Decision Making and Artificial Intelligence Trends

Volume 2, Issue 1, 23-53.

# Designing a new bi-objective resilient supply chain network with Additive Manufacturing capability and smart contracts

https://doi.org/10.22034/dmait.2025.541082.1008

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**ARTICLE INFO**

***Article history:***
Received: 2025/08/15
Revised: 2025/09/15
Accepted: 2025/09/25
Published: 2025/10/02

***Keywords***:
AM, Blockchain, Inflation, Optimization, Resilient supply chain, Smart contracts

**ABSTRACT**

Effective risk management in supply chains is critical for supporting managerial decisions on inventory control, cost management, and demand fulfillment. This study develops a bi-objective optimization model designed to minimize the total cost of a supply chain network while simultaneously enhancing its resilience by reducing unsatisfied demand under disruption scenarios. The model incorporates multi-level decision-making across suppliers, manufacturers, and distributors, and integrates Additive Manufacturing (AM) as a flexible tool to mitigate disruptions through on-demand production of critical parts. To address financial uncertainty, the framework considers exchange rate risks arising from inflation, evaluated under three scenarios. Transparency and supplier selection are further strengthened through smart contracts on a blockchain platform. The model employs robust optimization for risk management, the ε-constraint method for handling the bi-objective formulation, and the Benders decomposition algorithm to efficiently solve the resulting mixed-integer program. A case study of a household supply chain network shows that integrating AM significantly improves both cost efficiency and resilience. The findings highlight the importance of jointly considering technological enablers, risk factors, and multi-level supply chain structures when designing resilient networks.

## 1. Introduction

Nowadays, prioritizing customers and reducing transportation costs and environmental pollutants are the most important goals of the supply chain. However, other factories that apply conventional production systems can only serve customers to some degree, as they would usually have high production capacity but low flexibility in responding to design changes, limited product variety, and high costs of transportation and storage. Therefore, the conventional supply chain structure must be reviewed and modified to improve its performance more quickly (Daniel et al., 2020). Hence, the technologies that are consistent with prevailing conditions and can enhance efficiency are needed. On the other hand, digital technologies are suitable for achieving the stated goals, which can be used to have a flexible supply chain.

3D printers are a tool that has provided the necessary platform for forming digital manufacturing (Roozkhosh et al., 2023).

Supply chain needs sophisticated production technology to gain more flexibility and quickly respond to changes in customers' needs, improve logistics functionality, minimize time, increase customer satisfaction, and develop the supply chain's capability. Leveled production technology, which is also called Rapid Prototyping (RP) technology due to its speed, is widely considered to be one of the most appropriate production technologies to manufacture products in low volume and large variety. There are other names that describe this technology, such as AM (AM) and 3D printing (Chua et al., 2017). This type of production can occupy less space and can be in the location of the distributor, saving the time and money of transportation and production and reducing the levels of the supply chain (Yang and Zhao, 2018). For example, Rinaldi et al. (2020) made a simulation-based comparison between TM and AM in a supply chain. They chose the jet supply chain as a case study and showed that both types of supply chain can have advantages and limitations. They concluded that the use of the supply chain via 3D printers is centralized and decentralized in transport expenses, warehousing, and customer satisfaction, which creates substantial savings compared to traditional production. In total, the use of an innovative supply chain with changing levels due to AM technology combined with TM can increase customer satisfaction. Transportation and maintenance costs compared to TM should be advantageous as the levels of supply chain are reduced and the number of factories is increasing. However, TM might have priority when it comes to some costs due to using their maximum usable capacity and having fewer machines. As these factories are fewer in number, considering the size and the building cost, they have a tendency to produce at their full capacity (Rinaldi et al., 2020). Apart from this, fluctuations in the exchange rate can bring a significant difference in supply chain operations, particularly in the scenario of international trade.

Companies that import or export goods from other countries must manage exchange rate risk, which can affect their profitability and pricing. A resilient supply chain can help companies mitigate such risks by being responsive and adaptive to unforeseen events, such as sudden exchange rate changes. AM can play a vital role in creating a more resilient supply chain. It allows for the production of goods locally rather than relying on global supply chains (Arian et al., 2021). It reduces lead times and transportation costs, especially when exchange rates are volatile and unpredictable (Chowdhury et al., 2023). By incorporating AM into their supply chain designs, organizations are able to make themselves more resilient to exchange rate volatility and other types of disruptions. In addition, exchange rate risk is among the major concerns that firms face in their supply chain management, particularly in global markets. Exchange rate volatility can have a significant impact on supply chain performance, affecting pricing, inventory, and transportation costs. In order to mitigate the impact of exchange rate risk, firms can adopt a resilient supply chain strategy that involves risk management and flexibility in the face of uncertainty. A supply chain can be made resilient by an optimization model that is designed to minimize the impact of exchange rate risk on performance (Ferreira et al., 2023). Demand forecasting is one of the most important aspects in creating a resilient supply chain. Demand forecasting would allow companies to predict their inventory levels, production schedules, and transportation requirements, thus reducing the impact of exchange rate volatility. Another important aspect is inventory management. Firms can apply inventory optimization techniques to minimize inventory levels to the bare minimum without compromising demand. This decreases the holding cost of inventory as well as the impact of exchange rate fluctuations on inventory value.

Blockchain and smart contracts are two of the most advanced technologies that have the potential to transform the AM sector and create a stronger supply chain model. Blockchain is a secure, decentralized digital ledger that enables transactions to be recorded and traced in an open and secure manner. Smart contracts, which are self-executing contracts with the agreement's terms between the seller and buyer written directly into lines of code, execute these transactions automatically. Blockchain and smart contracts can assist in secure and transparent transactions between the manufacturer and supplier, leading to a more reliable and efficient supply chain (Xiao et al., 2023). By offering an unalterable and secure electronic ledger of all transactions, blockchain technology ensures that every process along the supply chain will be traceable, from raw material purchasing at the start to delivery of the final product (Sargent and Breese, 2024).

Furthermore, the combination of smart contracts with blockchain technology enables manufacturers to create self-executing contracts that can be automatically executed when certain conditions have been met, such as when a certain order quantity has been reached. This can reduce the time and cost of processing orders and supply chain effectiveness (Tan et al., 2023). Together, blockchain and smart contracts in AM and supply chain management can create a stronger and more efficient model of the supply chain with greater transparency, security, and automation. It can help manufacturers and suppliers in terms of reducing costs, improving efficiency, and coping with unexpected events or disruptions in the supply chain better. Additionally, robust planning is a decision-making approach that endeavors to create less sensitive plans in preparation for future change. This is achieved by considering multiple potential futures and defining what they have in common, and thus having a flexible and robust plan to accommodate future alterations. Robust planning is achievable through epsilon constraints, which set limits on the worst case while optimizing for the most likely case. Epsilon constraints make the plan resistant to the worst-case scenario, yet also execute well in the most probable scenario.

Benders' decomposition algorithm is a robust optimization method for solving large-scale structured optimization problems. The problem is decomposed into subproblems and solved sequentially. The algorithm has its application in the solution of mixed integer programming problems, as it is efficient in solving the linear programming subproblems but employs integer programming in a bid to ensure that the overall solution is feasible. The Benders algorithm can be applied with epsilon constraints to efficiently and effectively solve robust planning problems. As a rule, the combination of robust planning, epsilon constraints, and the Benders algorithm presents a strong solution to optimization problems. By examining different possibilities, placing limits on the worst-case, and breaking down complex problems into smaller subproblems that are easier to handle, one can establish robust and sound plans that will withstand future changes. The approach has extensive applicability across a range of disciplines from supply and logistics management to ecological planning and resource management (Kumar et al., 2020). Robust plan formulation. Blockchain can play a role in creating disruptions to the supply chain through the creation of smart contracts and increasing resiliency and response rate within the network. The disruptions can be caused by a natural disaster such as an earthquake or flood, or by an event such as the breakdown of machinery, inflation, or a worker strike.

This quantitative study-based analysis is able to be used to analyze the impact of exchange rate risk and inflation on the supply chain and AM. Firstly, there is a literature review conducted to gather data about theoretical exchange rate risk, inflation, supply chain, and AM concepts. Second, supply chain experts, analysts, and AM professionals conduct a survey to identify the latest industry trends and best practices for managing exchange rate risk and inflation, enabling the design of an optimization model tailored to these risks. Third, the case study approach is utilized to examine the use of AM for handling exchange rate risk and inflation within supply chain operations. The results of this study provide a comprehensive understanding of the impact of exchange rate risk and inflation on the supply chain, as well as how AM can be utilized to create a stronger, cost-effective, and demand-driven supply chain. In general, the main contribution of this paper can be summarized as follows:

1. Presenting a Mixed Integer Linear Programming (MILP) model using some linearization techniques for the optimization model to design a supply chain network with changeable multi-levels

2. Considering a resilient supply chain and investigating exchange rate risks on the supply chain for the first time

3. AM-TM supply chain network design by using additive and traditional manufacturing in the supply chain structure, and test it on a real case for the first time

4. Locating AM and TM factories and finding the optimal number of factories and modes of transportation for the first time

5. Minimizing the unsatisfied demand to increase resilience by applying intelligent contracts on the blockchain platform for the first time

In the continuation of other parts of this research, the literature review and methodology, including the conceptual model of the problem, the solution method, the mathematical model, the results and sensitivity analysis, and the conclusion, are presented.

## 2. Literature review

One of the most critical technologies that can help the supply chain is AM. In this regard, Strong et al. (2018) discussed the optimal location for establishing AM hubs in the supply chain of metal parts. They used an integrated structure to deploy traditional and AM plants in the supply chain. But they did not consider the capacity of each hub. Chung et al. (2018) aimed to optimize supply chain design and operations by dynamically connecting smart factories consisting of 3D printers to minimize total fixed, production, and transportation costs. Rinaldi et al. (2021) presented a conceptual model for combining 3D printers with the supply chain. They used a simulation for a jet supply chain. They showed that using AM in the supply chain can significantly save transportation and maintenance costs.

Arbabian (2022) investigated the impact of AM on a supply chain consisting of a manufacturer and a retailer that uses a wholesale price contract and fulfills random customer demand. They determined the economic conditions under which each company would adopt AM. They found that companies benefit more if the manufacturer adopts AM than in the supply chain without AM and concluded that AM at the retail location is a new mechanism for coordinating the supply chain. Therefore, supply chain managers should carefully consider the possibility of retail manufacturing products through AM. Kristianto et al. (2014) evaluated the potential impact of improving AM on spare parts supply chain configuration. Through scenario modeling of the supply chain of spare parts in the aviation industry, they presented a total of four scenarios that changed the designs of the supply chain and the specifications of the AM machines. They found that using current AM technology, distributed spare parts production is feasible because AM machines require less capital and offer shorter production cycles.

Basu et al. (2022) developed a conceptual model for truck production using AM method. They showed how AM could help the auto parts industry to save on ordering costs. Many current studies examine the production of individual parts, and those that examine assemblies tend not to analyze supply chain effects, such as inventory and transportation costs. AM systems and material costs form a significant part of an AM product. However, these costs decrease over time. Therefore, this technology may be widely used and change supplier, manufacturer, and consumer interactions by reducing the costs of AM systems. Also, more research has recently been done on using AM in the supply chain. For instance, Chung et al. (2018) developed an optimization model using 3D printers in supply chain outsourcing. They stated that some parts could be sent from TM to AM to complete the production processes. Their study was done to minimize transportation and production costs. Also, Ekren et al. (2023) presented a conceptual model for using AM in the supply chain. They pointed out the need to implement 3D printers in the supply chain and compared it with TM. They pointed out that this method can be superior to TR for making samples at high speed, improving transportation costs, repairing parts, and in some environmental issues.

Due to the advantages of each of the factories (traditional, AM-TM, and AM), designing and implementing an optimal mixed supply chain network with changeable levels can be very useful. This study seeks to find the number of factories, their optimal type, and the optimal number of means of transportation according to their style and capacity. This means that if the optimal mode is to choose a TM, this factory can entrust some of its parts to AM factories or produce all the goods itself, and then distribute them through the main distributor or place to use for broadcasting. This study aims to find a model for deciding the traditional or additional establishment of facilities, their capacity, optimal routing of transportation modes, and their capacity to reduce network costs.

Supply chain management refers to the links within and between suppliers, focal companies, distributors, and customers to maintain the efficient and effective flow of materials, information, and money to meet the needs of stakeholders (Das, 2018). However, in the past few decades, supply chains and their various stages have faced various internal (operational) and external challenges. These external challenges are related to disturbances and increased environmental risks (Dey et al., 2019). Torabi et al. (2015) developed a stochastic model to create supplier resilience under operational risk and disruption. Their model was a two-stage probabilistic hybrid dual-objective stochastic programming to address the supplier selection and order allocation problem to create a flexible supply base under operational risks and disruption. This model applied data uncertainty and several strategies, such as supplier business continuity plans, supplier reinforcement, and contracts with backup suppliers to increase choice chain flexibility. They presented a five-step method to solve the problem. Their calculation results showed a significant effect of considering destructive events on the level of the selected supplier. Chaudhuri et al. (2016) showed that cooperation with suppliers and logistics reduces risk and positively affects income. They examined experts' opinions from food processing companies to clarify the contextual relationships between risk drivers and performance measures. Also, they used fuzzy interpretive structural modeling to determine direct and indirect relationships. Sawik (2022) presented a resilient supply chain model to minimize production costs and maximize estimated demand. To solve the model, he used a multi-portfolio approach and stochastic models with scenario-based mixed integer programming (MIP). Also, he calculated the amount of inventory to reduce the risk, which is used as the excess capacity for more chain resilience, production, and the supply of parts by the factory and the supplier. Taleizadeh et al. (2022) optimized a sustainable supply chain by considering resilience factors and pricing decisions, utilizing a two-level planning approach and the Stackelberg game model to calculate the optimal amount of emergency inventory. Also, they considered preventive and recovery policies at the same time. The results of their study state that maintaining a contingency stock strategy is always recommended, but considering multiple suppliers and additional reserve capacity is not always preferred to reduce the adverse effect of disruptions in the case study under investigation (cartridge manufacturing). Hasani et al. (2021), using a multi-objective nonlinear model, maximized profit, minimized facilities, and considered resilience criteria.

Kurpjuweit et al. (2019) showed that AM in the supply chain faces challenges, including copying and manipulating digital files created during production and processing. These problems can be solved with the help of blockchain technology. Also, they used interviews and the Delphi method to investigate the potential that blockchain creates in AM and found that an AM platform based on blockchain expands the visibility of the supply chain. It advances the digitalization of the chain and helps the emergence of common factory systems. Ghimire et al. (2021) discussed how and why blockchain technology can be used with AM and other new technologies to keep pace with current consumer production demands. They addressed the problems in the manufacturing industry and how blockchain can be used in AM to reduce problems, and provided rough guidelines for researchers or organizations looking to integrate blockchain into their supply chain.

Although prior studies have explored the role of AM, blockchain, and resilience in supply chain management, most have been limited to conceptual models, simulations, or narrow aspects such as facility location, cost reduction, or isolated risk factors. To date, there is no comprehensive optimization model that simultaneously designs a resilient multi-level supply chain network, integrates traditional and AM capabilities, employs blockchain-based smart contracts for transparency and supplier selection, and incorporates exchange rate risks in a realistic operational context. This paper addresses these gaps by proposing a novel MILP-based optimization framework that unifies these dimensions and validates its effectiveness through a real-world case study. Table 1 shows the review of each paper by its constraints and objective function.

**Table 1.** Summary of past related optimization studies

| Classification | Authors | Decision variables | Model solution method | The purpose of the model | Case Study |
|---|---|---|---|---|---|
| Resilient supply chain | Torabi (2015) | The amount of stock, the choice of suppliers | Two-stage probabilistic combined two-objective stochastic programming form | Minimize costs, minimize risk | Numerical examples |
| | Cardoso et al. (2015) | Supplier selection, stock level | Integer combinatorial linear programming, uncertainty in demand | Minimize costs | European Company |
| | Aloui et al. (2021) | Inventory, location selection | Two-stage random mixed integer programming demands uncertainty | Minimize costs | Numerical examples |
| | Taleizadeh et al., (2022) | Unit purchase price of used items, emergency inventory amount, the tax rate | Two-level programming, Stackelberg game model | Optimizing a sustainable supply chain by considering resilience factors and pricing decisions | Manufacturing/renovating cartridges in Iran |
| | Hasani et al., (2021) | Inventory amount, number of suppliers, the quantity of each product | Multi-objective nonlinear model | Maximizing profit, minimizing facilities and carbon dioxide | New medical equipment manufacturing company in Iran |
| | Wang et al. (2022) | Retailer's choice, customer's choice | The bi-objective nonlinear model developed an elitist non-dominant sorting genetic algorithm | Minimizing operational and green costs | Numerical examples |
| | Sawik (2022) | The amount of inventory to reduce risk, production in the factory, the amount of supply of | A multi-portfolio approach and scenario-based MIP (mixed integer | Minimizing production costs and maximizing estimated demand | Original equipment manufacturer in China |

| Classification | Authors | Decision variables | Model solution method | The purpose of the model | Case Study |
|---|---|---|---|---|---|
| | | parts by the supplier, production inventory in the factory, lack of production in the factory | programming) stochastic models | | |
| | Boskabadi et al., (2022) | Choosing the optimal number, location of factories and distribution centers to open | Multi-objective mixed integer nonlinearity, demand uncertainty | Minimizing the total cost of the network, maximizing net profit per capita for each human resource, and increasing resilience | Italian International Electronics Company |
| | Shokouhifar and Ranjbarimesan (2022) | Demand | Deep learning, multivariate time series | Demand forecasting | Iranian blood donation organization |
| Supply chain considering AM | Chung et al., (2018) | Number of factories, number of vehicles, amount of production | An optimization model for supply chain design and operations, with dynamic connectivity of smart factories | Minimization of total costs consisting of fixed costs, production, and transportation costs | Numerical examples |

## 3. Methodology

Due to the expansion of digital technologies, many manufacturers have gradually started producing 3D printers. It is a new mode of production where manufacturers are located at the place of distributors. Consumers can participate in the design of their order plan and receive their goods within a shorter period after placing the order (Chowdhury et al., 2023). Low transportation costs and no need to store final products are essential features of this type of production. The main difference between AM and TM is that manufacturing with 3D printers occurs through a digital file, eliminating the cutting, casting, and machining processes, reducing supply chain levels, and bringing consumers directly to manufacturing. They can directly interact and benefit from lowered costs, which implies that the use of AM is essential to create an unshakeable supply chain. First, the problem studied in this work is described, and then the optimization model is introduced. According to Fig 1, the research method provides a general framework for modeling and problem-solving. Transportation optimization is another critical element in the resilient supply chain model. By optimizing transportation routes and modes, companies can reduce transportation costs and minimize the impact of exchange rate fluctuations on transportation expenses. In addition, supplier relationship management can help companies develop a more diverse supplier base, thereby reducing the reliance on a single supplier and mitigating the impact of exchange rate fluctuations on supply chain performance.

Overall, exchange rate risk is crucial in supply chain management, particularly for international markets (Han et al., 2023). Organizations may adopt a resilient supply chain approach that applies measures of risk management and flexibility to counteract the impact of exchange rate volatility. A combination of an optimization model with demand forecasting, inventory management, transportation optimization, and supplier relationship management can help organizations develop a resilient supply chain that can withstand exchange rate issues.

In a healthy supply chain, cost and demand are equally important objective functions that need to be optimized together. The cost objective function aims at minimizing the total cost of supply chain operations, including procurement cost, production cost, inventory cost, and transportation cost. In the meantime, the demand objective function aims to fulfill customer orders and make the supply chain adaptive to changes in the market environment. Companies have to optimize different parameters to achieve the utmost cost and demand objective functions. Demand forecasting is among the means through which companies can effectively predict the demand for products and services. It provides a guarantee that production and inventory quantities are consistent with customer demand, and this lowers the possibility of stockout or overstocking. Secondly, inventory optimization techniques can be used to decrease the costs of holding inventory without compromising the target inventory levels. The cost reduction and satisfaction of customers are guaranteed as the products are provided whenever needed (Arabsheybani et al., 2023).

Third, transportation optimization techniques can be used to minimize the transportation cost while delivering the products at the right time. It may involve choosing the most appropriate routes and modes of transportation at suitable costs, speed, and dependability. Fourth, supplier relationship management can be utilized in creating efficient relationships with the suppliers and making the supply chain agile and robust towards accommodating changes in the market. This can involve discovering and working with several suppliers, negotiating favorable terms and conditions, and having contingency arrangements for supply disruptions. Lastly, cost and demand objective function optimization is crucial in building a sustainable supply chain. Through the use of advanced technologies and techniques such as demand planning, inventory management, transport planning, and supplier relationship management, companies are capable of generating a supply network that is immune to turmoil in the market and delivers customer satisfaction at lower costs. The epsilon constraint method is used in order to simplify the model to a single objective, and the Benders decomposition algorithm is used in order to solve the model.

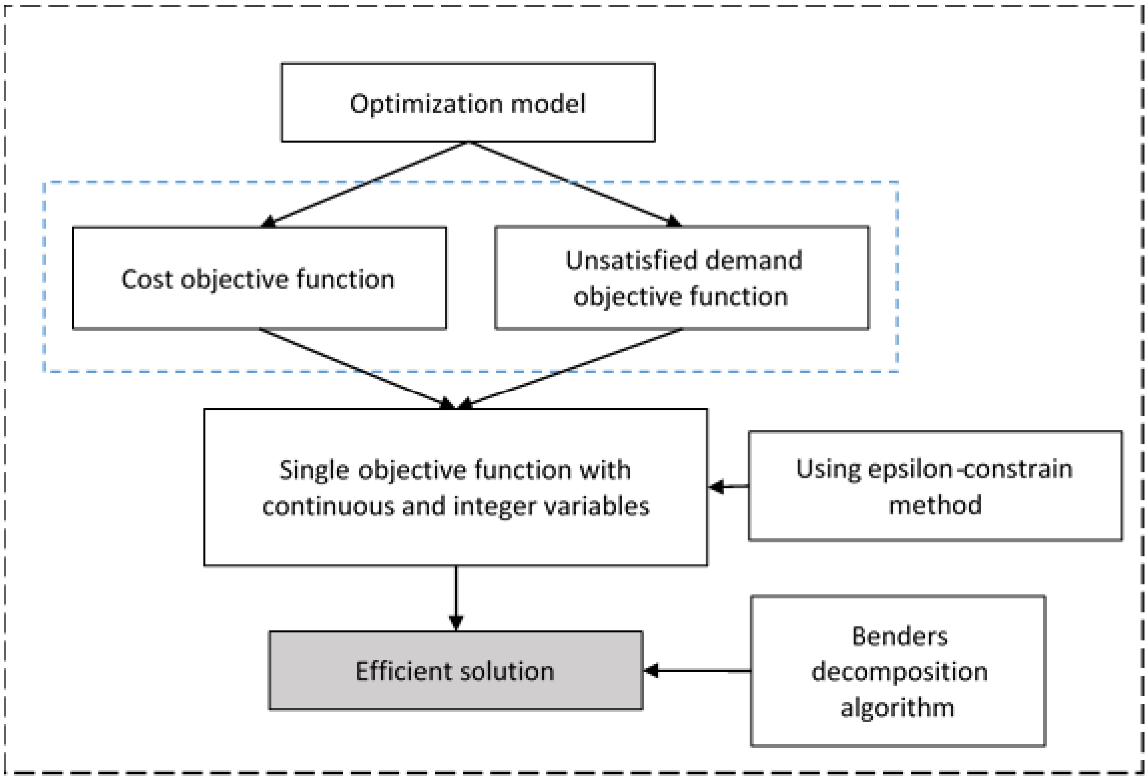


**Fig 1.** The framework of the study

### 3.1 Problem description and model formulation

In this model, there are two routes for the supplier to transfer the raw materials through the modes of transportation, and according to the capacity of each of the means of transportation, to the traditional manufacturer, the main and local distributors with the ability of AM. Each of these places has a limited capacity, so the maximum amount of materials transported can be as much as its capacity. Further, with the aim of cost optimization, only those that create lower costs for the supply chain are selected among the candidate points for TM and AM. After establishing each of the factories, the production process begins. This process can be done in two ways for traditional factories: the traditional manufacturer can do all the steps of manufacturing the product itself, or outsource a part of the production process to the main distributors with AM capability. In this transition, the flow of parts is limited by the capacity of vehicles and the main and local distributors with AM capabilities. Also, the product produced in the traditional factory is transferred to the main distributor (the capacity of the main distributor and means of transportation are limited; according to this limitation, the optimal amount of product flow is estimated). Also, the products produced in the main distributor with add-on capability are transferred to the local distributor. Finally, all the product flows that have been transferred from the traditional manufacturer and the main distributor with add-on capability to the local distributor are allocated to the customers. It will be given. In general, this network has changeable levels, which are determined by specifying the type of production. Since each of the levels of the supply chain may undergo disruptions during the supply chain network, it is vital to examine the risks that may affect consumer demand. Disturbances such as inflation and an increase in the exchange rate can increase the price of raw materials and products and reduce the power of producers and consumers. Therefore, these risks are checked in this network to prevent maximum damage to the network.

On the other hand, changes in exchange rates and inflation require infrastructure in the supply chain that helps to make information more transparent in the network, which includes new technologies such as blockchain, smart contracts, and smart factories. The application of these technologies creates changes in the product demand, which is used in this network to improve the system's resilience and reduce the exchange rate risk using the blockchain platform and smart contract. On the other hand, inflation affects all levels of the network and can reduce the demand elasticity of producers, distributors, and customers. In general, in the network, the disturbance of the exchange rate and inflation is investigated with three low, medium, and severe levels with different probabilities. The risk level refers to the severity of the disruption, which is determined by the disruption's duration, the supplier's available capacity, the order fulfillment rate, etc. The higher the risk level, the more severe the disruption and the greater the business impact.

The low level indicates normal conditions without disruptions, including the full available capacity and the complete fulfillment of the full order. These smart contracts with backup suppliers can help make the network more resilient. Therefore, to increase resilience and reduce the risks of any risk, management arrangements in the supply chain should be considered, which include smart contracts with supporting suppliers for additive manufacturers to deal with the risk of accepting digital currency and traditional contracts for traditional manufacturers. Since these disturbances can cause untimely responses to demand, this model seeks to minimize the unmet demand in the network to increase resilience and deal with disturbances. The multi-level supply chain considered in this work consists of suppliers, TM and AM manufacturing, the Regional Distribution Centers (RDC), and the Local Distributor Center (LDC). Figure 2 shows the conceptual model of the research. That shows the changeable levels of the supply chain, which have been created due to the presence of factories with AM of this structure (the supplier can be connected to both additive and traditional factories. Additionally, the additive factory can be connected to the distributor, the main one, or it can be installed in the place of the Regional distributors; in this case, the number of levels increases to five. A hybrid AM and TM in a supply chain is obtained by combining them. In addition, due to the ability of AM, the RDC is removed, and production is done using a 3D printer at the LDC location. In this case, the number of levels is reduced to four. On the other hand, AM factories can produce part of their components and products through 3D printers or produce all their products in a traditional factory. In general, the relationship between factories and other components of the supply chain is shown in Fig. 2.

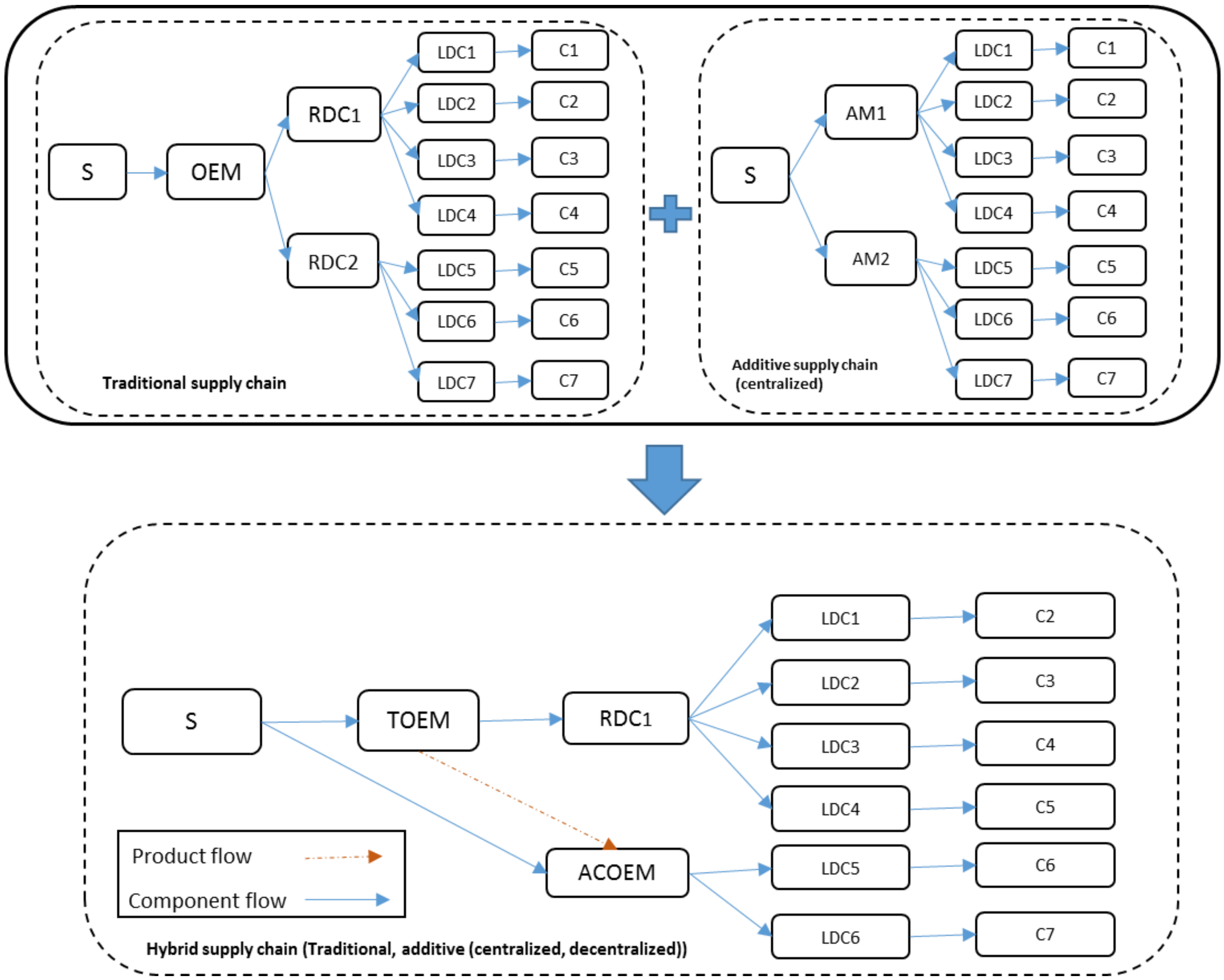


**Fig 2.** The structure of the AM-TM supply chain

## 3.2 Case study

The subject of study in this paper is the supply chain of the Electrolux home appliance industry with vacuum cleaner products. Since many foreign companies are operating in this competitive industry, in this study, an attempt has been made to examine a company that has experience implementing this technology, has published its expertise in the form of reports, or has been previously studied by other researchers. Therefore, the Electrolux company has been investigated. This company operates in Europe. In the competitive industries of home appliances, providing services and products while having the necessary quality, with lower costs, and in shorter times is essential. Today, the use of AM technology in prototyping and the early stages of product development has provided many benefits to companies. In recent years, the use of AM has been growing in the home appliance industry. Therefore, this paper investigates the effect of this technology's introduction on the supply chain of foreign home appliance companies.

Multinational home appliance manufacturer Electrolux is conducting a feasibility study on on-demand AM spare parts. Swedish home appliance manufacturer Electrolux has partnered with Upper Parts Trade, a tech startup in Singapore, to conduct a feasibility study on 3D-printed spare parts that can be manufactured and distributed on demand. The goal is to reduce inventory costs and delivery time. Today, it is common practice for manufacturers to keep a stock of spare parts after the production of a device is finished. For example, when a customer needs a broken washing machine repaired, readily available spare parts increase customer satisfaction. But these parts must be stored in warehouses, which incurs labor and maintenance costs. In addition, some components gather dust in a warehouse until they are finally unusable. If other factors cannot be obtained through mass production methods, costs can increase further. For these back-to-back scenarios, manufacturers typically stock parts centrally in factories or distribution centers. Shipping parts from distribution centers to consumers takes weeks. Electrolux is investigating the possibility of implementing AM for spare parts to deal with the challenges of reducing inventory and improving efficiency. On the other hand, the Asia-Pacific division of Electrolux wants to switch to a model that can produce parts on demand and close to demand points (through a network of AM service providers). This means zero physical inventory and fast shipping. For this purpose, this research introduces the optimal combination of three-dimensional parts and traditional production for the supply chain of home appliances (Lauth et al., 2023). A vacuum cleaner is a product selected for production using additive and traditional. Since this product can be produced both traditionally and additively, this product in the Electrolux factory consists of 25 components, which are parts.

In this model, the marginal values (shadow prices) of the constraints reveal where the Electrolux supply chain experiences its most critical bottlenecks. Each constraint, such as transportation capacity, facility capacity (TM, AM, RDC, and LDC), and cost or disruption limits, has an associated marginal value that shows the improvement in cost efficiency or demand fulfillment if that constraint were relaxed by one unit. The case study results indicate that the highest marginal values are associated with transportation flows and local distributor capacity under AM deployment, meaning that even small increases in these areas generate significant reductions in unmet demand and delivery times. In contrast, the marginal values for traditional manufacturing capacity were relatively low, suggesting that expanding TM facilities yields limited benefits compared to strengthening AM-enabled nodes.

Under disruption scenarios such as inflation and exchange rate volatility, the marginal values change dynamically, highlighting the supply chain’s shifting vulnerabilities. For example, in severe disruption cases, the marginal value of supplier capacity and backup AM-enabled production increases substantially, showing that these points become critical for resilience. This indicates that investments in local AM capacity, blockchain-supported smart contracts, and backup suppliers provide the highest returns under risk conditions.

### 3.3 Assumptions of the model

Strategic and operational decisions include (1) the location of the physical TRs, AMs, RDCs, and LDCs, (2) the quantity of TR and AM orders from suppliers, (3) the inventory levels of TRs and physical AM, RDC, and LDC and (4) quantity of product shipped from the supplier to TR or AM and from TR or AM to DRC or LDC and ultimately to consumers. This study aims to design a mixed and multi-level supply chain network. The assumptions of the suggested optimization model are:

1. Two modes of transportation, if any, are considered in each of the supply chain routes (air and land)
2. Each level of the supply chain has a specific and limited capacity.
3. It is a single-product and single-period model.
4. Both production methods (traditional and AM) can carry out the entire production process. Still, due to the production costs, it may be completed by combined production (part of the process is carried out in the traditional manufacturing factory, and another factor in the AM factory).
5. The supply chain levels are changeable; they can have five, four, or three levels depending on the selected production method.

### 3.4 Introduction of model symbols

Table 2 describes the model's symbols, parameters, and variables.

**Table 2.** Description of the notations

| Classification | Index | Description |
|---|---|---|
| Manufacturer location index | a | The set of production locations with the traditional production method (a∈A) |
| | k | A set of manufacturing locations with an AM method (k∈ $K$) |
| | h | The set of customer locations (h∈H) |
| Distributor location index | b | Set of supplier locations (b∈B) |
| | d | The set of regional distribution locations (d∈D) |
| | l | The set of local distribution locations (l∈L) |
| | v | Set of means of transportation (v∈V) |
| Process | m | Set of product manufacturing processes (m∈M) |
| Scenario | s | Number of scenarios (s∈S) |
| | **Parameters** | **Definition** |
| Costs parameters | $CFA_a$ | The fixed cost of establishing the factory in the location a |
| | $CFD_d$ | The fixed cost of establishing the regional distributor in location d |
| | $CFL_l$ | The fixed cost of establishing the regional distributor in location l |
| | $CFK_k$ | The fixed cost of establishing the factory in K |
| | $CM_{ma}$ | The cost of setting up process m in a factory of type a |
| | $CMK_{mk}$ | The cost of setting up process m in a factory of type k |
| | $CPA_{ma}$ | Operating cost of process m in type a factory |
| | $CPK_{mk}$ | Operating cost of process m in factory type k |
| | $CV_{vba}$ | The cost of transportation by vehicle v from supplier location b to factory a |
| | $CVD_{vad}$ | The cost of transportation by vehicle v from the factory a to the regional distributor d |
| | $CVM_{vbk}$ | The cost of transportation by vehicle v from supplier b to factory k |
| | $CVK_{vamk}$ | Transportation cost to carry out process m with vehicle v from manufacturer a to factory k |
| | $CVL_{vdl}$ | Transportation cost by vehicle v from the regional distributor d to the local distributor l |
| | $CVH_{vkl}$ | Transportation cost with vehicle v from producer location k to local distributor l |
| | $CB_b$ | The cost of making a smart contract with the supplier b |
| | $CC_b$ | The cost of making a traditional contract with a supplier b |
| | $G_b$ | The purchase price through the blockchain platform from the supplier b |

| | | |
|---|---|---|
| Price | $G1_b$ | The traditional purchase price from the supplier b |
| | $LA_{ma}$ | Process envelope matrix m for plant a |
| | $LK_{mk}$ | Process coverage matrix m for plant k |
| Capacity | $pca_a$ | Factory capacity a |
| | $pcd_d$ | The capacity of the regional distributor d |
| | $pcl_l$ | The capacity of the local distributor l |
| | $pck_k$ | Factory capacity k |
| | $pcv_v$ | The capacity of vehicle type v |
| Demand | $R_h$ | Customer demand h |
| | $\bar{M}$ | A big number |
| | **Variables** | **Definition** |
| | $\varphi b_{vba}$ | If it is transported by vehicle v from supplier b to a, one, otherwise zero |
| | $\varphi d_{vad}$ | If it is transported from the factory a to d by vehicle v, one, otherwise zero |
| | $\varphi k_{vbk}$ | If transportation from supplier b to factory k is done with vehicle v, one, otherwise zero |
| | $\varphi a_{vamk}$ | If transportation from the factory a to k is done by vehicle v for process m, one, otherwise zero |
| | $\varphi l_{vdl}$ | If transportation from the factory a to k by vehicle v is done for process m, one, otherwise zero |
| | $\varphi h_{vkl}$ | If transportation from supplier b to k is done by vehicle type v, one, otherwise zero |
| Location | $\alpha_a$ | If the traditional factory is established in location a, one, otherwise zero |
| | $\delta_d$ | If the regional distributor is established in location d, one, otherwise zero |
| | $\varepsilon_l$ | If the local distributor is established at location l, one, otherwise zero |
| | $\gamma_k$ | If the additive manufacture is established at location k, one otherwise zero |
| Contract | $w_b$ | If the smart contract is closed with supplier, one, otherwise zero |
| | $n_b$ | If the traditional contract is closed with supplier b, one, otherwise zero |
| Buy | $U_b$ | The number of smart purchases from the supplier b |
| | $U1_b$ | The number of traditional purchases from the supplier b |
| Process | $ya_{ma}$ | If process m is done in factory a, one, otherwise zero |
| | $yk_{mk}$ | If process m is carried out in factory k, one, otherwise zero |
| | $\theta_{ma}$ | The production value from process m in factory a |
| Product flow | $\tau_{vba}$ | The product flow that is transported from place b to place a by vehicle v |
| | $\omega_{vad}$ | The product flow that is transported from a to d by vehicle v |
| | $\mu_{vdl}$ | The product flow that is transported from d to l by vehicle v |

| | | |
|---|---|---|
| | $\sigma_{vkl}$ | The product flow that is transported from k to l by vehicle v |
| | $\vartheta_{vbk}$ | The product flow that is transported from b to k by vehicle v |
| | $\pi_{mk}$ | The production value from process m in factory k |
| Product flow in scenario s | $\theta_{ma}^{s}$ | The production value from process m in factory a in scenario s |
| | $\tau_{vba}^{s}$ | The product flow that is transported from place b to place a by vehicle v in scenario s |
| | $\vartheta_{vbk}^{s}$ | The product flow that is transported from b to k by vehicle v in scenario s |
| | $\sigma_{vkl}^{s}$ | The product flow that is transported from k to l by vehicle v in scenario s |
| | $\omega_{vad}^{s}$ | The product flow that is transported from a to d by vehicle v in scenario s |
| | $\mu_{vdl}^{s}$ | The product flow that is transported from d to l by vehicle v in scenario s |
| | $\pi_{mk}^{s}$ | The production value from process m in factory k in scenario s |

### 3.5 Model formulation

The strategic and operational decisions, such as the locations of the physical supply chain's facilities, the type of vehicles, the manufacturing process, and the type of factory, are influenced by transportation and operational costs. All notations used in the mathematical programming model are listed in Table 2. The total costs of the supply chain with hybrid types of manufacturing, represented by costs, are given as follows:

$$
\begin{aligned}
min \sum_{a\in A} CFA_a\,\alpha_a &+ \sum_{k\in K} CFK_k\,\gamma_k + \sum_{d\in D} CFD_d\delta_d + \sum_{l\in L} CFL_l\varepsilon_l + \sum_{m\in M}\sum_{a\in A}(CMA_{ma}\,ya_{ma} + CPA_{ma}\,\theta_{ma}) \\
&+ \sum_{m\in M}\sum_{k\in K}(CMk_{mk}\,yk_{mk} + CPk_{mk}\,\pi_{mk}) + \sum_{a\in A}\sum_{m\in M}\sum_{k\in K}\sum_{v\in V} CVK_{vamk}\,\varphi a_{vmak}\theta_{ma} \\
&+ \sum_{b\in B}\sum_{a\in A}\sum_{v\in V} CV_{vba}\,\tau_{vba}\,\varphi b_{vba} + \sum_{b\in B}\sum_{k\in K}\sum_{v\in V} CVM_{vbk}\,\vartheta_{vbk}\,\varphi k_{vbk} \\
&+ \sum_{d\in D}\sum_{a\in A}\sum_{v\in V} CVD_{vad}\,\omega_{vad}\,\varphi d_{vad} + \sum_{l\in L}\sum_{v\in V}\sum_{d\in D} CVL_{vdl}\,\mu_{vdl}\varphi l_{vdl} + \sum_{k\in K}\sum_{v\in V}\sum_{l\in L} CVH_{vkl}\,\sigma_{vkl}\varphi h_{vkl} \\
&+ \sum_{b\in B} CB_b w_b + \sum_{b\in B} CC_b n_b + \sum_{b\in B} G_b U_b\,\rho + \sum_{b\in B} G1_b U1_b\,\beta \\
&- \sum_{S} Pr_s\Big(\sum_{m\in M}\sum_{a\in A} CPA_{ma}\,(\theta_{ma} - \theta_{ma}^{s}) + \sum_{m\in M}\sum_{a\in A} CPk_{mk}\,(\pi_{mk} - \pi_{mk}^{s}) \\
&+ \sum_{m\in M}\sum_{a\in A}\sum_{v\in V}\sum_{k\in K} CVK_{vamk}\,\varphi a_{vmak}\,(\theta_{ma} - \theta_{ma}^{s}) \\
&+ \sum_{b\in B}\sum_{a\in A}\sum_{v\in V} CV_{vba}\varphi b_{vba}(\tau_{vba} - \tau_{vba}^{s}) + \sum_{b\in B}\sum_{k\in K}\sum_{v\in V} CVM_{vbk}\varphi k_{vbk}(\vartheta_{vbk} - \vartheta_{vbk}^{s}) + \\
&+ \sum_{k\in K}\sum_{v\in V}\sum_{l\in L} CVH_{vkl}\,\varphi h_{vkl}(\sigma_{vkl} - \sigma_{vkl}^{s}) + \sum_{d\in D}\sum_{a\in A}\sum_{v\in V} CVD_{vad}\,\varphi d_{vad}(\omega_{vad} - \omega_{vad}^{s}) \\
&+ \sum_{d\in D}\sum_{l\in L}\sum_{v\in V} CVL_{vdl}\,\varphi l_{vdl}(\mu_{vdl} - \mu_{vdl}^{s})\Big)
\end{aligned} \tag{1}
$$

Eq. 1 shows the objective function of cost minimization, which consists of two main parts (including 24 parts): establishment and operational and transportation costs. The establishment and operating costs include the first to sixth parts of Eq. 1, which show the costs of establishing type TOEM, AOEM factories in the producer's places, the cost of establishing the RDC in place D, the cost of establishing an LDC in place L, the setup and operating cost of process m in the factory of type A and K. Transportation costs include parts 7 to 12 of Eq. 1, which show the transportation cost between two factories (A and K), transportation cost from the supplier to the manufacturer, transportation cost and the transfer from the manufacturer to the RDC, and the cost of transportation from the RDC to the LDC. Also, the costs that are imposed to create resilience in the system are the cost of signing a smart contract, the cost of signing a traditional contract, the cost of purchasing from a backup supplier smartly, the cost of traditional purchase from a backup supplier, and the difference in production and transportation costs in the second stage (parts 13-16). The different product cost values in each scenario are examined in parts 17-24 of Eq. 1. The Second objective function for minimizing unsatisfied demand is examined below.

$$\min(\sum_{v\in V}\sum_{h\in H}\sum_{l\in L}\sum_{d\in D}\max\{0,R_h-\mu_{vdl}\}+\sum_{v\in V}\sum_{h\in H}\sum_{l\in L}\sum_{k\in K}\max\{0,R_h-\sigma_{vkl}\} \\ +\sum_{s\in S}P_s(\sum_{v\in V}\sum_{h\in H}\sum_{l\in L}\sum_{d\in D}\max\{0,R_h-\mu^s_{vdl}\}+\sum_{v\in V}\sum_{h\in H}\sum_{l\in L}\sum_{k\in K}\max\{0,R_h-\sigma^s_{vkl}\})) \tag{2}$$

Eq. 2 minimizes unsatisfied demand. So that the difference between the demand and the amount of inventory available in the LDC is minimized, this objective function can contribute to system resilience by minimizing unsatisfied demands. The third and fourth parts of the equation describe the difference between the demand and the inventory of the LDC in the disturbance's occurrence stage.

$$\sum_{a\in A}LA_{ma}\alpha_a+\sum_{k\in K}LK_{mk}\gamma_k\geq 1 \quad \forall m \tag{3}$$

$$ya_{ma}\leq LA_{ma}\alpha_a \quad \forall m,a \tag{4}$$

$$yk_{mk}\leq LK_{mk}\gamma_k \quad \forall m,k \tag{5}$$

$$\sum_{m\in M}\sum_{a\in A}\theta_{ma}\leq\sum_{a\in A}\alpha_a pca_a \tag{6}$$

$$\sum_{m\in M}\sum_{k\in K}\pi_{mk}\leq\sum_{k\in K}\gamma_k pck_k \tag{7}$$

$$\sum_{b\in B}\sum_{v\in V}\tau_{vba}\leq\alpha_a pca_a \quad \forall a \tag{8}$$

$$\sum_{a\in A}\sum_{v\in V}\omega_{vad}\leq\delta_d pcd_d \quad \forall d \tag{9}$$

$$\sum_{k\in K}\sum_{v\in V}\sigma_{vkl}+\sum_{d\in D}\sum_{v\in V}\mu_{vdl}\leq\varepsilon_l pcl_l \quad \forall l \tag{10}$$

$$\sum_{b\in B}\sum_{v\in V}\vartheta_{vbk}\leq\gamma_k pck_k \quad \forall k \tag{11}$$

$$\sum_{v\in V}\varphi k_{vmak}\leq ya_{ma} \quad \forall m,a,k \tag{12}$$

$$\sum_{v \in V} \varphi b_{vba} = 1 \quad \forall a, b \tag{13}$$

$$\sum_{v \in V} \varphi k_{vbk} = 1 \quad \forall b, k \tag{14}$$

$$\sum_{v \in V} \varphi h_{vkl} = 1 \quad \forall l, k \tag{15}$$

$$\sum_{v \in V} \varphi l_{vdl} = 1 \quad \forall d, l \tag{16}$$

$$\sum_{v \in V} \varphi d_{vad} = 1 \quad \forall d, a \tag{17}$$

$$\sum_{v \in V} \varphi d_{vad} + \sum_{v \in V} \sum_{m \in M} \varphi a_{vmak} = 1 \quad \forall k, a, d \tag{18}$$

$$\sum_{l \in L} \varepsilon_l \geq 1 \tag{19}$$

$$\sum_{d \in D} \delta_d \geq 1 \tag{20}$$

$$\sum_{a \in A} \alpha_a \geq 1 \tag{21}$$

$$\sum_{k \in K} \gamma_k \geq 1 \tag{22}$$

$$\sum_{b \in B} \sum_{v \in V} \tau_{vba} \leq \sum_{b \in B} \sum_{v \in V} \varphi b_{vba} pcv_v \quad \forall a \tag{23}$$

$$\sum_{a \in A} \sum_{v \in V} \omega_{vad} \leq \sum_{a \in A} \sum_{v \in V} \varphi d_{vad} pcv_v \quad \forall d \tag{24}$$

$$\sum_{k \in K} \sum_{v \in V} \sigma_{vkl} + \sum_{d \in D} \sum_{v \in V} \mu_{vdl} \leq \sum_{k \in K} \sum_{d \in D} \sum_{v \in V} (\varphi l_{vdl} + \varphi h_{vkl}) pcv_v \quad \forall l \tag{25}$$

$$\sum_{b \in B} \sum_{v \in V} \vartheta_{vbk} \leq \sum_{b \in B} \sum_{v \in V} \varphi k_{vbk} pck_k \quad \forall k \tag{26}$$

$$\tau^s_{vba} \leq \alpha_a \bar{M} \quad \forall b, a, v \tag{27}$$

$$\vartheta^s_{vbk} \leq \gamma_k \bar{M} \quad \forall b, k, v \tag{28}$$

$$\sigma^s_{vkl} \leq \varepsilon_l \bar{M} \quad \forall l, k, v \tag{29}$$

$$\omega^s_{vad} \leq \delta_d \bar{M} \quad \forall a, d, v \tag{30}$$

$$\mu^s_{vdl} \leq \varepsilon_l \bar{M} \quad \forall d, l, v \tag{31}$$

$$\rho = \frac{\sum_{a \in A} \alpha_a}{\sum_{a \in A} \alpha_a + \sum_{k \in K} \gamma_k} \tag{32}$$

$$\beta = \frac{\sum_{k \in K} \gamma_k}{\sum_{a \in A} \alpha_a + \sum_{k \in K} \gamma_k} \tag{33}$$

$$\sum_{d \in D} \sum_{l \in L} \sum_{v \in V} \mu_{vdl}^{s} + \sum_{b \in B} G_b U_b \alpha + \sum_{b \in B} G1_b U1_b \beta \geq \sum_{h \in H} R_h \quad \forall s \tag{34}$$

$$\sum_{k \in K} \sum_{l \in L} \sum_{v \in V} \sigma_{vkl}^{s} + \sum_{b \in B} G_b U_b \alpha + \sum_{b \in B} G1_b U1_b \beta \geq \sum_{h \in H} R_h \quad \forall s \tag{35}$$

$$U_b \leq w_b \bar{M} \quad \forall b \tag{36}$$

$$U1_b \leq n_b \bar{M} \quad \forall b \tag{37}$$

$$\alpha_a, \delta_d, \varepsilon_l, \gamma_k \in \{0,1\} \tag{38}$$

$$\varphi d_{vad}, \varphi l_{vdl}, \varphi b_{vba}, \varphi k_{vbk}, \varphi h_{vkl}, \varphi a_{vmak} \in \{0,1\} \tag{39}$$

$$ya_{ma}, yk_{mk} \in \{0,1\} \tag{40}$$

$$\theta_{ma}, \tau_{vba}, \omega_{vad}, \mu_{vdl}, \sigma_{vkl}, \vartheta_{vbk}, \pi_{mk} \geq 0 \tag{41}$$

Eq. 3 states that all processes should be covered. Eqs. 4 and 5 show that the activities are first assigned in the factory and then performed (if an activity is executed, it is assigned to the factory). Eqs 6 and 7 emphasize that the amount of production should be less than or equal to the production capacity (Shukla and Shyam, 2023). Eqs. 8 to 11 show that the number of goods transported from the manufacturer to the RDC and the RDC to the local should equal the factory's capacity. Eq. 12 shows that the first process m is done in factory a, then transportation is done to factory k. Eqs 13 to 17 display that the modes of transportation must cover all routes (Chung et al., 2018). Eq. 18 states that the raw materials are transferred from the supplier to the TM or from the supplier to the AM, which is supposed to carry out part of the process in the factory. Eqs 19 to 22 show that there must be at least one manufacturer, RDC, and local distributor. Also, Eqs 23-26 show that the amount of stock flow in each level should be, at most, equal to the capacity of each vehicle. Eqs. 27 to 31 are auxiliary constraints for getting the value of the variables after the scenario occurs. Eqs. 32 and 33 show the rate of creation of 3D and traditional factories. Eqs. 34 and 35 show that the total inventory under scenario s is always greater than the total demand. Eqs. 36 and 37 state that the smart and traditional contract is first closed, and then the purchase is made. Eqs. 38 to 41 show each variable's allowed change intervals.

### 3.5.1 Linearization method

Two independent non-linear expressions of the objective function multiply binary variables by themselves and contain a continuous variable. However, there are ways to linearize these nonlinear factors. First, Williams (2013) proposes the linearization of a product of two continuous and binary variables: $A_1$ and $B_1$ should be binary and continuous, respectively. The non-linear expression $a_1 \times b_1$ can be changed to the continuous expression $z = a_1 \times b_1$ by defining a continuous variable z. The following constraints in Eq. 42 should then be embedded into the problem formulation.

$$
\begin{aligned}
& z \le b_1 \\
& z \le M .a_1 \\
& z \ge b_1 - M .(1-a_1) \\
& z \ge 0
\end{aligned} \tag{42}
$$

As a result, the objective function was a separable quadratic function that piecewise linear formulas might approximate. Additionally, problems involving Mixed Integer Quadratic Programming (MIQP) can be solved in both convex and non-convex situations using the barrier technique and the GAMS solver. For finding the variables' value, the model in GAMS is run based on the procedure given before.

## 4. Results

### 4.1 Robust optimization

To deal with the problem of this study, the skills and knowledge available in household appliance supply chain management are used. Mathematical programming is used to model it, including stochastic programming and scenario-based robust optimization. In two-stage stochastic planning, decisions are divided into two stages, and in this study, decisions are divided into two stages before the event of a disturbance and after the occurrence of an event. In the first stage, the decision maker makes a decision, and then after the event of a stochastic event that affects the performance of the first stage (which in this research are the same disturbances that the chain is facing), it is decided to compensate for these possible adverse effects, in this regard, measures such as strengthening projects, increasing the capacity of suppliers and distributors, signing a contract with a foreign supplier, or covering several areas a distributor or supplier in the model applies it. But since the parameters must follow a probability distribution to be able to use stochastic programming. Due to the lack of access to high-dimensional data that can be used to estimate the probability distribution, it becomes difficult to solve this model. So, the best thing to do is to convert the two-stage planning model to robust planning. Robust planning looks for an answer that is not sensitive to the model's inputs and remains manageable and relatively efficient in the worst cases of uncertainty (Hashemi et al., 2023). There are different approaches and uncertainty spaces for this method. This paper uses a pessimistic approach and a scenario-based uncertainty environment. Because of the existence of disturbances in the network, we are looking for a model that can work well even in the worst conditions. So the result obtained from the robust model can be resistant to uncertainties (Al-Ashhab, 2023).

In this study, disruption with three levels is considered, reducing the capacity of each transportation level and route. Also, the variables affected by the scenario considered for the model are the amount of product production by TM or AM, the amount of product that is transferred from the manufacturer to the main distributor, the amount of product that is sent from the distributor the main one is transferred to the local distributor, the amount of the product that is transferred from the local distributor to the customer and the number of product sales by the local distributor.

Fig 3 shows the overview of the steps mentioned to implement the disturbance and uncertainty process in the model. Also, the smart contract model uses it as a binary variable to contract a foreign supplier after creating a disruption scenario in the model. In general, the problem of designing a home appliance supply chain with the combination of additive and traditional manufacturing that is resilient to possible risks (scenarios) in the form of a mathematical model with linear functions, continuous variables, and integers, along with objective cost functions, and the decrease in the amount of unsatisfied demand is expressed. The model has continuous and integer variables. The problem of interest in this paper is solved in small dimensions by GAMS, But in large dimensions, we need a solution method such as using meta-heuristic algorithms to solve it. To validate the model solution results, the problem is solved with two different methods, and the solution results are compared. Due to the presence of two objective functions in the problem, among the solving methods, the epsilon constraint method has been chosen for the model to create efficient solutions. The model is based on the existence of continuous variables and correct numbers. We know that integer complex models belong to the category of NP-hard problems. So that with the increase in the dimensions of the problem, the time to solve the problem increases exponentially. However, the problem of interest in this study can be solved in small dimensions by GAMS, but in large dimensions, we need another solution method to solve it. Among the available methods, the Benders decomposition algorithm, suitable for mixed integer models, has been selected in the category of exact methods. This means that it guarantees that the obtained answer is optimal. Significantly, this method loses its effectiveness in very large dimensions. However, it is efficient in the dimensions considered in this paper.

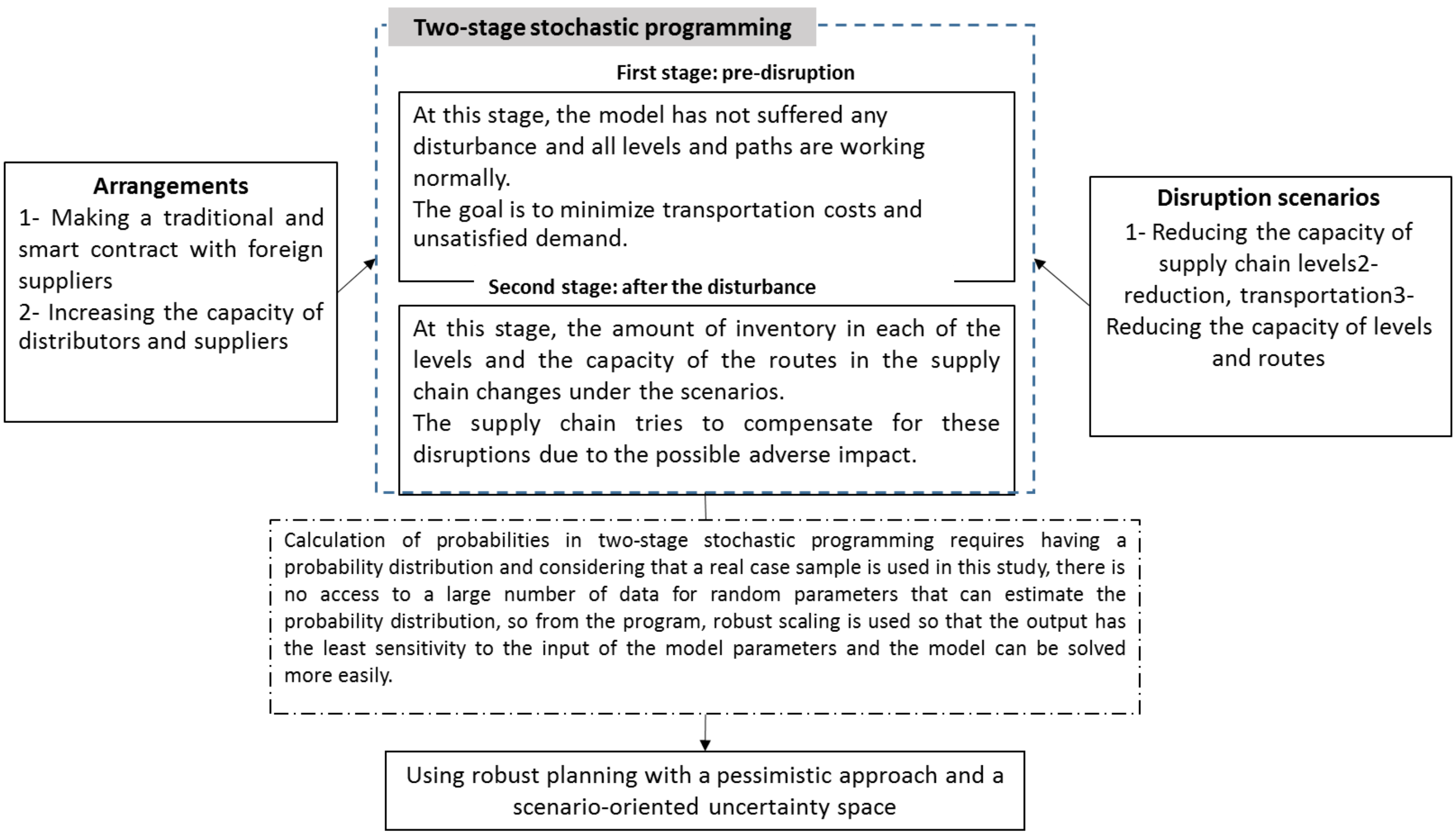


**Fig 3.** Robust planning framework

### 4.2 Epsilon constraint method

Among the existing methods in multi-objective planning, the epsilon constraint method is one that does not require the decision maker's preferred information. As a result, its output is the Pareto answer. To generate several Pareto solutions, it converts the objective function into a constraint, changes the side of the new constraint, and generates the Pareto solution. Eq. 43 shows the exact model in this study (Hu et al., 2023).

$$\begin{aligned} &\min \quad TC(x) \\ &\min \quad \mathrm{Re}(x) \\ &x \in S \end{aligned} \tag{43}$$

*TC(x)* and *Re(x)* show the objective functions. Using the $\varepsilon$-constraint approach, the single-objective model is obtained as Eq. 44.

$$\begin{aligned} &\min \quad TC(x) \\ &\mathrm{Re}(x) \geq \varepsilon \\ &x \in S \end{aligned} \tag{44}$$

### 4.3 Benders decomposition algorithm

Benders' decomposition is a mathematical optimization algorithm for solving mixed-integer linear programming problems involving many constraints. There are many methods to solve this model; in this regard, the Benders decomposition algorithm has a higher ability to solve this type of model, which was first presented by Benders in 1962. This algorithm is based on the decomposition strategy, which seeks to decompose a hard model into several models that are easier to solve. The algorithm decomposes the problem into a master problem and a subproblem. The subproblem is solved repeatedly and used to generate constraints for the master problem. The process is repeated until a feasible solution is found (Borajee et al., 2023). The Benders decomposition algorithm can be expressed mathematically in Eq. 45. Let the mixed-integer linear programming problem be defined.

$$\begin{aligned} &\min\ c_T x \\ &Ax = b \\ &x_j \in Z \text{ for } j \in J \\ &x_j \in R \text{ for } j \notin J \end{aligned} \tag{45}$$

Where *c* is the objective function, *x* is the vector of decision variables, *A* is the constraint matrix, *b* is the right-hand side vector, *J* is the set of integer variables, and *Z* is the set of integers. The Benders decomposition algorithm can be expressed using the following Eqs. 46.

$$\begin{aligned} &\min\ c_T x + \theta \\ &Ax = b \\ &x_j \in R \text{ for } j \notin J \\ &\theta \geq f(y) \end{aligned} \tag{46}$$

Where θ is the dual variable associated with the Benders subproblem, f(y) is the optimal value of the subproblem, and y is a vector of variables in the subproblem. Solve the Benders subproblem is shown in Eq. 47.

$$\max \{f(y) \mid G_y \leq h\} \tag{47}$$

Where *G* is a matrix of coefficients, and *h* is a vector of constants in the Benders subproblem. If the optimal solution of the subproblem is less than $\vartheta$, add the following constraint to the master problem in Eq. 48.

$$\sum_{j\in J} g_j y_j \leq h_0 \tag{48}$$

Where $g_j$ is the coefficient associated with the jth integer variable in the subproblem, and $h_0$ is a constant that is updated after each iteration. Repeat steps 45-48 until a feasible solution is found. The Benders decomposition algorithm is an iterative process that involves solving the master problem and the subproblem repeatedly until a feasible solution is found. The algorithm can be used to solve mixed-integer linear programming problems with a large number of constraints and integer variables.

### 4.4 Sensitivity analysis

We also calibrated the model under three different conditions to better compare the results. First, we assumed that the production and transportation costs of the AM method are very high (we made the costs of this type of production 1000 times higher), so that the model has an optimal value only for the traditional production method. Second, we increased the TM costs by 100 times so that the production could be implemented only through additives, and third, we solved the model with our standard values. Table 3 shows the results of these investigations.

**Table 3.** The comparison between traditional, additive, and hybrid manufacturing

| Type of Manufacturing | Cost Function | Number of factories | Number of main distributors | Number of local distributors |
|---|---|---|---|---|
| TM | 209321 | $\alpha_a$ =6 | $\delta_d$ =20 | $\varepsilon_l$ =35 |
| AM | 160932 | $\gamma_k$ =46 | 0 | $\varepsilon_l$ =20 |
| Hybrid (TM-AM) | 110675 | $\alpha_a$ =3, $\gamma_k$ =10 | $\delta_d$ =14 | $\varepsilon_l$ =29 |

Table 3 notes that AM can be more cost-effective than TM methods for end-usable metal parts. Additionally, Table 2 highlights the high cost of tooling and molds for conventional product casting, which can be reduced using AM. Also, using AM alone may not be economically advantageous relative to hybrid AM-TM due to high material costs and energy expenditure. Therefore, it can be inferred that when AM and traditional manufacturing methods are combined, the total costs can be lower than using either technique alone. Furthermore, AM can be more cost-effective than traditional manufacturing methods due to its ability to remove intermediaries such as tooling and molds.

### 4.5 Computational results

The model is tested in the Electrolux company for a vacuum cleaner product. This product is composed of 25 components. Regarding the study of selected locations for establishing traditional factories in 7 regions, AM in 35 regions, RDC in 25 regions, and local distributors in 60 regions have been considered. The number and optimal points will be determined during the optimization model. It also determines the total amount of customer demand, the amount of production, and product flow at each stage. In this research, the total demand of 40,000 products is considered. This model was implemented in the GAMS software. As a result, the objective function was a separable quadratic function that piecewise linear formulas might approximate. Additionally, problems involving Mixed Integer Quadratic Programming (MIQP) can be solved in both convex and non-convex situations using the barrier technique and the GAMS solver. The cost-effective response based on demand is shown in Fig. 4. This answer is determined according to 5 values for epsilon. As can be seen, with the decrease in the amount of unsatisfied demand, the costs increase, which is self-explanatory of the trade-off between cost and resilience, which is one of the characteristics of efficient solutions.

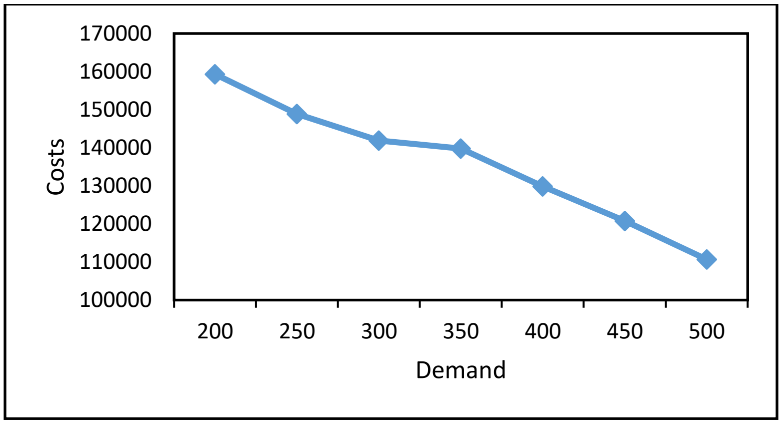


**Fig 4.** The efficient solution in the goal space

Also, the average of costs and demand based on exchange rate risk due to inflation changes is reported in Table 4. Three levels of low, medium, and high inflation have been considered, and the exchange rates for these three levels are 0.2, 0.4, and 0.6. According to Table 4, the more the inflation increases, the more the cost and unsatisfied demand increase.

**Table 4.** Average of the cost and demand function based on scenarios

| Inflation | Exchange rate | Unsatisfied demand | Costs ($) |
|---|---|---|---|
| Low | 0.6 | 500 | 110675 |
| Medium | 0.4 | 200 | 171031 |
| High | 0.2 | 150 | 203462 |

The number of decision variables according to each scenario is specified in Table 5. Figure 5 displays the variations in cost across multiple scenarios. Figure 5 clearly depicts the extent of cost changes for each scenario. It is a well-established fact that inflation impacts the average total cost of goods and services. Therefore, Figure 5 reveals that as the inflation rate increases, there is a corresponding rise in average total costs. However, it is essential to note that other factors beyond inflation may also impact cost changes. For instance, changes in production methods or technology advancements may result in cost fluctuations. Moreover, external factors such as government regulations, taxes, and market competition may also impact cost changes. Therefore, while it is true that inflation plays a critical role in determining the average total costs, it is vital to consider other factors that may influence these costs to obtain a comprehensive understanding of the trends and changes in the data presented in Fig. 5.

**Table 5.** Decision variables' value in each scenario

| Inflation | Exchange rate | Number of vehicles | Number of TM | Number of AM | Number of RDC | Number of LDC |
|---|---|---|---|---|---|---|
| Low | 0.6 | 21 truck, 4 plan | 3 | 29 | 17 | 21 |
| Medium | 0.4 | 32 Truck, 2 Plan | 2 | 25 | 13 | 19 |
| High | 0.2 | 23 Truck, 3 Plan | 2 | 22 | 10 | 16 |

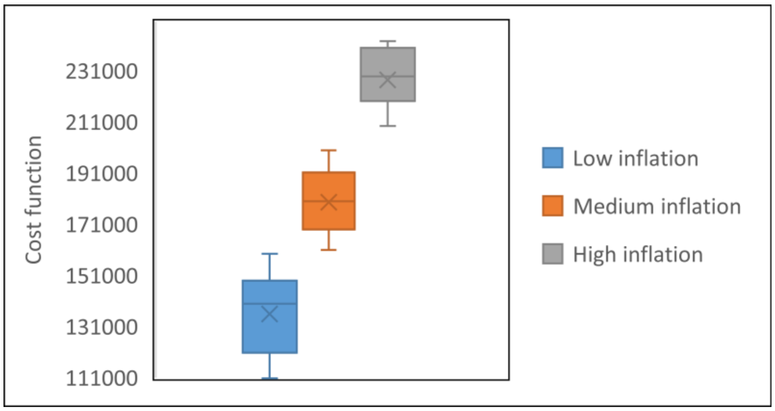


**Fig 5.** High and low limits of the costs in each scenario

In this study, we have analyzed the impact of demand levels, which we consider a variable ranging from 2000 to 5000, on the cost objective function and the decision variables associated with the number of traditional and AM factories and distributors. We utilized a robust modeling approach to optimize the various scenarios and generate meaningful insights. The results demonstrate that the value of the cost objective function is directly proportional to the demand level. As demand increases, so does the total cost associated with manufacturing and distribution. Moreover, the decision variables related to the number of traditional and AM factories and distributors also vary with the changes in demand. However, it is crucial to note that the relationship between demand levels, the objective cost function, and decision variables is not linear. The impact of demand on these factors varies across different scenarios. Other factors like production capacity, supplier lead times, and inventory holding costs may also affect the decision variables. Therefore, the results presented in this study provide valuable insights into the relationship between demand levels, objective cost function, and decision variables. However, further research is required to comprehensively understand the factors that may impact the results and make informed decisions regarding manufacturing and distribution strategies. Table 6 shows calculations, and Fig. 6 provides a better representation.

**Table 6.** Result of the test problem

| Demand | Scenario | Cost function | Number of TM | Number of AM | Number of RDC | Number of LDC |
|---|---|---|---|---|---|---|
| 2000 | 1 | 110675 | 3 | 29 | 17 | 21 |
| 2500 | 1 | 120741 | 4 | 29 | 17 | 22 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 3000 | 1 | 129908 | 4 | 30 | 18 | 22 |
| 3500 | 1 | 139810 | 4 | 31 | 18 | 23 |
| 4000 | 1 | 141893 | 5 | 33 | 19 | 23 |
| 4500 | 1 | 148897 | 5 | 33 | 19 | 23 |
| 5000 | 1 | 159313 | 5 | 34 | 19 | 24 |
| 2000 | 2 | 160932 | 2 | 25 | 20 | 19 |
| 2500 | 2 | 168903 | 2 | 25 | 13 | 19 |
| 3000 | 2 | 171234 | 2 | 26 | 13 | 20 |
| 3500 | 2 | 179901 | 3 | 27 | 13 | 20 |
| 4000 | 2 | 184621 | 3 | 27 | 14 | 21 |
| 4500 | 2 | 191219 | 3 | 28 | 14 | 21 |
| 5000 | 2 | 199814 | 3 | 29 | 15 | 21 |
| 2000 | 3 | 209321 | 2 | 22 | 10 | 16 |
| 2500 | 3 | 219012 | 2 | 22 | 10 | 17 |
| 3000 | 3 | 220921 | 2 | 22 | 10 | 18 |
| 3500 | 3 | 228761 | 2 | 23 | 11 | 18 |
| 4000 | 3 | 231092 | 2 | 23 | 11 | 18 |
| 4500 | 3 | 239819 | 3 | 23 | 11 | 18 |
| 5000 | 3 | 242518 | 3 | 24 | 12 | 18 |

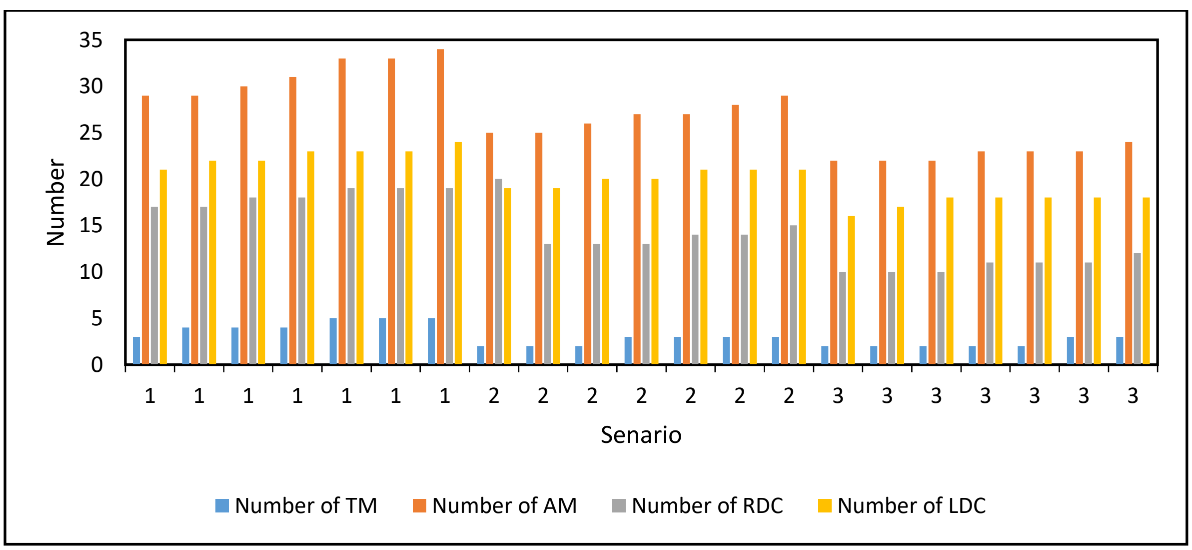


**Fig 6.** Results of decision variables in each scenario

### 4.6 Managerial Implications and Suggestions

AM has the potential to revolutionize supply chains by reducing lead times, lowering inventory costs, and enabling greater customization (Rinaldi et al., 2021). However, implementing AM in the supply chain has several managerial implications and suggestions. In this answer, I will discuss the managerial implications of AM in the supply chain, exchange rate risk in the supply chain, and a resilient supply chain with smart contracts. Redefining supply chain strategy: AM can change the traditional supply chain strategy. Companies need to consider the cost of producing locally vs. outsourcing. Companies must evaluate whether having in-house production facilities or outsourcing production is beneficial.

1. Reducing lead times: AM can reduce lead times by enabling the production of parts and products on demand. This reduces the need for inventory and shortens the time required to bring products to market. This, in turn, can improve a company's ability to respond to customer demand.
2. Enhancing customization: AM can enable greater customization of products, improving customer satisfaction and increasing sales. This can also help companies differentiate their products in the marketplace.
3. Ensuring quality control: Companies need to ensure that the quality of products produced through AM meets the required standards. This requires implementing quality control measures in the production process and ensuring that the equipment is properly maintained.

Exchange rate risk is a significant challenge that businesses face in international supply chain management. Fluctuations in exchange rates can impact the profitability of companies and increase the cost of sourcing raw materials, transportation, and manufacturing. The exchange rate risk can lead to significant company losses if not managed effectively. In this answer, I will discuss the managerial implications and suggestions for considering exchange rate risk in the supply chain and building a resilient supply chain with smart contracts. This paper can help companies in several aspects.

1. Redefine supply chain strategy: Businesses should consider exchange rate fluctuations when defining their supply chain strategy. Evaluating the cost-benefit of outsourcing vs. in-house production facilities and the impact of exchange rate risk on the supply chain is essential.
2. Forecast exchange rate fluctuations: Forecasting exchange rate fluctuations can help businesses better plan their supply chain operations. Companies can use financial models and economic indicators to forecast exchange rate fluctuations and develop contingency plans.
3. Assess risk exposure: It is essential to assess the risk exposure of the supply chain to exchange rate fluctuations. Businesses should evaluate their exposure to currency risk and prioritize risk mitigation strategies.
4. Develop risk management plans: Businesses should develop risk management plans to manage exchange rate risk. This includes developing contingency plans and hedging strategies to mitigate risk exposure.
5. Automate supply chain transactions: Automating supply chain transactions can improve supply chain efficiency and reduce the impact of disruptions. Smart contracts can automate transactions, such as payments and logistics, and provide real-time visibility into the status of goods and payments.
6. Use blockchain technology: Blockchain technology can provide a secure and transparent record of supply chain transactions. This can help reduce fraud and improve supply chain resilience.

7. Build relationships with suppliers: Strong relationships with suppliers can help businesses quickly recover from disruptions. This requires building trust and communication with suppliers and developing contingency plans in case of disruptions.

In conclusion, exchange rate risk is a significant challenge businesses face in international supply chain management. It is essential to consider exchange rate fluctuations when defining supply chain strategy, assessing risk exposure, and developing risk management plans. The suggestions for managing exchange rate risk include using hedging strategies, diversifying suppliers and customers, and sourcing locally. Additionally, building a resilient supply chain with smart contracts can improve supply chain efficiency, reduce the impact of disruptions, and provide real-time visibility into the status of goods and payments.

## 5 . Conclusion

This paper proposed a new framework for designing an AM technology-integrated resilient supply chain network. The proposed approach is based on a bi-objective optimization model to minimize the total cost of the supply chain network and maximize its disruption resilience with minimal unsatisfied demand. A resilient supply chain is crucial to viable business activities, particularly in the current era of rapid changes and uncertainty globally. Organizations must consider a number of factors to achieve resilience, which include exchange rate risk, smart contract technology, and AM. Exchange rate risk has the capability of profoundly impacting supply chain management as it can add cost, reduce profit, and diminish competitiveness. Organizations can minimize these risks and increase their resilience through effective risk management methods such as hedging, diversification, and scenario analysis. Besides, Smart contract technology is also another technology able to improve supply chain resilience. Smart contracts have the ability to automate supply chain operations, such as procurement, inventory management, and payment, in a more efficient manner, at a lower cost in terms of transactions, and with greater transparency and accountability. Finally, AM can produce a more resilient supply chain. This technology enables firms to produce parts and products on demand, reducing reliance on the traditional supply chain while enhancing responsiveness and flexibility.

Finally, building a resilient supply chain requires an holistic strategy based on many determinants, including exchange rate risk, smart contract technology, and AM. With the assistance of sound strategies in these areas, firms can maximize their capabilities to adapt to situations, reduce risks, and place themselves competitively in the global economy.

The study emphasizes the need to consider multiple layers of the supply chain network while designing and the potential benefits of leveraging AM capabilities within the network. The exchange rate risk is also discussed in this paper, along with how it affects the supply chain. Also, make use of smart contracts to improve the trustworthiness of the suppliers in the peak season. The study utilizes the epsilon-constraint method and Benders decomposition in robust optimization for solving the model and managing risk. Findings from the case study indicate that AM can improve the resilience of the supply chain network with a reduction in its overall cost. The paper provides valuable information for supply chain managers who desire to design more resilient supply chains amid increasing uncertainty and disruption. The proposed approach could be applied to numerous industries and sectors, and supply chain effectiveness, as well as resistance against various types of disruptions, would increase. This paper is a valuable addition to supply chain management literature and discloses the possible benefits of AM technology in designing flexible supply chains. This model can expand in a larger size in order to be solved in future studies using the new metaheuristic algorithms. Moreover, the model can expand to a multi-period stage.

Despite its contribution, this research has some limitations. Firstly, the model in this study is tested with one case study (Electrolux) and thus could have the tendency to limit the generalizability of the findings across other industries and geographic regions. The model also assumes static disruption probability and capacity parameters, whereas in practice, these may vary dynamically over time. In addition, the combination of blockchain technologies and smart contracts was theoretically modeled without considering prospective implementation barriers like regulatory barriers, technology readiness, or issues of interoperability. Methodologically, the optimization problem was addressed using robust optimization and decomposition methods; however, computational efficiency might be more of an issue in large-scale, practical cases, which again raises concerns about scaling the model. Finally, the model makes a static, single-period assumption, whereas disruptions and supply chain resilience are dynamic and vary across multiple time horizons. Potential avenues for future studies are to extend this research by developing multi-period, stochastic, or simulation models, validating the framework in different industries, and studying advanced metaheuristic algorithms for the solution to address scalability.

Extensions can be made to enhance the proposed mathematical model further. To begin with, the model can be generalized to a multi-period, dynamic model that incorporates the time-varying aspects of disruptions, demand variability, and restoration plans. Second, the integration of stochastic and simulation-based techniques would allow for a more authentic representation of uncertainties such as exchange rate volatility, inflation, and transportation delay. Third, the incorporation of metaheuristic or hybrid optimization algorithms would allow for better scalability of the model for large supply networks with multiple products, suppliers, and geographies. Fourth, the model could be extended to incorporate environmental and sustainability objectives aligned with green supply chain practices. Finally, empirical testing across industry sectors—such as aerospace, automotive, or healthcare, for instance—would provide stronger evidence of usability of the model and characterize industry-specific findings for sound supply chain design.

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