ENHANCING SUSTAINABILITY AND PERFORMANCE OF AUTOMATED AIR CONDITIONERS THROUGH OPTIMIZING PRODUCT RECOVERY IN CLOSED-LOOP SUPPLY CHAINS

by

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Original scientific paper
https://doi.org/10.2298/TSCI220907221P

This article investigates the use of closed-loop supply chains (CLSC) to improve the sustainability and performance of automatic air conditioning systems. With the growing use of automated air conditioning systems in automobiles, it is necessary to analyze and optimize their efficiency even after their life span. To reliably anticipate the performance of automatic air conditioning systems, the suggested method employs a unique soft computing technology based on support vector machines (SVM). Furthermore, the research focuses on the deployment of CLSC, which allows for optimal product recovery and resource utilization. To optimize the multi-product, multi-time, multi-echelon network, a generalized CLSC model is built, considering costs, product recovery possibilities, unknown parameters, and environmental performance. The study sheds light on reverse logistics decision-making, such as centre placement and allocation, as well as cultivation of supplier relationships. Overall, this study's incorporation of CLSC and the SVM-based performance prediction approach supports sustainable manufacturing practices. It emphasizes the significance of resource efficiency, waste minimization, and environmental effect mitigation in air conditioning system design, manufacture, and operation. Manufacturers may increase not just their environmental sustainability but also the performance and durability of their air conditioning systems by optimizing product recovery and utilizing CLSC. This study provides industry stakeholders with practical information, supporting the adoption of sustainable practices and contributing to a more sustainable and efficient manufacturing ecosystem.

Key words: *CLSC, sustainability, waste minimization, automatic air conditioning systems, SVM, resource utilization, sustainable manufacturing practices,reverse logistics, resource efficiency, product recovery, soft computing*

Introduction

The study is to improve the performance and sustainability of automated air conditioning (AC) systems that has been spurred by the growing concern for environmental sustainability and the rising demand for energy-efficient systems. Product recovery techniques and CLSC have shown promise in addressing these issues. Manufacturers may minimise waste, consume fewer resources, and increase the lifespan of air conditioners by using CLSC concepts and improving product recovery procedures. Through this integration, materials and compo-

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nents from decommissioned or end-of-life air conditioning systems may be used effectively, promoting a more circular and sustainable production process.

The collection, disassembly, refurbishing, and reuse of components reduces the demand for new resources and lessens the environmental effect of product recovery within CLSC. This not only adheres to the fundamentals of sustainable growth but also offers chances to save expenses and generate new sources of income. Manufacturers may lessen their carbon footprint, protect precious resources, and support a more circular economy by recovering and reusing materials.

Accurate prediction and optimisation approaches are necessary to improve AC systems' performance and sustainability. The precise prediction of system performance is made possible by the application of cutting-edge technologies like SVM-based soft computing approaches. The SVM-based models may offer insights into the behaviour and features of AC systems by analysing historical data and taking into account a variety of criteria, enabling well-informed decision-making for system optimisation and energy efficiency gains.

The purpose of this study is to investigate the integration of CLSC and the use of product recovery mechanisms to improve the sustainability and performance of AC systems. It emphasises the significance of resource efficiency, waste minimization, and environmental effect mitigation in air conditioner design, manufacture, and operation. Manufacturers may uncover potential for sustainable manufacturing practises, enhance system performance, and contribute to a greener, more sustainable future by using CLSC and sophisticated prediction methodologies.

Literature review

The survey of literature provides a thorough examination of existing research on CLSC management and sustainability. It emphasises the significance of include product recovery and sustainable practises in supply chain networks. The examined papers emphasise mathematical models for optimising CLSC, with goals such as cost reductions, resource efficiency, and environmental impact in mind. Product recovery from automatic air conditioner provides solutions such as recycling, refurbishing, and remanufacturing have been highlighted as critical for lowering costs, waste, and energy usage. Carbon footprint modelling, green logistics, and eco-design are used to emphasise environmental sustainability, with a realisation of the relationship between sustainable practises and economic advantage. The assessment also recognises the need of incorporating social sustainability into CLSC, such as fair labour practises and community participation. Overall, the literature analysis offers useful insights on how to improve the performance, sustainability, and cost of CLSC, while also indicating the gaps that future research should fill to further the knowledge and implementation of sustainable practises. To improve the sustainability and performance of AC systems, the literature review emphasises the necessity of integrating CLSC, optimising product recovery, and utilising sophisticated prediction algorithms. The study lays the groundwork for the proposed research by emphasising the importance of resource efficiency, waste reduction, and environmental impact reduction in establishing sustainable manufacturing practises in the AC business [1-13].

Methodology

The creation of a generalised CLSC model especially adapted for optimising product recovery in the context of AC systems is a critical component of this work. This model is a great tool for improving the sustainability and efficiency of air conditioners by properly regulating resource recovery and utilisation. The model created considers a variety of aspects that impact the optimisation process, such as costs, product recovery possibilities, unknown parameters, and environmental performance. The model allows decision-makers to make educated choices that minimise costs, maximise resource utilisation, and limit environmental impact by taking these aspects into account.

Advanced modelling methods including simulation and mathematical optimisation are used to generate the model. The most effective configuration and resource allocation inside the CLSC may be found through mathematical optimisation. By taking into account aspects like transportation costs and recovery efficiency, it assists in choosing the optimal locations for collection centres, disassembly centres, refurbishing centres, and outside suppliers. The effectiveness of the optimised CLSC is assessed using simulation approaches under a variety of settings. This makes it possible to evaluate the system's effectiveness in terms of resource use, waste minimization, and environmental impact. Decision-makers can learn more about the potential advantages of implementing optimised product recovery techniques by modelling supply chain processes.

The creation of a generalised CLSC model utilising cutting-edge modelling techniques offers a thorough framework for improving the performance and sustainability of air conditioners. It enables decision-makers to take well-informed decisions that enhance resource efficiency, minimise waste production, and lessen the AC systems' total environmental impact over the course of their lifetimes the model used is as shown in fig. 1.

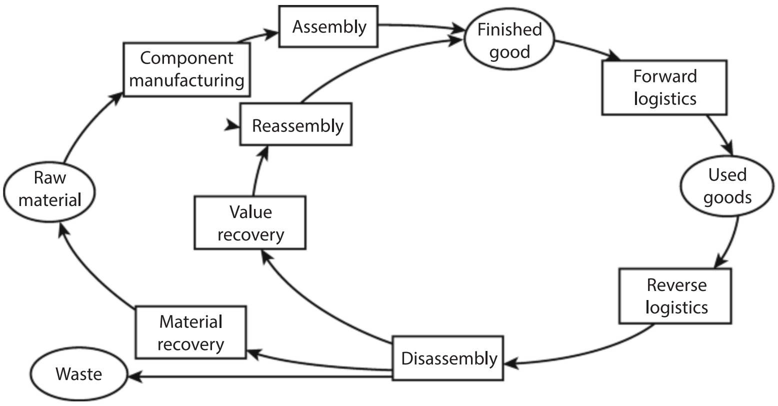

Figure 1. The model adopted

Objective function

$$\begin{aligned}\text{Min total cost } (Z_{\min}) = &\sum_k\sum_p\sum_m C_{kp}^m QP_{kp}^m + \sum_k\sum_n\sum_m hp_{kn}^m \left(\sum_k\sum_p QT_{kpn}^m - \sum_k\sum_p QD_{knr}^m\right) + \\ &+\sum_k\sum_p\sum_m hd_{kp}^m Def_{kp}^m + \sum_k\sum_p\sum_m Re_{kp}^m Def_{kp}^m + \sum_k\sum_p\sum_n\sum_m TP_{kpn}^m QT_{kpn}^m + \sum_k\sum_p\sum_n\sum_m TN_{knr}^m QD_{knr}^m + \\ &+\sum_k\sum_p\sum_m TD_{kp}^m Def_{kp}^m + \sum_k\sum_p\sum_m \psi_{kp}^m SQ_{kp}^m + \sum_k\sum_p\sum_m \beta_{kr}^m SP_{kr}^m + \sum_m CT^m TT^m \end{aligned} \tag{1}$$

Constraints

$$QP_{kp}^{m} \le QC_{kp}^{m}, \Delta k, p, m \tag{2}$$

$$\sum_{p} QT_{kpn}^{m} \le QN_{n}^{m}, \Delta k, n, m \tag{3}$$

$$\sum_{n} QD_{knr}^{m} \le QR_{r}^{m}, \Delta k, r, m \tag{4}$$

$$Def_{kp}^{m} = Pe_{kp}^{m} QP_{kp}^{m}, \Delta k, p, m \tag{5}$$

$$SQ_{kp}^{m} = \alpha_{kp}^{m} Def_{kp}^{m}, \Delta k, p, m \tag{6}$$

$$PQ_{kp}^{m} = (1 - Pe_{kp}^{m}) QP_{kp}^{m}, \Delta k, p, m \tag{7}$$

$$TQ_{kp}^{m} = PQ_{kp}^{m} + Def_{kp}^{m} - SQ_{kp}^{m}, \Delta k, p, m \tag{8}$$

$$\sum_{r} Dm_{kr}^{m} + \sum_{p} SQ_{kp}^{m} \le \sum_{p} QP_{kp}^{m},\ \Delta k, p, m \tag{9}$$

$$\sum_{r} Dm_{kr}^{m} \le \sum_{p} TQ_{kp}^{m},\ \Delta k, m \tag{10}$$

$$\sum_{p} PQ_{kp}^{m}, \le \sum_{r} Dm_{kr}^{m},\ \Delta k, m \tag{11}$$

$$\sum_{r} SP_{kr}^{m} = \sum_{r} Dm_{kr}^{m} - \sum_{p} PQ_{kp}^{m},\ \Delta k, m \tag{12}$$

$$\sum_{n} QD_{knr}^{m} = Dm_{nr}^{m}, \Delta k, r, m \tag{13}$$

$$\sum_{r}\sum_{m} QD_{knr}^{m} \le \sum_{p}\sum_{m} QT_{kpn}^{m}, \Delta k, n \tag{14}$$

$$\sum_{m} In_{kn}^{m} = \sum_{p}\sum_{m} QT_{kpn}^{m} - \sum_{n}\sum_{m} QD_{knr}^{m}, \Delta k, n \tag{15}$$

$$\sum_{p}\sum_{m} QT_{kpn}^{m} = \sum_{n}\sum_{m} QD_{knr}^{m}, \Delta k, n \tag{16}$$

$$\sum_{m} QT_{kpn}^{m} \le TQ_{kp}^{m}, \Delta k, p, m \tag{17}$$

$$\sum_{k}\sum_{p} QP_{kp}^{m} P\theta_{kp}^{m} \le TP\theta^{m},\ \Delta m \tag{18}$$

$$\sum_{k}\sum_{p} Def_{kp}^{m} R\theta_{kp}^{m} \le TR\theta^{m},\ \Delta m \tag{19}$$

$$TP\theta^{m} \leq TR\theta^{m}, \ \Delta m \tag{20}$$

$$PQ_{kp}^{m}, QT_{kpn}^{m}, QP_{kp}^{m}, Def_{kp}^{m}, SQ_{kp}^{m}, TQ_{kp}^{m}, QD_{knr}^{m}, SP_{kr}^{m} \geq 0, \ \Delta k, p, n, r, m \tag{21}$$

Supply chain management, which involves the co-ordination and administration of operations across multiple stages and entities engaged in producing and delivering products to clients. In this situation, the goal is to reduce the whole cost of the supply chain, which typically includes charges for production, shipping, inventory holding, and sometimes additional expenses.

A set of constraints is placed to ensure that the solution is workable and realistic. These limitations act as limits on the decision variables, which are the quantities of products manufactured, transported, and stored in inventory at various points of the supply chain. The first set of limitations, labelled eqs. (2)-(4), limit the amounts of production and transportation the capacity of the facilities concerned. This guarantees that the supply chain runs within the physical boundaries of the facilities and avoids overloading them. The handling of damaged items is covered by restrictions eqs. (5)-(9). These restrictions specifically ensure that any defective products are identified and separated from the perfect ones, that the scrap produced by defective goods is disposed of or recycled properly, and that the perfect goods, both before and after reworking, are counted accurately. Constraint eq. (10) ensures that consumer demand is entirely satisfied with faultless items exclusively, without any defective products or scrap reaching the buyers. This is critical for preserving client happiness and avoiding reputational damage. Shortages at the retailer are permitted by constraints eqs. (11) and (12). In many supply chains, it is possible for the retailer to have less inventory than there is demand.

The amounts that the distribution hub transports to the retailer in order to meet their demand are guaranteed by constraint eq. (13). This restriction guarantees that the correct quantities are supplied to the shop and aids in streamlining the transportation process. Inventory limitations eqs. (14) and (15) make sure that both the retailer's and the distribution center's inventory levels are kept at zero. This is a fundamental component of just-in-time (JIT) logistics, a key idea in contemporary supply chain management. A balancing constraint, constraint eq. (16) ensures that the quantities obtained from the manufacturer are equal to the total of the quantities provided to the retailer and the quantity held in inventory. This restriction aids in preserving inventory levels and supply chain optimization. Only flawless products are delivered from the factory to the distribution hub, thanks to constraint eq. (17). This is a crucial quality assurance measure that promotes client happiness. The time restrictions in eqs. (18)-(20) make sure that the transportation operation is finished within the appropriate time limits. This promotes prompt deliveries and supply chain optimization. Subsequently constraint eq. (21) assures that all of the model's decision variables are greater than or equal to zero. This constraint helps to ensure that the model remains realistic and complies to modern supply chain management concepts.

Computational experiments

The outcome of a realistic defective goods SCN problem using the suggested approach is provided in this section, and random cases are depicted. Complications and computational properties. The possibilities for resolving the problem are investigated. The ILOG CPLEX, GA, and PSO results are compared. The experimental inquiry involves evaluating a small AC unit appropriate for a range of uses, including room cooling, portable refrigerator storage, and cooling systems for automobiles. A denso AC system with R134a refrigerant and other essential components was employed in the investigation.

Using the specific tools specified in tab. 1, precise measurements of a number of parameters were obtained. The *K*-type thermocouples were used to measure the temperature of the air entering and leaving the system as well as the temperature of the refrigerant flowing through various components. The pressure within the system was measured using a bourdon tube pressure gauge. The amount of refrigerant circulating in the system was measured using a flow metre. A sight glass tube was added in addition the flow metre in order to check the refrigerant's condition.

Table 1. Parameters and values

Parameters	Values	Parameters	Values
Pe^m_{kp}	Uniform (0, 0.09)	$P\theta^m_{kn}$	Normal (6, 3)
ϕ^m_{kp}	Normal (11, 3)	QP^m_{kp}	Normal (15, 3)
$R\theta^m_{kp}$	Normal (5, 2)	$\alpha^{\mathrm{m}}_{\mathrm{kp}}$	Uniform (0, 0.9)
Re^m_{kp}	Normal (6, 2)	TP^m_{kpn}	Normal (12, 3)
β^m_{kr}	Normal (6, 1)	hp^m_{kn}	Normal (6, 2)
TN^m_{knr}	Normal (8, 2)	Dm^m_{kr}	Normal (2000, 1000)
hd^m_{kp}	Normal (10, 3)	TD^m_{kp}	Normal (5, 2)
CT^m	Normal (0, 0.6)		

This careful data gathering procedure made sure that the system's performance was measured with accuracy and dependability. The experimental set-up allowed for complete monitoring and analysis of crucial data, providing a full assessment of the durability and performance of the AC system.

Modelling of support vector machine for automatic air conditioning system

The suggested model seeks to forecast the cooling effect, C_{effect}, compressor input power, P_{comp}, and COP of an autonomous AC system. Four input variables – compressor speed, S_{comp}, evaporator temperature, T_{evap}, condenser velocity, V_{cond}, and condenser temperature, T_{cond} – are used to make this prediction. The model tackles the challenging classification issue related to the automated AC system using SVM, a potent machine learning approach.

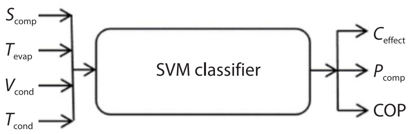

Figure 2. The SVM set-up

Training and testing are the two primary stages of the SVM classifier. The SVM model is trained in the training phase using data gathered from experimental trials, allowing it to forecast the performance of the automated AC system with accuracy. The SVM model is then used in the testing phase to forecast the performance based on the input variables as shown in fig. 2.

The suggested system uses the SVM classifier, which is modelled with three outputs (cooling effect, evaporator input power, and COP) and four inputs (compressor speed, evaporator temperature, condenser temperature, and velocity). Test data from the literature is used to assess the system's performance, and the outcomes are contrasted with an ANN method.

The efficiency of the suggested approach is shown by the examination of the system's performance. The SVM-based model's dependability and accuracy for forecasting the performance of automatic AC systems are further validated by comparison with the ANN approach.

Based on the results provided in the article lead to the conclusion that the suggested method is a workable substitute for precisely forecasting the performance of automatic AC systems. Utilizing SVM modelling and prediction helps to improve the performance and sustainability of air conditioners, encouraging resource efficiency and assisting CLSC in the sector.

Description of data

The network constitutes of three levels, raw-materials used by manufacturer, assembly done by distributors and finished goods provided by retailers as shown in fig. 1. The required parameter values are given in tab. 1. The sample problem is described in tab. 2.

The MILP formulation eqs. (1)-(21) of the sample instances will be computed on a PC with an Intel i7 2.54 GHz processor with 8 GB RAM using ILOG CPLEX solver exact optimum solution is obtained and using MATLAB R R2013a heuristic based on GA and PSO to get the best solution is obtained.

Table 2. Description of sample problems

Sample problem	Manufacturers	Distribution hub	Retailers	Products	Time period
1	2	2	2	2	2
2	3	2	3	2	3
3	4	5	3	1	3
4	3	6	2	2	2
5	4	3	4	1	4
6	3	4	4	3	3
7	4	3	6	1	4
8	6	2	4	1	3
9	2	2	2	2	2
10	3	3	2	3	3
11	4	5	3	2	3
12	3	6	2	4	2
13	4	3	4	1	4
14	3	4	4	3	3
15	4	3	6	2	4
16	6	4	4	1	3
17	2	1	2	1	2
18	3	2	3	1	3
19	4	5	3	1	3
20	3	6	2	2	2
21	4	3	4	2	4
22	3	4	4	3	3
23	4	4	6	1	4
24	6	4	4	1	3

Results and discussion

Especially in the context of automated air conditioner systems, building a solid model that can fulfil manufacturing and transportation restrictions while optimizing costs is crucial for managing supply chains. However, the effectiveness of these models may differ based on variables like facility size and time period. To verify the usefulness and application of these models, it is essential to test and assess them in a variety of circumstances.

To solve the optimization difficulty in this work, the researchers used a variety of optimization methodologies. Even though precise methods like ILOG CPLEX provide excellent accuracy, they can be computationally costly and may not be appropriate for issues of a vast size. The researchers suggested using heuristic optimization techniques as an alternative, such as PSO and GA, which are better suited for specific problem types.

The study compares the outcomes of each optimization approach in order to identify the best successful optimization strategy. The results, as shown in tab. 3, showed how the best outcomes obtained with GA and CPLEX and the best outcomes with PSO and CPLEX differed from one another. These comparisons demonstrated how accurate and practical the suggested model is. An important finding was that PSO surpassed GA in terms of both result quality and computational effectiveness, making it a better option for optimizing automatic air conditioner systems.

Table 3. Comparison of results between CPLEX, GA, and PSO

Sample Problem	CPLEX		GA		PSO		GAP [%]	
	Z_{min}	RT	Z_{min}	RT	Z_{min}	RT	GA	PSO
1	339526	0.007	340864	118	340840	102	0.39	0.38
2	785294	0.011	804349	197	793300	184	2.42	1.01
3	512837	0.009	525108	159	517876	147	2.39	0.98
4	483710	0.007	489579	143	484889	134	1.21	0.24
5	727192	0.011	741740	186	728490	177	2	0.17
6	985961	0.013	989458	211	988401	203	0.35	0.2
7	870296	0.013	879472	205	874121	193	1.05	0.44
8	1391027	0.016	1651802	243	1449190	229	2.28	0.51
9	349826	0.007	350764	120	350428	104	0.38	0.37
10	798294	0.011	814652	199	804758	187	2.41	1.02
11	501347	0.009	514207	157	506996	145	2.37	1.0
12	485620	0.007	488755	141	484889	131	1.20	0.25
13	726203	0.011	741602	186	729666	178	2.1	0.16
14	985661	0.013	989258	211	988421	202	0.38	0.21
15	861254	0.013	870014	204	865132	194	1.04	0.45
16	1259845	0.015	1451614	222	1299190	204	2.22	0.55
17	326754	0.007	334680	116	330345	102	0.37	0.36
18	765480	0.011	794849	194	779362	180	2.4	1.02
19	506749	0.009	518481	155	510824	141	2.2	0.99
20	464632	0.007	469981	145	465561	132	1.2	0.25
21	708742	0.011	721859	181	709237	170	2.05	0.18
22	982634	0.013	987348	211	985701	202	0.35	0.21
23	844392	0.013	861421	202	852154	190	1.08	0.46
24	1546723	0.019	1792162	267	1607688	249	2.39	0.50

Note: where RT is the running time in sec GAP % = (Best results – CPLEX)/CPLEX) × 100

The research's objective is to develop a generalized CLSC model that optimizes the use of automated sir conditioning system under CLSC network while taking into account a variety of prices, product recovery options, unknown parameters, and environmental performance.

Optimization results

Mixed-integer linear programming was used to solve the mathematical model eq. (1) that was described in the preceding section. The model's objective function intended to reduce supply chain costs overall while considering various cost factors and performance metrics. The optimization's results shed light on the CLSC network's ideal set-up and functioning.

Evaluation of performance

The CLSC network's performance was assessed using a number of different factors, such as social effect, economic efficacy, and environmental performance. To evaluate the sustainability of the supply chain, environmental performance metrics including carbon emissions, energy use, and trash creation were examined. To assess the CLSC network's financial feasibility, economic efficiency indicators such total cost, revenue, and profitability were employed. Stakeholder satisfaction, community involvement, and other social impact considerations were also taken into account.

Trade-offs and decision-making

The CLSC network's adoption of sustainability principles necessitates making decisions that balance social, environmental, and economic goals. The study's findings and analyses illustrate the trade-offs and difficult choices that organizations must make while putting in place a CLSC. For instance, while network environmental performance optimisation may result in higher expenses, it may also improve brand reputation and client loyalty. The organization's interests and goals must be carefully taken into account in order to balance these trade-offs.

Sensitivity analysis

To evaluate the robustness of the CLSC model, sensitivity analysis was carried out by changing important parameters and seeing how they affected the network's performance. This analysis aids in determining the most important factors and how they affect the decision-making process. Sensitivity analysis offers important insights into the CLSC network's durability and flexibility under various scenarios and uncertainty.

Managerial implications

For organizations looking to create a CLSC for automated air conditioner, the study's findings have significant managerial implications. The recommended CLSC model offers managers a set of tools to help them decide where to locate collection centres, disassembly centres, refurbishing centres, and outside suppliers, as well as how much of each to allocate. The study's suggested multi-criteria decision-making techniques aid in assessing and choosing service providers for reverse logistics operations. These insights give managers the capacity to priorities tasks, build rapport with suppliers, and make tactical decisions that advance efficiency and sustainability in their supply chain operations.

Conclusion

It is typical practice to use metaheuristic techniques to handle complicated optimization problems, such as supply chain network design, such as GA and PSO. These techniques are intended to iteratively search the search space until they locate the best or nearly best solutions. In this instance, the objective was to adhere to the JIT logistics philosophy while minimizing total cost while satisfying all requirements and guaranteeing zero inventory level. The findings show that PSO performed better than GA in resolving the given problem and helping in finding out the process of product recovery in automated air conditioner. The study also provided a table that illustrates the discrepancy between the answers generated via GA and CPLEX, a commercial optimization software, as well as between CPLEX and PSO. The outcomes imply that both heuristics techniques (GA and PSO) can deliver solutions that are near to the ideal answer acquired from the commercial software and meet the requirements of the problem. In conclusion, this study shows that metaheuristic approaches, such as GA and PSO, can be successful in addressing complicated supply chain network design issues, yielding results that are close to optimal and satisfy the objectives. Also, the study provides useful insights into how sustainability may be attained within the framework of supply chain management by optimizing product recovery in closed-loop supply networks. This study might aid in the creation of supply chain management systems that are more effective for reuse of air conditioners also, which would ultimately result in cost savings and environmental advantages. Overall, the findings of this study provide valuable insights and practical implications for those people involved in adopting sustainable practices and improving the sustainability and performance of air conditioners. The optimized product recovery strategies and SVM-based performance prediction techniques offer promising avenues for achieving environmental sustainability, cost efficiency, and overall system optimization in the air conditioning sector.

Future scope

There are specific areas of research relating to the parameter tuning and performance comparison of GA and PSO in addition the broad future work areas stated previously. A few of these are: The parameter values chosen for each algorithm have a significant impact on the performance of GA and PSO. The parameters of both algorithms can be tweaked in the future to enhance their effectiveness in solving supply chain network design difficulties. Hybrid algorithms: to enhance their performance, hybrid algorithms integrate the benefits of various optimization techniques. Future research might look into the possibilities of hybrid algorithms that combine GA and PSO to solve supply chain network design issues more effectively. Performance evaluation of more complex problems: This study assessed the effectiveness of GA and PSO on supply chain network design issues of a small to medium level. Future research can analyze how well they perform on increasingly challenging challenges to see how scalable and effective they are in complex situations. Real-world validation: to assess the effectiveness of GA and PSO, this study used a simulation-based methodology. Future research can evaluate the findings using real-world data to determine their applicability in the actual world and potential for use in supply chain network design issues.

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Paper submitted: September 7, 2022
Paper revised: July 28, 2023
Paper accepted: August 31, 2023