optimization'. Table 1 shows the most commonly implemented optimization techniques are epsilon constraint method and Non-dominated Sorting Genetic Algorithm (NSGA-II). Minimizing cost and emissions simultaneously is common. This forms the basis for understanding and developing a closed loop supply chain network model.

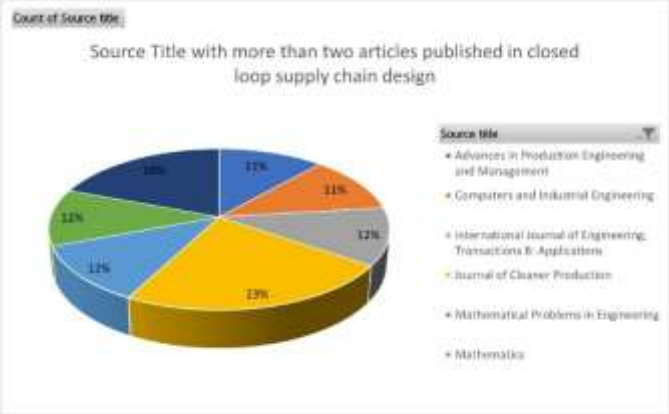


Fig.1 Details of top journals for publication

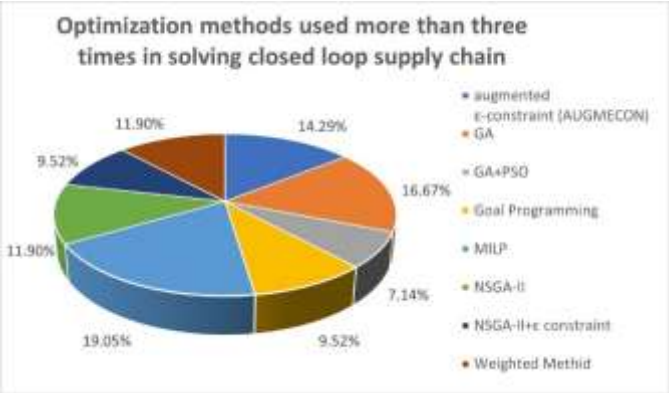


Fig. 2 Prominent Optimization techniques

TABLE 1 LITERATURE REVIEW OF OPTIMIZATION TECHNIQUES

Author	Objective Function	Optimization Method
(A. M. Golmohammadi et al., 2025)	min cost/emission	NSGA-II+ε constraint
(Sun et al., 2025)	min cost/emission	NSGA-II, Prim algo (NSGA-II)
(Labbi O. & Ahmadi A., 2024)	min cost/ emission	NSGA-II
(Rodríguez-Escoto et al., 2025)	min cost/ emission/distance	AUGMECON2
(Shafiee Roudbari et al., 2024)	Maxprofit/min emissions/max jobs	augmented ε constraint
(Afshar M. et al., 2024)	min cost/emission/risk min cost	NSGA-II+ ε constraint
(Li B. et al., 2023)	Min cost/emission	augmented ε constraint
(Guo et al., 2022)	min cost/emission/lost working days	NSGA-II, MOPSO, DEA
(Mogale et al., 2022)	min cost/emission	NSGA-II+ co-kriging
(Soon et al., 2022)	min cost/emission/max social performance	augmented ε constraint
(Tirkolaee et al., 2022)	min cost/emission/human risk	MOGWO + NSGA-II
(Hassangaviar et al., 2022)	max prof-it/satisfaction	NSGA-II+ε con-straint
(Amirian et al., 2022)	min cost/emissions	ε constraint
(Tehrani & Gupta, 2021)	maxprofit/min emission/maxjob opportunity	Augmented ε-constraint
(Antucheviciene et al., 2020)	max prof-it/emission/customer service	NSGA-II

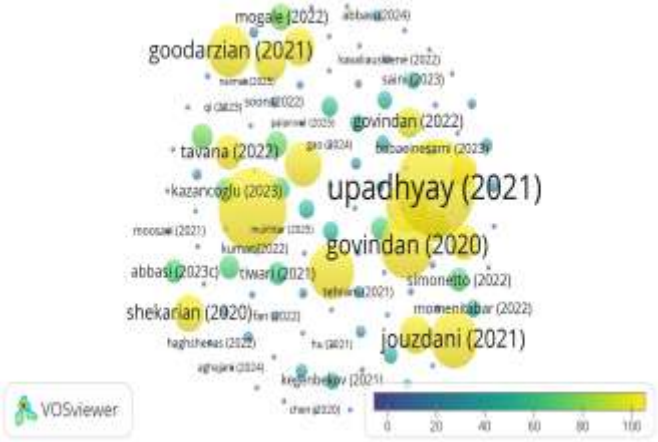


Fig 3. Result of Citation clusters

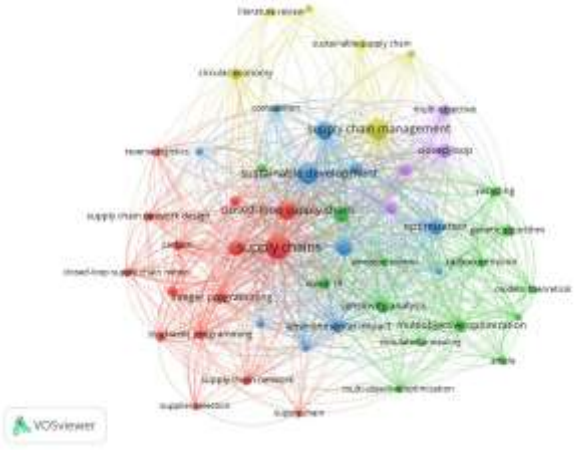


Fig4. Results of co-occurrence of all keywords

3. METHODOLOGY

In this closed loop supply chain network Fig.5 design raw material are sent form supplier to manufacturing/remanufacturing centers where they are converted to finished products. Thes items move to distribution/collection center from there they are transported to the individual customers. The reverse logistics is triggered when a portion of the forward demand is assumed to be returned from the customers to collection/distribution centers. Further segregation diverts the reusable items to remanufacturing centers. The items of recyclable quality are directed towards the recycling/landfill centers for extraction of raw material which are finally directed to the suppliers. Manufacturing/remanufacturing are merged into single entity. The same is applicable to collection/ distribution center and recycling/landfill centers. Customers demand is always met. The location of the suppliers and customers are fixed while those of manufacturing centers and distribution centers are potential in nature. The quality of the remanufactured items is assumed to equivalent of items manufactured using original raw materials. There is no wastage of raw materials or recycled goods. To solve the multi-objective optimization model, we optimize the cost associated with production, processing, transportation and emission. The list of indices, parameters, decision variables are shown in table 2, Table 3 and Table 4 respectively. The data for input parameters were based on (Abbasi et al., 2025)



Fig.5 Proposed Model framework

TABLE 2 LIST OF INDICES

l	Set of suppliers l∈ {1,2, …L}
m	Set of manufacturers m∈ {1, 2, …M}
n	Set of collection/distribution/centers n∈ {1, 2, …N}
o	Set of customers o∈ {1, 2, …O}
p	Set of recycling/disposal centers p∈ {1, 2, …}

TABLE 3 LIST OF PARAMETERS AND ITS VALUES

dem_o	Demand for customer o	U (1;1000)
Cap_l	Maximum capacity of supplier l	U (10;5000)
Cap_m	Maximum Capacity of manufacturer m	U (10;5000)
Cap_p	Maximum Capacity of recycling/disposal center p	U (10;5000)
Cap_n	Maximum Capacity of collection/distribution n	U (10;5000)
Cap_{rm}	Maximum Capacity of remanufacturing at m	U (10;5000)
Cap_{rn}	Maximum Return Capacity of collection/distribution/centers n	U (10;5000)
FC_m	Fixed cost of setting up manufacturer m	U (100;900)
FC_n	Fixed cost of setting up collection/distribution/center n	U (1000;7000)
FC_p	Fixed cost of setting up recycling/disposal centers p	U (1000;6000)
VC_l	Variable cost of mining raw material from supplier l	U (10;200)
VC_m	Variable cost of manufacturing in manufacturer m	U (15;500)
VC_{rm}	Variable cost of remanufacturing in m	U (15;500)
VC_n	Variable cost of distributing in n	U (5;100)
VC_{rn}	Variable cost of collecting in n	U (5;100)
VC_p	Variable cost of operating recycling/disposal centers p	U (5;150)
TC_{lm}	Cost of transportation of a unit raw material from l to m	U (5;50)
TC_{mn}	Cost of transportation of a unit manufactured item from m to n	U (5;50)
TC_{no}	Cost of transportation of a unit item from n to o	U (5;50)
TC_{on}	Cost of transportation of a unit returned item from o to n	U (5;50)
TC_{nm}	Cost of transportation of a unit reusable item from n to m	U (5;50)
TC_{np}	Cost of transportation of a unit recyclable item from n to p	U (5;50)
TC_{pl}	Cost of transportation of a unit recyclable item from p to l	U (5;50)
e_l	Emission due to extraction of raw material from supplier l	U (1;1000)
e_m	Emission due to manufacturing at manufacturer m	U (1;1000)
e_n	Emission due to distribution of finished from collection/distribution center n	U (1;1000)
e_{rn}	Emission due to collection/inspection of returned items at center n	U (1;1000)
e_{rm}	Emission due to remanufacturing/renovation at m	U (1;1000)
e_p	Emission due to recycling/disposal at center p	U (1;1000)
EC_{lm}	Emission due to transportation of unit raw material from l to m	U (1;200)
EC_{mn}	Emission due to transportation of unit manufactured item from m to n	U (1;200)
EC_{no}	Emission due to transportation of unit finished good from n to o	U (1;200)
EC_{on}	Emission due to transportation of unit returned good from o to n	U (1;200)
EC_{nm}	Emission due to transportation of unit returned good for refurbishment from n to m	U (1;200)
EC_{np}	Emission due to transportation of unit returned good for recycling from n to p	U (1;200)
EC_{pl}	Emission due to transportation of unit recycled item for substituting raw material from n to p	U (1;200)
d_{lm}	Distance between l and m	U (1;2000)
d_{mn}	Distance between m and n	U (1;2000)
d_{no}	Distance between n and o	U (1;2000)

d_{np}	Distance between n and p	U (1;2000)
d_{pl}	Distance between p and l	U (1;2000)
R_{rem}	Rate of return of goods from consumer o to collection center n for remanufacturing/refurbishment	U (0.1;0.6)
R_{rec}	Rate of return of goods from consumer o to collection center n for recycling	U (0.1;0.6)

TABLE 4 DECISION VARIABLES

x_m	If manufacturer m is open, 1; otherwise, 0;
x_n	If collection/distribution center n is open, 1; otherwise, 0;
x_p	If recycling/landfill center p is open, 1; otherwise, 0;
Y_{lm}	Raw material item sent form l to m
Y_{mn}	Finished goods sent form m to n
Y_{no}	Finished goods sent form n to o
Y_{on}	Returned goods sent form o to n
Y_{nm}	Returned goods sent form o ton for remanufacturing
Y_{np}	Returned goods sent form n top for recycling
Y_{pl}	Returned items sent form p to l for remanufacturing

3.2 Defining the linear programming model

Objective Function 1 Minimize cost

$$Z1 = FC + VC + TC \quad (1)$$

where, FC is fixed cost, VC is variable cost, TC is transportation cost.

$$FC = \sum_m FC_m x_m + \sum_n FC_n x_n + \sum_p FC_p x_p \quad (2)$$

$$\mathrm{VC} = \sum_l \mathrm{VC_l} \sum_m \mathrm{Y_{lm}} + \sum_m \sum_n \mathrm{VC_m Y_{mn}} + \sum_n \sum_o \mathrm{VC_n Y_{no}} + \sum_o \sum_n \mathrm{VC_{rn} Y_{on}} + \sum_n \sum_m \mathrm{VC_{rm} Y_{nm}} + \sum_n \sum_p \mathrm{VC_p Y_{np}} + \sum_p \sum_l \mathrm{VC_p Y_{np}} \quad (3)$$

$$TC = \sum_l \sum_m TC_{lm} Y_{lm} d_{lm} + \sum_m \sum_n TC_{mn} Y_{mn} d_{mn} + \sum_n \sum_o TC_{no} Y_{no} d_{no} + \sum_o \sum_n TC_{on} Y_{on} d_{no} + \sum_n \sum_p TC_{np} Y_{np} d_{np} + \sum_p \sum_l TC_{pl} Y_{pl} d_{pl} \quad (4)$$

Objective function 2 Minimize emission cost

$$Z2 = CP + \mathrm{CT} \quad (5)$$

where CP is environmental cost due to the processing at the facilities, CT is environmental cost due to transportation activities between facilities.

$$CP = \sum_l \sum_m e_l Y_{lm} + \sum_m \sum_n e_m Y_{mn} + \sum_n \sum_o e_n Y_{no} + \sum_o \sum_n e_{rn} Y_{on} + \sum_n \sum_m e_{rm} Y_{nm} + \sum_n \sum_p e_p Y_{np} \quad (6)$$

$$\boldsymbol{CT} = \sum_{\boldsymbol{l}} \sum_{\boldsymbol{m}} EC_{lm} Y_{lm} d_{lm} + \sum_{\boldsymbol{m}} \sum_{\boldsymbol{n}} EC_{mn} Y_{mn} d_{mn} + \sum_{\boldsymbol{n}} \sum_{\boldsymbol{o}} EC_{no} Y_{no} d_{no} + \sum_{\boldsymbol{l}} \sum_{\boldsymbol{m}} EC_{on} Y_{on} d_{on} + \sum_{\boldsymbol{n}} \sum_{\boldsymbol{m}} EC_{nm} Y_{nm} d_{nm} + \sum_{\boldsymbol{n}} \sum_{\boldsymbol{p}} EC_{np} Y_{np} d_{np} + \sum_{\boldsymbol{p}} \sum_{\boldsymbol{l}} EC_{pl} Y_{pl} d_{pl} \quad (7)$$

Constraints are as follows:

$$\sum_l \sum_m Y_{lm} \le Cap_l \quad (8)$$

$$\sum_m \sum_n Y_{mn} \le Cap_m x_m \quad (9)$$

$$\sum_n \sum_o Y_{no} \le Cap_n x_n \quad (10)$$

$$\sum_o \sum_n Y_{on} \le Cap_{rn} x_n \quad (11)$$

$$\sum_n \sum_m Y_{nm} \le Cap_{rm} x_m \quad (12)$$

$$\sum_n \sum_p Y_{np} \le Cap_p x_p \quad (13)$$

$$\sum_m \sum_n Y_{mn} \le \sum_l \sum_m Y_{lm} \quad (14)$$

$$\sum_n \sum_o Y_{no} \le \sum_m \sum_n Y_{mn} \quad (15)$$

$$\sum_n \sum_m Y_{nm} \le \sum_o \sum_n Y_{on} \quad (16)$$

$$\sum_n \sum_p Y_{np} \le \sum_o \sum_{mn} Y_{on} \quad (17)$$

$$\sum_p \sum_l Y_{pl} \le \sum_n \sum_l Y_{nl} \quad (18)$$

$$\sum_o d_o \le \sum_n \sum_o Y_{no} \quad (19)$$

$$\sum_o d_o \ge \sum_o \sum_n Y_{on} \quad (20)$$

$$\sum_o \sum_n Y_{on} \ge R_{rem} \sum_o d_o \quad (21)$$

$$\sum_n \sum_m Y_{nm} \ge R_{rec} \sum_o \sum_n Y_{on} \quad (22)$$

$$x_m, x_n x_p \in \{0,1\}, Y_{lm}, Y_{mn}, Y_{no}, Y_{on}, Y_{nm}, Y_{np}, Y_{pl} \ge 0; \quad (23)$$

First objective (1) is the sum of fixed cost(2), variable cost (3) and transportation cost (4). Second objective (5) is the sum of emissions related to processing (6) and emissions related to transportation (7). The maximum capacity constraint of the supplier shall be less than the items moving from the supplier, defined by (8). Maximum capacity of the manufacturer is shown by (9). Capacity of the distribution center is given by (10). Capacity of collection center shown by (11). The remanufacturing capacity is given by (12). Maximum capacity of recycler is given by (13). Raw materials moving from supplier to manufacturer will be greater than finished goods moving to distribution center (14). The items moving toward customers shall be less than items moving towards the collection center (15). The returned items from customer shall be greater than the items sent for remanufacturing form collection center (16). Similarly, the items sent for recycling from the collection center shall be less than the items returned to collection center from the customer (17). To recycled raw materials sent to the supplier shall be less than items sent to recycling center from collection center (18). The finished goods sent from the distribution center to customer shall be greater the actual demand (19). The returned items cannot be greater than the actual demand of customer (20). The returned items from customers shall be greater be at least a percentage of the customer demand (21). The items returned for remanufacturing shall be at least a percentage of the returned items from the customer (22). (23) indicates the non-negativity constraints and the binary variable constraint for manufacturer, collection/distribution center and the recycling center.

3.3. Understanding solution methodology

3.3.1Epsilon constraint method

For solving multi-objective optimization models, ε-constraint (epsilon) converts the two objective functions, in our case, into a single function and the other function becomes the constraint. While minimizing the cost function, emission function will be a constraint with fixed upper bounds. By varying epsilon, various values of objective functions can be deduced(A. M. Golmohammadi et al., 2025). The pareto front generated can be used for making managerial decisions. The framework of the epsilon constraint is given as follows:

$$minQ_i(y) \quad (24)$$

subject to:

$Q_j(y) \leq \varepsilon_i$

$y \in Y$

3.3.2 Non-Dominated Sorting Genetic Algorithm (NSGA-II) As the complexity of the problem increases, exact methods will be unable to yield solutions in a short span of time. Hence, we resort to one of the most acceptable approximate techniques. NSGA-II is a metaheuristic algorithm which is essential for solving multi-objective functions by using certain performance indicators such as non-dominated sorting and crowding distance(K. Deb et al., 2002). The pareto front would assist in taking managerial decisions without compromising either one of the objectives. NSGA-II can be one of the efficient methods to solve NP-hard problems in designing closed loop supply chain.

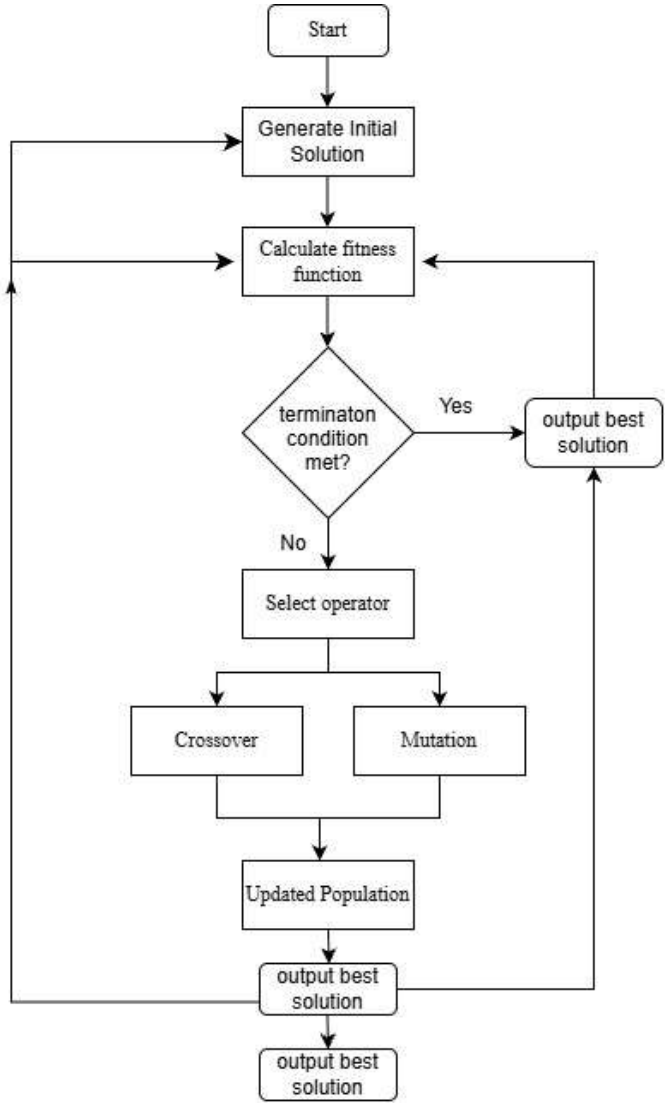


Fig.6 NSGA-II algorithm

An initial set of randomly generated solutions is chosen for solving the objective functions Fig.6. This solution indicates the possible facilities that are either closed or open within the network design. The fitness function quantifies solution quality relative to the optimization goal (minimizing cost or emissions). Solutions with higher fitness scores correspond to higher quality outcomes, whereas lower scores indicate sub-optimal solutions. Next sorting and separating the values of objective function which are not dominated by other values leads to the formation of the pareto front. While performing crossover, the non-dominated solutions obtained are paired using roulette wheel mechanism. This method aims to improve the solution by varying the features. Random modification of the input solution defines the mutation step which assists the solution escape the local optimal trap. Finally the solution is obtained which consists of minimized values of cost and emission(Tirkolaee et al., 2022).

4. Results

The optimization was solved in a system with the following configuration 13th Gen Intel Core (TM) i7-1360P. Further equations were modeled in python using the anaconda environment. For solving the linear programming model packages such as puLp (Python Linear Programming). Pymoo (Python Multi-Objective Optimization), matplotlib (MATLAB Plot Library) etc. were also installed. The input data for the problem involves 2 suppliers, 3 manufacturers, 4 collection/distribution centers, 2 recycling/landfill centers and 100 customers. Based on literature survey, we found that epsilon constraint and Non-dominated Sorting Genetic Algorithm (NSGA-II) are the commonly used for optimization of closed loop supply chain network design. Epsilon constraint reduces the search space for the non-dominated solution points. Also, it solves much quicker than metaheuristic methods like NSGA-II. The optimality is first obtained for both minimizing cost and emissions respectively. Based on the step length calculated we generate the pareto frontier(Hassangaviar et al., 2022). Whereas, NSGA-II improves the diversity and convergence of pareto solutions in multi-objective optimization through efficient non-dominated sorting and performs better in solution efficiency(Sun et al., 2025). The results of the optimization are given in Table 5. Model is run for 15 different scenarios which is a variation of customer demand under fixed capacities of the facilities such as supplier, manufacturer, distributor, recycler. Analysis of sensitivity analysis is given in Table 6. The pareto front for two different scenarios are given in Fig.7 and Fig.8. A comparative visualization of the pareto front for both exact and metaheuristic methods is shown in Fig.9. To understand the validity of the study, statistical study has been conducted and shown in Tables7-10.

TABLE 5 OPTIMIZATION RESULTS

S.no	ε-constraint		NSGA-II	
	Z1(cost)	Z2 (emission)	Z1(cost)	Z2 (emission)
1	106297.04	10571.52	106463.49	10562.02
2	120927.88	12529.96	121028.86	12518.69
3	34419.89	3800.06	36007.38	3614.70
4	80445.86	8577.71	81992.68	8519.53
5	120858.53	12513.87	120960.03	12502.63
6	121621.86	12691.60	121717.60	12680.20
7	70681.33	7957.71	70945.21	7850.59
8	102195.14	9628.75	102393.54	9624.09
9	81926.03	8935.42	83508.70	8625.10
10	58262.02	4822.11	60181.29	4512.16
11	123426.20	13111.88	123508.32	13100.11
12	102598.61	9721.05	102793.86	9716.34
13	110398.94	11510.32	110533.44	11499.96
14	30932.99	2944.64	32643.28	2801.00
15	59801.85	5210.57	60150.58	5138.93

TABLE 6 SENSITIVITY ANALYSIS

Demand	Z1	Z2
10%	106767.75	10679.25
15%	108852.33	11156.35
20%	110869.65	11618.05
25%	119124.77	12111.78
30%	121344.27	12626.94
35%	123356.80	13095.71
40%	125634.18	13634.22

TABLE 7 MEAN, STANDARD DEVIATION, AND 95% CONFIDENCE INTERVAL(Ɛ-CONSTRAINT)

	Epsilon constraint	
	Z1(cost)	Z2 (emission)
Count (n):	15	15
Mean	88319.61	8968.48
Std. Dev	31622.56	3399.64
95% CI	(70807.62,105831.60)	(7085.82,10851.13)

TABLE 8 MEAN, STANDARD DEVIATION, AND 95% CONFIDENCE INTERVAL (NSGA-II)

	NSGA-II	
	Z1(cost)	Z2 (emission)
Count (n):	15	15
Mean	88988.55	8884.4
Std. Dev	31052.04	3469.94
95% CI	(71792.50106184.60)	(6962.82,10805.99)

TABLE 9 RESULTS OF PAIRED T-TEST

	t-statistic	p-value
Cost (Z1)	3.5014	3.5255e-03
Emissions (Z2)	3.0262	9.0673e-03

TABLE 10 RESULTS OF WILCOXON SIGNED-RANK TEST

	statistic	p-value
Cost (Z1)	0.0	6.1035e-05
Emissions (Z2)	0.0	6.1035e-05

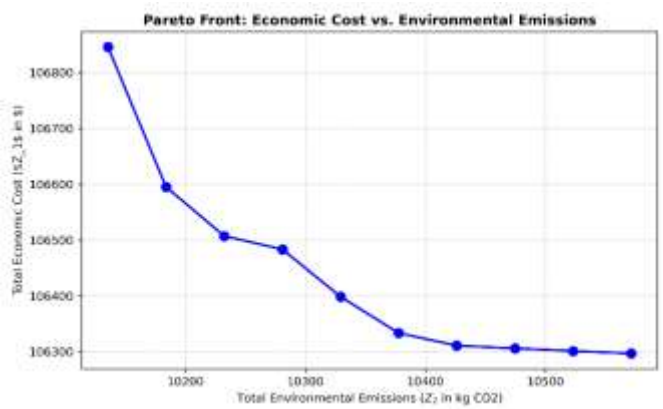


Fig.7 Pareto front case-1

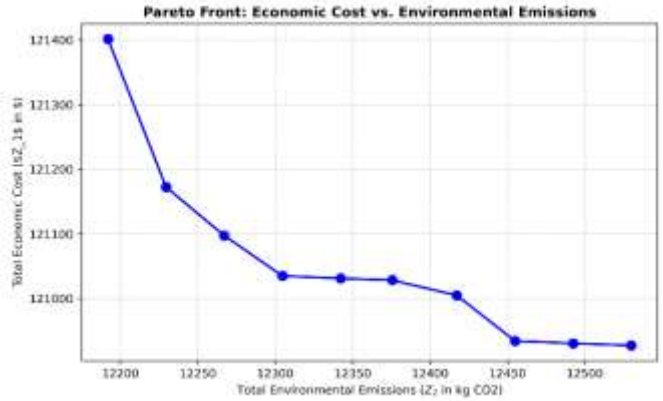


Fig.8 pareto front case-2

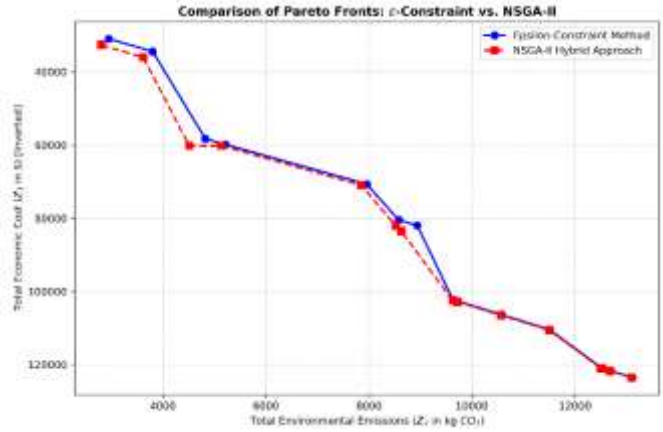


Fig.9 ε-constraint versus NSGA-II

5. DISCUSSION

In the current global uncertainty, it is very critical to understand the importance of optimizing the supply chain that can affect the economy. By observing the Z1(cost) and Z2(emission) values, we can infer that for fixed model capacity, it costs more when demand increases and consequently it cost more to transport. The pareto front comparing both exact and approximate methods show there is a significant difference between the two results. This makes sense as the epsilon constraint has a smaller search space while the metaheuristic NSGA-II algorithm looks at only the approximate solutions which can be indeed higher in value but can satisfy the required optimization goals.

Also, NSGA-II produces Pareto trade-off points that yield lower environmental emissions compared to the corresponding ε-constraint points, since both methods (ε-constraint/NSGA-II) were evaluated on the same 15 test instances. Two complimentary statistical tests were conducted as shown by (Kalantari Khalil Abad & Pasandideh, 2021). To understand the difference between mean of the two optimization methods, paired sample t-Test was implemented. Wilcoxon Signed-Rank Test evaluated the median rank differences between the two methods. The Null Hypothesis (H_o) assumes no difference between the means. Alternative Hypothesis (H_a) there is a statistically difference between the two optimization methods. We reject the (H_o) as the p-values falls below the standard threshold (0.05). Wilcoxon test confirms that the directional difference between the two methods is completely systematic across all 15 instances (i.e., NSGA-II costs are consistently slightly higher, and emissions are consistently slightly lower).

6. CONCLUSION

In optimization research, a statistically significant difference between exact solvers and metaheuristics is both expected and standard. Exact solvers execute complete search routines to arrive at exact mathematical bounds, whereas population-based algorithms like NSGA-II explore stochastic trade-off frontiers. The slight shift (higher Z1, lower Z2) indicates that NSGA-II locates alternative efficient trade-off points along the continuous Pareto frontier, providing practical flexibility for decision-makers at a fraction of the computational burden required by full exact solvers on large-scale instances. We have used a deterministic model was used under a single echelon and single time period. This model can be further extended to multi-period, multi-product under fuzzy or stochastic uncertainty. This significantly increases the complexity of the model. The main areas to incorporate uncertainty are the forward demand, reverse demand from consumers, fixed cost, variable cost etc. There is also limitation on the number of modes of transportation. Currently, we are assuming just a single mode if transport. The study will be interesting for future contributors to differentiate between Internal Combustion (IC) engines and battery-operated vehicles as a choice for transport. Incorporating uncertainty in the quality of the returned items can also improve the quality of the solution. The study can also be extended to include other optimization methods such as Genetic Algorithm (GA), Particle Swarm Oprtimization (PSO), Grey Wolf Optimizer (GWO), Simulated Annealing (SA). The same methodology can be extended for comparison of conventional optimization techniques.

ACKNOWLEDGEMENT

I am thankful to Dr. Nilesh Ware, Assistant Professor, School of Defence Technology and Management, Defence Institute of Advanced Technology for providing the support and guidance in preparing this research article.

REFERENCES

A. M. Golmohammadi, F. Hajizadeh Ebrahimi, R. Sahraeian, & H. Abedsoltan. (2025). Closed-loop Supply Chain Network Design: A Comprehensive Mathematical Model and Approximate Solution Method. *International Journal of Engineering*, *38*(10). https://doi.org/10.5829/ije.2025.38.10a.10

Abbasi, S., Damavandi, S., RadmanKian, A., Zeinolabedinzadeh, K., & Kazancoglu, Y. (2025). Designing a green forward and reverse logistics network with an IoT approach considering backup suppliers and special disposal for epidemics management. *Results in Engineering*, *26*, 104770. https://doi.org/10.1016/j.rineng.2025.104770

Afshar M., Molana S.Y.H., & Parchicolaie B.R. (2024). A Multi Objective Optimization Model for Multi-commodity Closed-loop Supply Chain Network Considering Disruption Risk. *Materials and Energy Research Center*, *37*(3), 567–582. https://doi.org/10.5829/ije.2024.37.03c.14

Amirian, J., Amoozad Khalili, H., & Mehrabian, A. (2022). Designing an optimization model for green closed-loop supply chain network of heavy tire by considering economic pricing under uncertainty. *Environmental Science and Pollution Research*, *29*(35), 53107–53120. https://doi.org/10.1007/s11356-022-19578-0

Antucheviciene, J., Jafarnejad, A., Amoozad Mahdiraji, H., Razavi Hajiagha, S. H., & Kargar, A. (2020). Robust Multi-Objective Sustainable Reverse Supply Chain Planning: An Application in the Steel Industry. *Symmetry*, *12*(4), 594. https://doi.org/10.3390/sym12040594

Dastani, M., Davoodi, S. M., Karbassian, M., & Moeini, S. (2022). Developing a Mathematical Model for a Green Closed-Loop Supply Chain with a Multi-Objective Gray Wolf Optimization Algorithm. *Foundations of Computing and Decision Sciences*, *47*, 127–150. https://doi.org/10.2478/fcds-2022-0007

Govindan, K., Mina, H., Esmaeili, A., & Gholami-Zanjani, S. M. (2020). An Integrated Hybrid Approach for Circular supplier selection and Closed loop Supply Chain Network Design under Uncertainty. *Journal of Cleaner Production*, *242*, 118317. https://doi.org/10.1016/j.jclepro.2019.118317

Guo, Y., Shi, Q., & Guo, C. (2022). A Fuzzy Robust Programming Model for Sustainable Closed-Loop Supply Chain Network Design with Efficiency-Oriented Multi-Objective Optimization. *Processes*, *10*(10), 1963. https://doi.org/10.3390/pr10101963

Hassangaviar, B., Naderi, B., Etebari, F., & Vahdani, B. (2022). A Multiobjective Model for Optimizing Green Closed-Loop Supply Chain Network under Uncertain Environment by NSGA-II Metaheuristic Algorithm. *Discrete Dynamics in Nature and Society*, *2022*, 1–16. https://doi.org/10.1155/2022/2680892

K. Deb, A. Pratap, S. Agarwal, & T. Meyarivan. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–197. https://doi.org/10.1109/4235.996017

Kalantari Khalil Abad, A., & Pasandideh, S. H. R. (2021). Green closed-loop supply chain network design: A novel bi-objective chance-constraint approach. *RAIRO - Operations Research*, *55*. https://doi.org/10.1051/ro/2021035

Labbi O. & Ahmadi A. (2024). A dynamic bi-objective optimization model for a closed loop supply chain design under environmental policies. *International Academic Press*, *12*(6), 1725–1744. https://doi.org/10.19139/soic-2310-5070-2112

Li B., Liu K., Chen Q., Lau Y.-Y., & Dulebenets M.A. (2023). *A Necessity-Based Optimization Approach for Closed-Loop Logistics Considering Carbon Emission Penalties and Rewards under Uncertainty*. *11*(21). https://doi.org/10.3390/math11214516

Mogale, D. G., De, A., Ghadge, A., & Aktas, E. (2022). Multi-objective modelling of sustainable closed-loop supply chain network with price-sensitive demand and consumer's incentives. *Computers and Industrial Engineering*, *168*. Scopus. https://doi.org/10.1016/j.cie.2022.108105

Nandi, S., Sarkis, J., Hervani, A. A., & Helms, M. M. (2021). Redesigning Supply Chains using Blockchain-Enabled Circular Economy and COVID-19 Experiences. *Sustainable Production and Consumption*, *27*, 10–22. Scopus. https://doi.org/10.1016/j.spc.2020.10.019

Ren Y., Chen Q., Lau Y.-Y., Dulebenets M.A., Li M., Li B., Poo M.C.-P., & Zhang P. (2025). An Improved Migratory Birds Optimization Algorithm for Closed- Loop Supply Chain Network Planning in a Fuzzy Environment. *Public Library of Science*, *19*. https://doi.org/10.1371/journal.pone.0306294

Rodríguez-Escoto, J.-N., Olivares-Benitez, E., Nucamendi-Guillén, S., & Drzymalski, J. (2025). A multi-objective sustainable closed-loop supply chain network problem with hybrid facilities. *International Transactions in Operational Research*, *32*(6), 3497–3527. https://doi.org/10.1111/itor.13523

Shafiee Roudbari, E., Fatemi Ghomi, S. M. T., & Eicker, U. (2024). Designing a multi-objective closed-loop supply chain: A two-stage stochastic programming, method applied to the garment industry in Montréal, Canada. *Environment, Development and Sustainability*, *26*(3), 6131–6162. https://doi.org/10.1007/s10668-023-02953-3

Soon, A., Heidari, A., Khalilzadeh, M., Antucheviciene, J., Zavadskas, E. K., & Zahedi, F. (2022). Multi-Objective Sustainable Closed-Loop Supply Chain Network Design Considering Multiple Products with Different Quality Levels. *Systems*, *10*(4), 94. https://doi.org/10.3390/systems10040094

Sun, J., Li, X., Wang, Z., & Chen, Z. (2025). Robust optimization of uncertain E-commerce closed-loop supply chain networks under carbon policies. *Scientific Reports*, *15*(1), 34308. https://doi.org/10.1038/s41598-025-21519-z

Tehrani, M., & Gupta, S. M. (2021). Designing a Sustainable Green Closed-Loop Supply Chain under Uncertainty and Various Capacity Levels. *Logistics*, *5*(2), 20. https://doi.org/10.3390/logistics5020020

Tirkolaee, E. B., Goli, A., Ghasemi, P., & Goodarzian, F. (2022). Designing a sustainable closed-loop supply chain network of face masks during the COVID-19 pandemic: Pareto-based algorithms. *Journal of Cleaner Production*, *333*. Scopus. https://doi.org/10.1016/j.jclepro.2021.130056

Upadhyay, A., Mukhuty, S., Kumar, V., & Kazancoglu, Y. (2021). Blockchain technology and the circular economy: Implications for sustainability and social responsibility. *Journal of Cleaner Production*, *293*, 126130. https://doi.org/10.1016/j.jclepro.2021.126130