Chapter 9

EMBRACING THE NEW NORMAL: LEVERAGING I4.0 FOR SUPPLY CHAIN OPTIMIZATION AND SUSTAINABILITY

9.1 Introduction

The goal of satisfying global demand across the world has led to profit-oriented practices that usually ignore sustainability concerns and frequently come at the expense of long-term effects on society and the environment. Traditional approaches to managing these issues have proven ineffective, necessitating the adoption of new capabilities and practices that are both cost-effective and sustainable. In response to this concern, this study pioneers an investigation into the adoption of I4.0 technologies and their dual impact on both cost optimization and carbon footprint reduction. This study develops a robust model for supply chain networks and seeks to delve into the impact and strategic adoption of I4.0 for cost optimization and the reduction of scope 1, 2, and 3 carbon footprints. The proposed model is solved using genetic algorithm (GA), adaptive genetic algorithm (AGA), differential evolution (DE), and adaptive differential evolution (ADE) approaches. The finding of the study suggests decision makers adopt I4.0 technologies by identifying the optimum stakeholder capacity ranges that would yield the highest value in terms of cost optimization and sustainability. Furthermore, this study expands the theoretical scope of supply chain management by integrating sustainability and cost aspects of the supply chain network.

This study makes a significant and novel contribution to the field by addressing a significant research gap in the adoption of I4.0 technologies to track and control emissions across scopes 1, 2, and 3 in supply chain networks. Despite the growing importance of sustainable practices, there has been limited exploration into the integration of I4.0 technologies for emissions tracking and management within supply chains (Hertwich & Wood, 2018; Cañas et al., 2021). In response to this gap, this study pioneers an investigation into the adoption of I4.0 technologies and their dual impact on both cost optimization and emissions reduction. This study goes beyond mere theory, delving into the practical implications of adopting I4.0 technologies within supply chains. This study develops a robust model for supply chain networks by comprehensively assessing the associated costs of technology integration alongside the environmental consequences in terms of carbon emissions. This model enables organizations to effectively track and manage their resource usage, energy consumption, and emissions output in real-time. This study seeks to delve into the impact and strategic adoption of I4.0 for supply chain optimization and the reduction of scope 1, 2, and 3 carbon footprints. In addition, this study investigates the interrelation between emission, I4.0 technologies adoption, and stakeholder capacity to bring new possibilities to the literature to move forward. This study has the following objectives:

1) To investigate the impact of I4.0 technologies on global supply chain sustainability and cost optimization.
2) To suggest a suitability model for I4.0 technology adoption.

9.2 Problem Statement and Formulation

The supply chain network under study consists of suppliers (i) that supply the raw material/components to manufacturers (j) that produce the finished products (p), these products are further sent to the distributors/markets (k). I4.0 technologies provide the necessary assistance in supply chain operations and create a significant impact on cost and emission reduction. Many industries are adopting I4.0 technologies in their operations and supply chains. The examples of the structure used in this study can be seen in the utilization of Big Data for decision-making purposes at the Bosch Automotive factory located in China, wherein the organization has integrated sensors into its factory machines to gather data pertaining to cycle time. After being gathered, sophisticated data analytics tools are employed to analyze the data in real time and notify employees upon the detection of any hindrances in the production processes. Adopting this approach facilitates the anticipation of equipment malfunctions, thereby allowing the factory to proactively plan maintenance procedures prior to the occurrence of any failures. Consequently, the factory is capable of maintaining the continuous operation and functionality of its machinery for extended durations. According to the company, the utilization of data analysis in this manner has resulted in a productivity enhancement of over 10% in specific domains, alongside enhancements in delivery efficiency, customer satisfaction, and emission reduction (Santos et al., 2017).

Another example of cloud computing can be seen at Volkswagen which has implemented cloud computing technology to establish an Automotive Cloud platform for the purpose of facilitating connectivity among their vehicles. The technology provides a variety of functionalities, such as integration with smart home systems, a personal digital assistant, a predictive maintenance service, media streaming capabilities, and software updates (Rooney, 2023). Similarly, the application of advanced robotics can be seen at the DHL distribution center in the Netherlands. DHL distribution center uses collaborative Autonomous Mobile Robots for locating, tracking, and moving inventory in warehouse and logistics facilities and are able to reduce order cycle time by up to 50% and provide up to twice the picking productivity gain (AMFG, 2019). This study has integrated the I4.0 technologies with the supply chain process for carbon footprint tracking and cost optimization. The context diagram is shown in Figure 1. With the help of available literature sustainable supply chain cost parameters are identified. The obtained scenario is formulated using mixed integer nonlinear programming (MINLP). When procedures get complicated, mathematical models can be useful for exploring the space of alternative strategies and proposing optimal solutions; nevertheless, the difficulty of solving such models grows as the number of strategies and investigated variables grows (Zokaee et al., 2017).

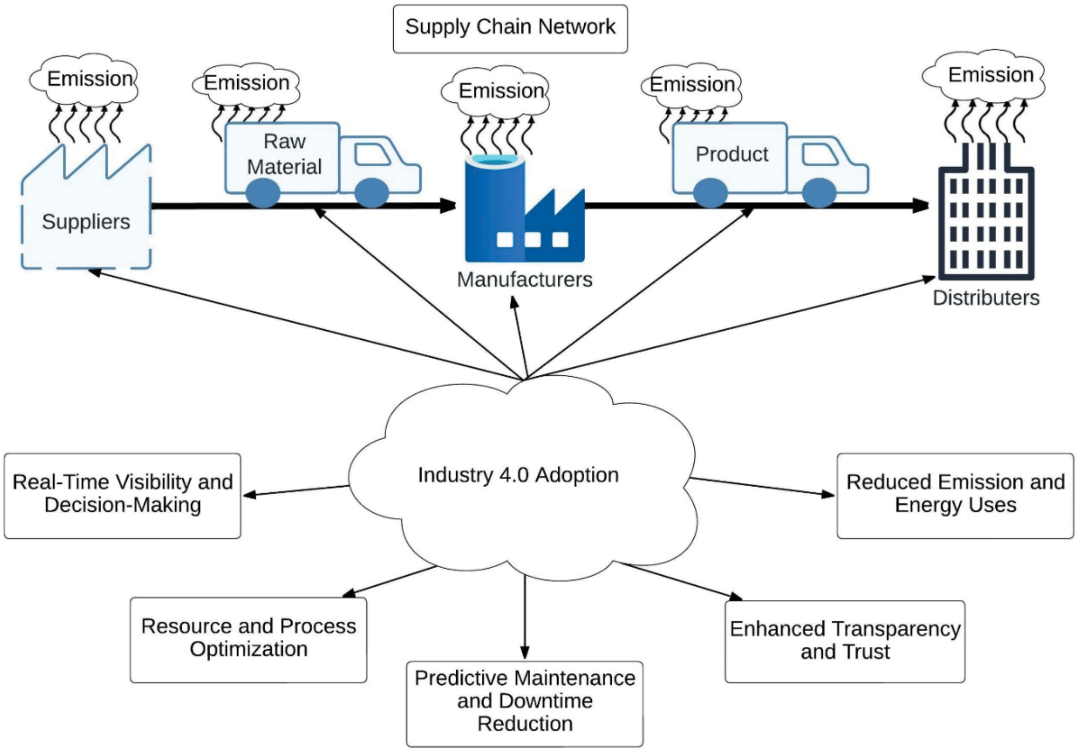

Figure 26: Sustainability and cost optimization through Industry 4.0 adoption

9.2.1 Network cost optimization

Optimizing network costs involves finding the most cost-effective configuration of suppliers, manufacturers, and distributors and determining the optimal allocation of products and transportation routes. The impact of technology is considered on operational cost, logistics, and operational emission of the network.

9.2.2 Industry 4.0 technology adoption

The term "industry 4.0" describes the incorporation of digital technologies into industrial processes to facilitate advanced automation, data sharing, and real-time information sharing. The technologies can be grouped as basic to advance for adoption in various supply chain processes. Further, the adoption cost is also important and should be taken into account while grouping for feasible adoption. The technologies enhancing visibility, communication, and analytical capabilities should grouped as level I. Level II technologies may include advanced automation and predictive capabilities in addition to level I. Level III of technology adoption considers the best analytical and predictive abilities the technology can provide in addition to level I and II. These technology adoption levels have an impact on cost and the associated emission of the network as they assist involved operations of the supply chain. The levels of I4.0 technologies adoption are divided with increasing impact on cost and emission. The adoption level is determined by the product quantity processed by stakeholders. The model considers the impact of technology adoption (σ_C) on the operational cost of the network, manufacturing facilities, logistics, and distribution centers.

9.2.3 Carbon footprint

Minimizing greenhouse gas emissions across the entire supply chain network is necessary to reduce the carbon footprint of the network. The model considers the scope 1, 2, and 3 emissions from the associated operation of supplier, manufacturer, distributor, and logistics. In addition, the model considers the impact of technology adoption on emission reduction (σ_E) on operational emission of the network, logistics, and emission by manufacturing and distribution.

The model has the following assumptions:

1. Demands of participants in the supply chain are fulfilled.
2. Unit transportation costs are defined by the distances between nodes.
3. A manufacturer M makes an output product, which may either be an intermediate or end product.
4. Starting point emissions are taken into account when calculating the transportation emissions between any two nodes.
5. The logistics emission is assumed to be based on the distance between facilities.

9.2.4 Model notations

The notations used in the mathematical formulation are given below

Sets and indices

i	Suppliers' index	$i = 1,2,3 \ldots \ldots I$
j	Manufacturers' index	$j = 1,2,3 \ldots \ldots J$
k	Distributors' index	$k = 1,2,3 \ldots \ldots K$
p	Products' index	$p = 1,2,3 \ldots \ldots P$
L	Level of technology adoption	$l = 1,2,3 \ldots \ldots L$

Parameters

$S =$ Number of suppliers
$M =$ Number of manufacturing facilities
$D =$ Number of distributors
$p =$ Number of products
$C_{ij} =$ Cost of transporting a product from node i to j
$C_{jk} =$ Cost of transporting a product from node j to k
$OS_i =$ Operational cost of supplier i
$OM_j =$ Operational cost of manufacturer j
$OD_k =$ Operational cost of distributer k
$CRM_j^p =$ Unit cost of regular time production of product p at Manufacturer j
$COM_j^p =$ Unit cost of overtime production of product p at Manufacturer j
$OE_i =$ Operational emission of supplier i
$OE_j =$ Operational emission of manufacturer j
$OE_k =$ Operational emission of distributer k
$\alpha =$ Emission cost per unit emission quantity
$TRM_j =$ Total regular time production at Manufacturer j
$TOM_j =$ Total overtime production at Manufacturer j
$T_p =$ Unit production time of product p
$a_{ip} =$ Available supply quantity of product p at supplier i
$b_{jp} =$ Demand quantity of product p at manufacturer j

d_{jp} = Available supply quantity of product p at manufacturer j

e_{kp} = Demand quantity of product p at distributer k

TD_{ij}= Distance between supplier i and manufacturer j

TD_{jk}= Distance between manufacturer j and distributor k

$\mathrm{EC_j}$ = Electricity consumed by the resources at each manufacturing facility j

μ_1= Emission factor based on fuel

μ_2= Emission factor based on electricity

γ = Cost factor based on distance

TE_{ij} = Emission due to transportation of product from node i to j

TE_{jk} = Emission due to transportation of product from node j to k

EM_j = Emission due to manufacturing at manufacturer j

$\Phi \mathrm{L}_{SL1}$= Lower limit of total quantity supplied for technology adoption level I at supplier i

$\Phi \mathrm{L}_{SL2}$= Lower limit of total quantity supplied for technology adoption level II at supplier i

$\Phi \mathrm{L}_{SL3}$= Lower limit of total quantity supplied for technology adoption level III at supplier i

$\Phi \mathrm{U}_{SL1}$= Upper limit of total quantity supplied for technology adoption level I at supplier i

$\Phi \mathrm{U}_{SL2}$= Upper limit of total quantity supplied for technology adoption level II at supplier i

$\Phi \mathrm{L}_{ML1}$= Lower limit of total quantity supplied for technology adoption level I at manufacturer j

$\Phi \mathrm{L}_{ML2}$= Lower limit of total quantity supplied for technology adoption level II at manufacturer j

$\Phi \mathrm{L}_{ML3}$= Lower limit of total quantity supplied for technology adoption level III at manufacturer j

$\Phi \mathrm{U}_{ML1}$= Upper limit of total quantity supplied for technology adoption level I at manufacturer j

$\Phi \mathrm{U}_{ML2}$= Upper limit of total quantity supplied for technology adoption level II at manufacturer j

$\Phi \mathrm{L}_{DL1}$= Lower limit of total quantity supplied for technology adoption level I at distributer k

$\Phi \mathrm{L}_{DL2}$= Lower limit of total quantity supplied for technology adoption level II at distributer k

$\Phi \mathrm{L}_{DL3}$= Lower limit of total quantity supplied for technology adoption level III at distributer k

$\Phi \mathrm{U}_{DL1}$= Upper limit of total quantity supplied for technology adoption level I at distributer k

$\Phi \mathrm{U}_{DL2}$= Upper limit of total quantity supplied for technology adoption level II at distributer k

C_{SL1}= Cost of technology adoption for supplier i for Level I

C_{SL2}= Cost of technology adoption for supplier i for Level II

C_{SL3}= Cost of technology adoption for supplier i for level III

C_{ML1}= Cost of technology adoption for manufacturer j for Level I

C_{ML2}= Cost of technology adoption for manufacturer j for Level II

C_{ML3}= Cost of technology adoption for manufacturer j for level III

C_{DL1}= Cost of technology adoption for distributer k for Level I

C_{DL2}= Cost of technology adoption for distributer k for Level II

C_{DL3}= Cost of technology adoption for distributer k for level III

IC_{SL1}= Impact factor of technology adoption on cost for level I at supplier i

IC_{SL2}= Impact factor of technology adoption on cost for level II at supplier i

IC_{SL3}= Impact factor of technology adoption on cost for level III at supplier i

IC_{ML1}= Impact factor of technology adoption on cost for level I at manufacturer j

IC_{ML2}= Impact factor of technology adoption on cost for level II at manufacturer j

IC_{ML3}= Impact factor of technology adoption on cost for level III at manufacturer j

IC_{DL1}= Impact factor of technology adoption on cost for level I at distributer k

IC_{DL2}= Impact factor of technology adoption on cost for level II at distributer k

IC_{DL3}= Impact factor of technology adoption on cost for level III at distributer k

IE_{SL1}= Impact factor of the adoption of technology on level I emission at supplier i

IE_{SL2}= Impact factor of the adoption of technology on level II emission at supplier i

IE_{SL3}= Impact factor of the adoption of technology on level III emission at supplier i

IE_{ML1}= Impact factor of the adoption of technology on level I emission at manufacturer j

IE_{ML2}= Impact factor of the adoption of technology on level II emission at manufacturer j

IE_{ML3}= Impact factor of the adoption of technology on level III emission at manufacturer j

IE_{DL1}= Impact factor of the adoption of technology on level I emission at distributer k

IE_{DL2}= Impact factor of the adoption of technology on level II emission at distributer k

IE_{DL3}= Impact factor of the adoption of technology on level III emission at distributer k

Decision variables

RM_j^p = Quantity of Regular time production of product p at Manufacturer j

OM_j^p = Quantity of Over time production of product p at Manufacturer j

λ_i^l = Cost of technology adoption level l ∈ L at supplier i

λ_j^l = Cost of technology adoption level l ∈ L at Manufacturer j

λ_k^l = Cost of technology adoption level l ∈ L at Distributer k

σ_{Ci} = Impact of technology adoption on cost for supplier i

σ_{Cj} = Impact of technology adoption on cost for manufacturer j

σ_{Ck} = Impact of technology adoption on cost for distributer k

σ_{Ei} = Impact of technology adoption on emission for supplier i

σ_{Ej} = Impact of technology adoption on emission for manufacturer j

σ_{Ek}= Impact of technology adoption on emission for distributer k

$$y_i = \begin{cases} 1, \text{if a supplier is open} \\ 0, \text{if a supplier is closed} \end{cases}$$

$$y_j = \begin{cases} 1, \text{if a manufacturer is open} \\ 0, \text{if a manufacturer is closed} \end{cases}$$

$$y_k = \begin{cases} 1, \text{if a distributor is open} \\ 0, \text{if a distributor is closed} \end{cases}$$

x_{ij} = Total flow quantity from Node i to Node j

x_{jk} = Total flow quantity from Node j to Node k

$$\beta_{ij} = \begin{cases} 1, \text{if supplier i is transporting to manufacturer } j \\ 0, \text{if not} \end{cases}$$

$$\beta_{jk} = \begin{cases} 1, \text{if manufacturer j is transporting to distributer } k \\ 0, \text{if not} \end{cases}$$

$$\Theta_j^p = \begin{cases} 1, \text{if manufacturer j is manufacturing product } p \\ 0, \text{if not} \end{cases}$$

$$\lambda_i^l = \begin{cases} C_{SL1}, \text{if } \Phi\text{L}_{SL1} < \sum_{j=1}^{J} x_{ij} \leq \Phi\text{U}_{SL1} \\ C_{SL2}, \text{if } \Phi\text{L}_{SL2} < \sum_{j=1}^{J} x_{ij} \leq \Phi\text{U}_{SL2} \\ C_{SL3}, \text{if } \Phi\text{L}_{SL3} < \sum_{j=1}^{J} x_{ij} \\ 0, \text{if } \sum_{j=1}^{J} x_{ij} \leq \Phi\text{L}_{SL1} \end{cases}$$

$$\lambda_j^l = \begin{cases} C_{ML1}, \text{if } \Phi\text{L}_{ML1} < \sum_{k=1}^{K} x_{jk} \leq \Phi\text{U}_{ML1} \\ C_{ML2}, \text{if } \Phi\text{L}_{ML2} < \sum_{k=1}^{K} x_{jk} \leq \Phi\text{U}_{ML2} \\ C_{ML3}, \text{if } \Phi\text{L}_{ML3} < \sum_{k=1}^{K} x_{jk} \\ 0, \text{if } \sum_{k=1}^{K} x_{jk} \leq \Phi\text{L}_{ML1} \end{cases}$$

$$\lambda_k^l = \begin{cases} C_{DL1}, \text{if } \Phi\text{L}_{DL1} < \sum_{j=1}^{J} x_{jk} \leq \Phi\text{U}_{DL1} \\ C_{DL2}, \text{if } \Phi\text{L}_{DL2} < \sum_{j=1}^{J} x_{jk} \leq \Phi\text{U}_{DL2} \\ C_{DL3}, \text{if } \Phi\text{L}_{DL3} < \sum_{j=1}^{J} x_{jk} \\ 0, \text{if } \sum_{j=1}^{J} x_{jk} \leq \Phi\text{L}_{DL1} \end{cases}$$

$$\sigma_{Ci} = \begin{cases} IC_{SL1}, \text{if } \Phi\text{L}_{SL1} < \sum_{j=1}^{J} x_{ij} \leq \Phi\text{U}_{SL1} \\ IC_{SL2}, \text{if } \Phi\text{L}_{SL2} < \sum_{j=1}^{J} x_{ij} \leq \Phi\text{U}_{SL2} \\ IC_{SL3}, \text{if } \Phi\text{L}_{SL3} < \sum_{j=1}^{J} x_{ij} \\ 1, \text{if } \sum_{j=1}^{J} x_{ij} \leq \Phi\text{L}_{SL1} \end{cases}$$

$$\sigma_{Cj} = \begin{cases} IC_{ML1}, \text{if } \Phi\text{L}_{ML1} < \sum_{k=1}^{K} x_{jk} \leq \Phi\text{U}_{ML1} \\ IC_{ML2}, \text{if } \Phi\text{L}_{ML2} < \sum_{k=1}^{K} x_{jk} \leq \Phi\text{U}_{ML2} \\ IC_{ML3},\ \Phi\text{L}_{ML3} < \sum_{k=1}^{K} x_{jk} \\ 1, \text{if } \sum_{k=1}^{K} x_{jk} \leq \Phi\text{L}_{ML1} \end{cases}$$

$$\sigma_{Ck} = \begin{cases} IC_{DL1}, \text{if } \Phi\text{L}_{DL1} < \sum_{j=1}^{J} x_{jk} \leq \Phi\text{U}_{DL1} \\ IC_{DL2}, \text{if } \Phi\text{L}_{DL2} < \sum_{j=1}^{J} x_{jk} \leq \Phi\text{U}_{DL2} \\ IC_{DL3}, \text{if } \Phi\text{L}_{DL3} < \sum_{j=1}^{J} x_{jk} \\ 1, \text{if } \sum_{j=1}^{J} x_{jk} \leq \Phi\text{L}_{DL1} \end{cases}$$

$$\sigma_{Ei} = \begin{cases} IE_{SL1}, \text{if } \Phi \mathrm{L}_{SL1} < \sum_{j=1}^{J} x_{ij} \leq \Phi \mathrm{U}_{SL1} \\ IE_{SL2}, \text{if } \Phi \mathrm{L}_{SL2} < \sum_{j=1}^{J} x_{ij} \leq \Phi \mathrm{U}_{SL2} \\ IE_{SL3}, \text{if } \Phi \mathrm{L}_{SL3} < \sum_{j=1}^{J} x_{ij} \\ 1, \text{if } \sum_{j=1}^{J} x_{ij} \leq \Phi \mathrm{L}_{SL1} \end{cases}$$

$$\sigma_{Ej} = \begin{cases} IE_{ML1}, \text{if } \Phi \mathrm{L}_{ML1} < \sum_{k=1}^{K} x_{jk} \leq \Phi \mathrm{U}_{ML1} \\ IE_{ML2}, \text{if } \Phi \mathrm{L}_{ML2} < \sum_{k=1}^{K} x_{jk} \leq \Phi \mathrm{U}_{ML2} \\ IE_{ML3}, \ \Phi \mathrm{L}_{ML3} < \sum_{k=1}^{K} x_{jk} \\ 1, \text{if } \sum_{k=1}^{K} x_{jk} \leq \ \Phi \mathrm{L}_{ML1} \end{cases}$$

$$\sigma_{Ek} = \begin{cases} IE_{DL1}, \text{if } \Phi \mathrm{L}_{DL1} < \sum_{j=1}^{J} x_{jk} \leq \Phi \mathrm{U}_{DL1} \\ IE_{DL2}, \text{if } \Phi \mathrm{L}_{DL2} < \sum_{j=1}^{J} x_{jk} \leq \Phi \mathrm{U}_{DL2} \\ IE_{DL3}, \text{if } \Phi \mathrm{L}_{DL3} < \sum_{j=1}^{J} x_{jk} \\ 1, \text{if } \sum_{j=1}^{J} x_{jk} \leq \Phi \mathrm{L}_{DL1} \end{cases}$$

9.2.5 The objective function

The first part of the model considers the operational cost of the network with operational emission cost and in the second part transportation cost of the network with associated emission cost is taken into account. The third part considers regular time and overtime manufacturing costs of products with associated emission costs and the last part is technology acquisition cost for different levels of adoption.

Total cost (TC) = $\sum_{i=1}^{I}\{\sigma_{Ci}(OS_i y_i) + \sigma_{Ei}(OE_i y_i \times \alpha)\} + \sum_{j=1}^{J}\{\sigma_{Cj}(OM_j y_j) + \sigma_{Ej}(OE_j y_j \times \alpha)\} + \sum_{k=1}^{K}\{\sigma_{Ck}(OD_k y_k + \sigma_{Ek}(OE_k y_k \times \alpha)\} + \sum_{i=1}^{I}\sum_{j=1}^{J}\{\sigma_{Ci}(C_{ij} x_{ij}) + \sigma_{Ei}(TE_{ij}\beta_{ij} \times \alpha)\} + \sum_{j=1}^{J}\sum_{k=1}^{K}\{\sigma_{Cj}(C_{jk} x_{jk}) + \sigma_{Ej}(TE_{jk}\beta_{jk} \times \alpha)\} + \sum_{j=1}^{J}\sum_{p=1}^{P}\sigma_{Cj}(RM_j^P \times CRM_j^p \times \Theta_j^p) + \sum_{j=1}^{J}\sum_{p=1}^{P}\sigma_{Cj}(OM_j^P \times COM_j^p \times \Theta_j^p) + \sum_{j=1}^{J}\{\sigma_{Ej}(EM_j \times \alpha)\} + \sum_{i=1}^{I}\lambda_i^l + \sum_{j=1}^{I}\lambda_j^l + \sum_{k=1}^{I}\lambda_k^l$

9.2.6 The constraints

The constraints are divided into the following parts:

Transportation-related constraints: Constraints (1) to (6) permit the transportation among facilities for product p. The first and second constraint ensures the supply and demand relation between suppliers and manufacturers for product p.

$$\sum_{j=1}^{J} x_{ij} \leq \sum_{p=1}^{p} a_i^p, \quad \forall i \in I, \forall p \in P \tag{1}$$

$$\sum_{i=1}^{I} x_{ij} \geq \sum_{p=1}^{p} b_j^p, \quad \forall j \in J, \forall p \in P \tag{2}$$

Constraint numbers (3) and (4) represent the supply-demand constraints among manufacturers and distributors and constraints (5) and (6) represent the nonnegativity of the flow of commodities between facilities.

$$\sum_{k=1}^{K} x_{jk} \leq \sum_{p=1}^{p} d_j^p, \quad \forall j \in J, \forall p \in P \tag{3}$$

$$\sum_{j=1}^{J} x_{jk} \geq \sum_{p=1}^{p} e_k^p, \quad \forall k \in K, \ \forall p \in P \tag{4}$$

$$x_{ij} \geq 0, \forall i \in I \tag{5}$$

$$x_{jk} \geq 0, \forall j \in J \tag{6}$$

Emission and cost functions : Constraints number (7) and (8) are emission functions for distance. The left side of constraint (7) represents emission due to the transportation of product from node i to j and the right side calculates the emission quantity based on distance between facilities. Similarly, constraint (8) represents the emission due to the transportation of product from node j to k.

$$TE_{ij} = TD_{ij} \times \mu_1, \quad \forall i \in I, \forall j \in J \tag{7}$$

$$TE_{jk} = TD_{jk} \times \mu_1, \quad \forall j \in J, \forall k \in K \tag{8}$$

Constraints number (9) and (10) are cost functions for distance. In constraints (9) and (10) the left-hand side represents the cost incurred in transporting the product from node i to j and j to k respectively.

$$C_{ij} = TD_{ij} \times \gamma, \forall i \in I, \forall j \in J \tag{9}$$

$$C_{jk} = TD_{jk} \times \gamma, \forall j \in J, \forall k \in K \tag{10}$$

The left side of constraint (11) shows emission due to manufacturing a product p and the right side calculates the emission based on power consumed during manufacturing of product p.

$$EM_j = EC_j \times \mu_2, \quad \forall j \in J \tag{11}$$

Capacity constraints: Constraints (12) and (13) represent the regular time manufacturing and over-time manufacturing constraints respectively.

$$\sum_{p=1}^{P} (RM_j^P \times T_p) \leq TRM_j, \ \forall j \in J \tag{12}$$

$$\sum_{p=1}^{P} (OM_j^P \times T_p) \leq TOM_j, \ \forall j \in J \tag{13}$$

Non-negativity constraint: Constraint (14) verifies both regular and overtime production is greater than or equal to zero.

$$RM_j^P, OM_j^P \geq 0, \forall j \in J,\ \forall p \in P \tag{14}$$

Logical constraint: The production of product p at the manufacturing facility M is ensured by constraint (15).

$$\Theta_j^p \leq y_j,\ \ \forall j \in J, \forall p \in P \tag{15}$$

Conditional constraints: Constraints (16) and (17) ensure that if the supplier is open then the product will be transported to manufacturers and vice versa.

$$\beta_{ij} \leq\ y_i, \quad \forall i \in I \tag{16}$$

$$\beta_{ij} \leq\ y_j, \quad \forall i \in I \tag{17}$$

Constraints (18) and (19) ensure that the manufacturer is open then the product will be transported to distributors and vice versa.

$$\beta_{jk} \leq\ y_j, \quad \forall j \in J \tag{18}$$

$$\beta_{jk} \leq\ y_k, \quad \forall j \in J \tag{19}$$

Constraints (20) ensure the integrality of the decision variables.

$$y_i, y_j, y_k, \beta_{ij}, \beta_{jk}, \Theta_j^p \in \{0,1\}\ \forall i, j, k, p \tag{20}$$

Constraints (21) ensure the non-negativity of the decision variables

$$\lambda_i^l, \lambda_j^l, \lambda_k^l, \sigma_{Ci}, \sigma_{Cj}, \sigma_{Ck}, \sigma_{Ei}, \sigma_{Ej}, \sigma_{Ek} \geq 0\ \ \forall i, j, k, l \tag{21}$$

9.3 Solution Methodology

GA and DE algorithms use the principle of natural selection and evolution to search for the optimal solution. The significance of employing these algorithms resides in their capacity to effectively navigate extensive solution spaces, rendering them especially suitable for addressing real-world optimization problems characterized by a substantial number of variables and non-linear associations (Kucukkoc et al., 2024). Both GAs and DE offer distinct advantages that complement each other, making them an excellent choice when compared to other optimization techniques. GA uses concepts like selection, crossover, and mutation to iteratively evolve from candidate solutions to optimal solutions. GAs retain a diversified set of candidate solutions and excel at investigating solution space through selection and recombination. Thus, enhancing the possibility of finding global optima (Mlekusch et al., 2024).

However, DE uses vector operations to generate new candidate solutions in population-based stochastic optimization. It efficiently finds global optima by using the best population members' information (Zhao et al., 2024). DE's simplicity and inexpensive computations make it ideal for continuous and nonlinear objective functions. The utilization of both GA and DE is motivated by their complementary capabilities. However, the traditional GA and DE algorithms can either lead to slow convergence or the search can stick at local optima as key parameters are fixed in the algorithms. The parameters can be dynamically adjusted in both algorithms to address this issue. The AGA and ADE algorithms are the adaptive versions of GA and DE algorithms that offer dynamic parameter control and better exploration vs exploitation balance. The parameters are adjusted dynamically in these algorithms during the search process and get adjusted based on the performance of the algorithm. This helps in exploring the new search spaces and focusing on the refinement of optimal solutions. In addition, with adaptive control premature convergence is avoided and the algorithm efficiently searches the solution space with faster convergence. This dynamic adaptability characteristic also makes these algorithms more versatile and can be applied to a broader range of problems.

9.3.1 Genetic algorithm (GA)

The GA mimics the principles of genetic variation and uses biologically inspired operators such as mutation, crossover, and selection to solve complex problems (Nezamoddini et al., 2020). It starts with the set of potential solutions to the problem at hand which is generally referred to as population. Each possible solution to the problem is represented as a chromosome and it has a fitness value that is measured on the basis of how well the chromosome performs in solving the problem at hand and the population evolves until the stopping criteria are satisfied (Li, X., & Gao, L., 2016). The GA operates in a cycle of generations involving the following steps.

Initialization: In this step, an initial population matrix is formed using the population of random solutions. Each solution in the initial population matrix is called a chromosome which is represented by a set of genes.

Fitness value function: To evaluate each chromosome in the initial population matrix a fitness value function is used. A fitness function uses individual chromosomes as input and determines the suitability of the chromosome as output. Better fitness value represents the better performance of the chromosome.

Selection and reproduction: This step is based on the basic concept that a better chromosome has a higher probability to create better offspring and it is necessary to transfer the best chromosomes of the particular generation to the next generation. This is done on the basis of the fitness value of the chromosomes and higher fitness value chromosomes are copied to the next generation. A fitness proportionate selection is used for every chromosome. A constant percentage of better chromosomes are directly transferred to the next generation.

Crossover: Crossover is performed on a pair of chromosomes to create new chromosomes also called offspring. This study used uniform crossover with a crossover probability of 0.5 to create the offspring.

Mutation: In mutation, the GA explores new solutions within the parameter boundaries by randomly replacing the genes. Incorporating a mutation in GA expands the search space in order to find new opportunities for improvements and also avoid convergence to a local optimum. In this study, the mutation probability is taken as 0.1. After crossover a random number between 0 and 1 is allotted to the offspring, mutation operation is performed when this random number is less than or equal to the mutation probability.

Replacement: A new population is created from the previous generation using crossover and mutation operation and the based chromosomes are directly copied to the new population. It also ensures that overall fitness increases in the new population.

Termination: Terminating requirements can be decided on the basis of maximum generations, suitable conclusions, or attaining suitable fitness. The algorithm terminates as it satisfies the predefined requirements.

9.3.2 Adaptive genetic algorithm (AGA)

The AGA follows the basic principles of traditional GA however, a mechanism is added to adapt mutation and crossover rate. The steps in addition to GA are presented below.

Initial mutation probability: In this step, the initial mutation probability is defined which will adapt based on the diversity of the initial population which can either decrease in the case of sufficient exploration or increase when the population stagnates. The chromosome similarity coefficient is used to decide when to trigger the adaptation. The following equation shows the calculation of chromosome similarity coefficient (Cs)

$$Cs = \frac{\sum_{m=1}^{M} \partial(C_{mnk}, C_{mnl})}{M} \tag{22}$$

where, C_{mnk} and C_{mnl} are the existing values of k and l chromosomes in the m-th row and n-th column (Budi et al., 2022).

$$\partial(C_{mnk,} C_{mnl}) = \begin{cases} 1, \text{if } C_{mnk} = C_{mnl} \\ 0, \text{if not} \end{cases} \tag{23}$$

The mean of the similarity coefficient between chromosomes of a population is defined by the following equation.

$$Mean\ (Cs) = \frac{\sum_{k=1}^{M-1} \sum_{l=k+1}^{M} Cs}{M} \tag{24}$$

Where M is the number of chromosomes. Therefore, the mutation operator can only be applied when the mean value exceeds the specific threshold.

Initial crossover probability: In this step, the crossover probability is set which will adapt dynamically to the diversity of the initial population.

Fitness threshold for adaptation: The fitness threshold for adaptation is dynamically adjusted when the fitness of the population does not improve. In addition, it has diversity-based adaptation which triggers when the diversity falls below a certain level. A low fitness threshold such as 0.001 represents the refinement of the solution and triggers the parameter adaptation when the difference between current and target fitness is greater than 0.001. The increase in the fitness threshold value will increase the exploration space.

Termination: The algorithm terminates as it satisfies the predefined requirements which is either the maximum number of iterations or the maximum number of iterations without improvement, whichever is satisfied earlier.

9.3.3 Differential evolution (*DE*)

Differential evolution is a population-based optimization algorithm that makes few or no assumptions about the problem being optimized and it can search a very large space of the candidate solutions. Unlike the classical approaches such as gradient descent, it does not have a differentiability requirement for the functions. It mimics the process of natural evolution similar to GA however, there are some key differences in the two approaches. The steps involved in differential evolution are discussed below:

Initialization: In this step, the initial population size is defined which consists of a set of candidate solutions. These candidate solutions are called individuals or vectors. The population is initialized randomly within the search space. The method uses a parallel direct search approach by utilizing NP D dimensional parameter vectors.

$$v_{i,G}^{j} = v_{min}^{j} + rand(0,1) \times (v_{max}^{j} - v_{min}^{j}) \tag{25}$$

where $i = 1,2,3 \ldots.., NP$; $j = 1,2,3, \ldots. D$; rand (0,1) returns the rand value between [0,1] and v_{max}^{j} and v_{min}^{j} denotes the upper and lower bounds of the variable j respectively.

Mutation: For every individual vector $v_{i,G}^{j}$ is mutated according to

$$u_{i,G+1} = v_{r1,G} + F.(v_{r2,G} - v_{r3,G}) \tag{26}$$

where $r_1,\ r_2,\ r_3\ \in \{1,2,3 \ldots.., \mathrm{NP}\}$, integer, mutually different and $F > 0$. To allow this condition the randomly chosen integers $r_1,\ r_2$, and r_3 are to be different from the index i. F is a scaling factor.

Crossover: A trial vector $x_{i,G} = [x_{i,G}^{1}, \ldots \ldots \ldots. x_{i,G}^{D}]$ is generated by

$$x_{i,G}^{j} = \begin{cases} u_{i,G}^{j}, rand(0,1) \leq CO \ or \ j = j_{rand} \\ v_{i,G}^{j} \qquad\qquad\qquad otherwise \end{cases} \tag{27}$$

Where CO is a crossover rate and j_{rand} is a random integer between $[1, D]$.

Selection: After generating $x_{i,G}$ vector, it is compared with vector $v_{i,G}$ according to their fitness value, as given below:

$$v_{i,G+1} = \begin{cases} x_{i,G},\ \ if\ x_{i,G}\ is\ better\ than\ v_{i,G} \\ v_{i,G} \qquad\qquad\qquad otherwise \end{cases} \tag{28}$$

9.3.4 Adaptive differential evolution (A*DE*)

The ADE follows the basic principles of traditional DE however, it dynamically adjusts the control parameters such as mutation rate, crossover rate, and population size during the optimization process. The steps in addition to DE are presented below.

Adaptive control parameter initialization: In this step mutation factor, crossover rate, and population size are initialized with ranges that allow them to be adopted throughout the process. The adaptation triggers on the basis of the current state of the population.

Adaptive mutation factor and crossover rate: The initial mutation factor is dynamically adjusted when there is no improvement in the current solution after the predefined number of iterations. If the difference between targeted and current fitness is significant the mutation factor is increased which leads to more exploration and vice-versa.

It regenerates each scale factor F of the traditional DE approach (equation 26) in the following manner (Li et al., 2020).

$$F_i = randc(\in_F, 0.1) \tag{29}$$

Where $randc$ is Cauchy distribution and $\in_F$ is initialized and can be adjusted as:

$$\in_F = (1-k).\in_F + k.mean_L(M_F) \tag{30}$$

Where k is constant (between 0 and 1), M_F represents successful mutation factors, and $mean_L$ represents the Lehmer mean defined as

$$mean_L = \frac{\sum_{i=1}^{|M_F|} F_i^2}{\sum_{i=1}^{|M_F|} F_i} \tag{31}$$

Similarly, the crossover rate gets dynamically adjusted and increased if stagnation in population is detected to promote a more diverse population and vice-versa. The crossover rate is generated using a normal distribution:

$$CO_i = randn\,(\in_{CO}, 0.1) \tag{32}$$

Where, CO_i is in between 0 and 1. $\in_{CO}$ is initialized with 0.5 and it generates a trail vector x_i between mutant and target vectors. The equation (27) of the DE approach can be modified as:

$$x_{i,G} = \begin{cases} u_{i,G}^{j}, if \;\; rand(0,1) \le CO_i \,\|j == j_{rand} \\ v_{i,G}^{j} \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{33}$$

The value of $\in_{CO}$ can be updated as

$$\in_{CO} = (1-k).\in_{CO} + k.mean_A(S_{CO}) \tag{34}$$

Where, $mean_A$ is arithmetic mean and S_{CO} is a set of successful CO at each generation. After that, the selection operation is performed as per equation (28) of the traditional DE approach.

Stagnation counter: Stagnation counter tracks the improvement of population and if there is no improvement for a predefined number of generations, it gets adjusted accordingly.

Adaptation rate: The adaptation rate is used to adjust the mutation factor and crossover rate to control their adaptation. It can be tuned for better performance.

Termination: The algorithm terminates when there is a convergence which means that the difference between best fitness and mean fitness is smaller than the predefined tolerance value.

9.4 Results and Discussions

The proposed model is solved using GA, AGA, DE, and ADE metaheuristics approach.

9.4.1 Data collection

The proposed model is tested with data from the electronic supply chain. The data relating to the carbon footprint associated with the electronic supply chain emission (Scope 1, Scope 2, Scope 3) and the parameter values such as the impact of technology on emission and cost are selected based on Apple's environmental progress report (2024) and Carbon Disclosure Project (CDP) Report 2023. The data relating to cost and margins in the supply chain is generated based on the findings of Carter, M et al. (2019) and D'Arcy, P et al. (2012). The remaining values of parameters are generated at random between their lower and upper boundaries. These sources of data served as the basis for preparing the required datasets of varying instance sizes to test the model.

9.4.2 Designing the test problem

Different problems of varying sizes are solved and compared to assess how well GA, AGA, DE, and ADE algorithms work. To simulate various real-world scenarios, various parameter combinations that include different lower and upper boundaries are taken into consideration.

9.4.3 Parameter fitting

The parameters' settings in an optimization problem are crucial in determining the balance between computational efficiency and the quality of the solution produced. In the present study, several parameters have been selected based on empirical studies in a similar domain and used by several researchers such as Deng et al. (2021), Kucukkoc et al. (2024), Zhao et al. (2024), and Wu et al. (2024). These values are further tuned to balance the exploration and exploitation of the approach. Population size, mutation probability, crossover probability, elite ratio, and parents’ portion are parameters of GA. These values are kept the same for the GA and AGA approach. The number of candidate solutions in each generation is kept to 50 which is referred to as population size. A larger population size can potentially explore a wider search space but requires more computational resources. The mutation probability of 0.1 determines the likelihood of random alterations in the genetic material of the individuals, enabling the exploration of new solutions. The elite ratio of 0.01 ensures that a small portion of the best-performing individuals is carried over to the next generation unchanged, preserving their high-quality genetic material. The crossover probability of 0.5 governs the chance of two individuals exchanging genetic information, allowing for the combination and recombination of traits. The parent portion of 0.3 determines the proportion of individuals selected as parents for crossover based on their fitness values. The choice of uniform crossover type indicates that genetic material is exchanged uniformly at randomly selected points. Finally, the maximum iteration without improvement of 100 sets a limit on the number of generations that can be generated without finding better solutions. These parameter settings aim to strike a balance between exploration and exploitation, allowing for efficient convergence toward high-quality solutions while avoiding premature convergence or stagnation. In addition, in the AGA algorithm adaptive mutation and adaptive crossover are considered. The fitness threshold is kept at 0.01 along with the diversity-based adaptation.

In DE and ADE algorithms the population size is kept at 50 and the maximum number of iterations is kept at 1000 similar to GA and AGA. The mutation factor to control the weight of differential mutation is tuned to 0.8. crossover probability to determine the likelihood of crossover is tuned to 0.9. The convergence tolerance for the difference between the best fitness and mean fitness is kept at 10^{-6}. In addition, for the adaptability aspect in the ADE algorithm, the adaptation rate to control the adaptation of mutation factor and crossover probability is tuned to 0.05.

9.5 Computational results

All formulations are implemented in Python and solved using GA, AGA, DE, and ADE algorithms on a PC with processor Core i5 Duo, CPU 2.4 GHz, and 32 GB RAM. For each scenario, the objective function values are calculated. The computational results comparison shows that ADE consistently outperforms GA, AGA, and DE in all sizes of test cases. ADE has explored the search space better than GA, AGA, and DE as it has performed a thorough search while avoiding local optima. The adaptive parameters of mutation and crossover operators have performed better compared to traditional DE and GA.

Figure 27 shows the small test case performance of 20 suppliers, 7 manufacturing facilities, 25 distribution centers, and 8 products. The comparison between GA, AGA, DE, and ADE algorithms shows that ADE performs better than other algorithms and DE is the second-best performer. While searching through the solution space GA has stuck over a local optimum and AGA has performed a better search through candidate solutions than GA. The performance gap between GA and AGA is 0.73%, while the difference between DE and ADE is 4.75%. The overall performance gap between the best (ADE) and the worst (GA) is 15.87%.

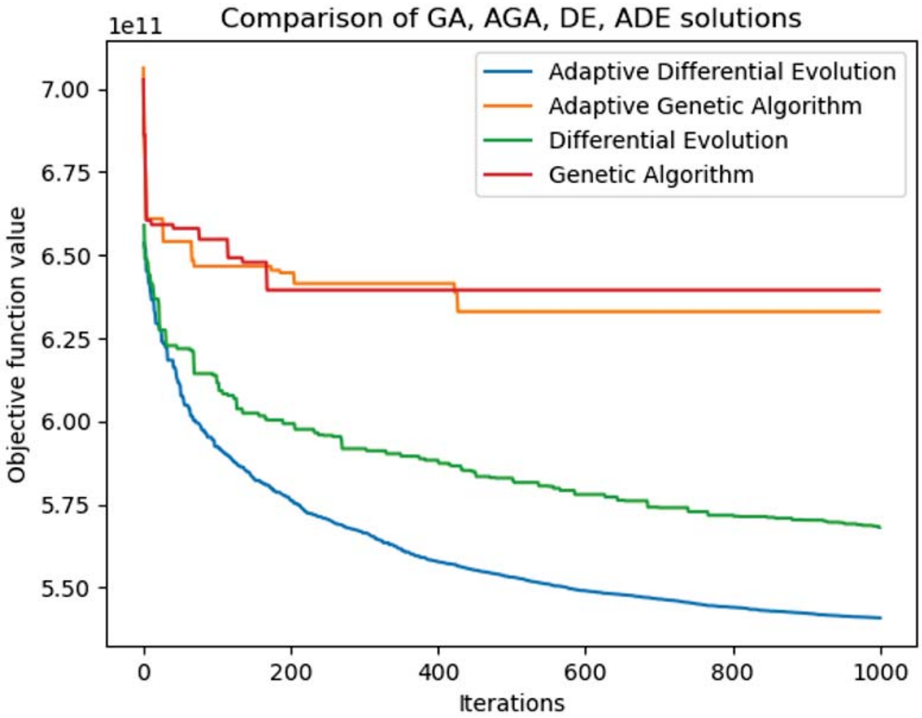

*Figure 27**:** Small test case performance comparison of algorithms*

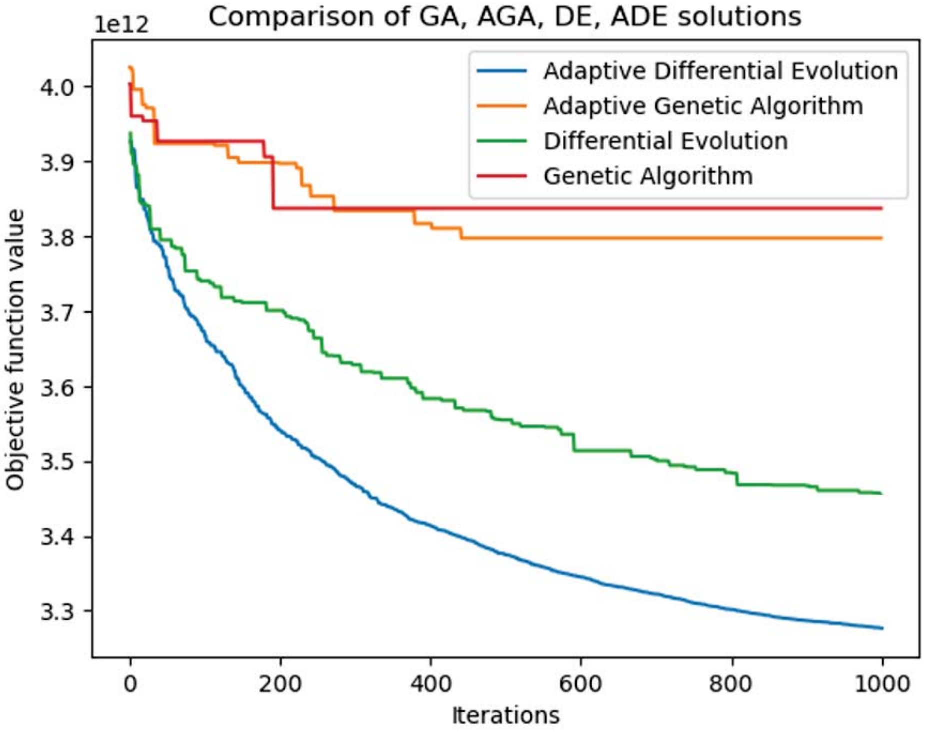

*Figure 28**:** Medium test case performance comparison of algorithms*

A similar pattern can be seen for medium test size (Figure 28) with 40 suppliers, 20 manufacturing facilities, 70 distribution centers, and 20 products. ADE has outperformed DE, AGA, and GA the best (ADE) to worst (GA) performance gap is 14.96%. The performance gap between GA and AGA is 0.64% whereas for DE and ADE, it is 5.24%.

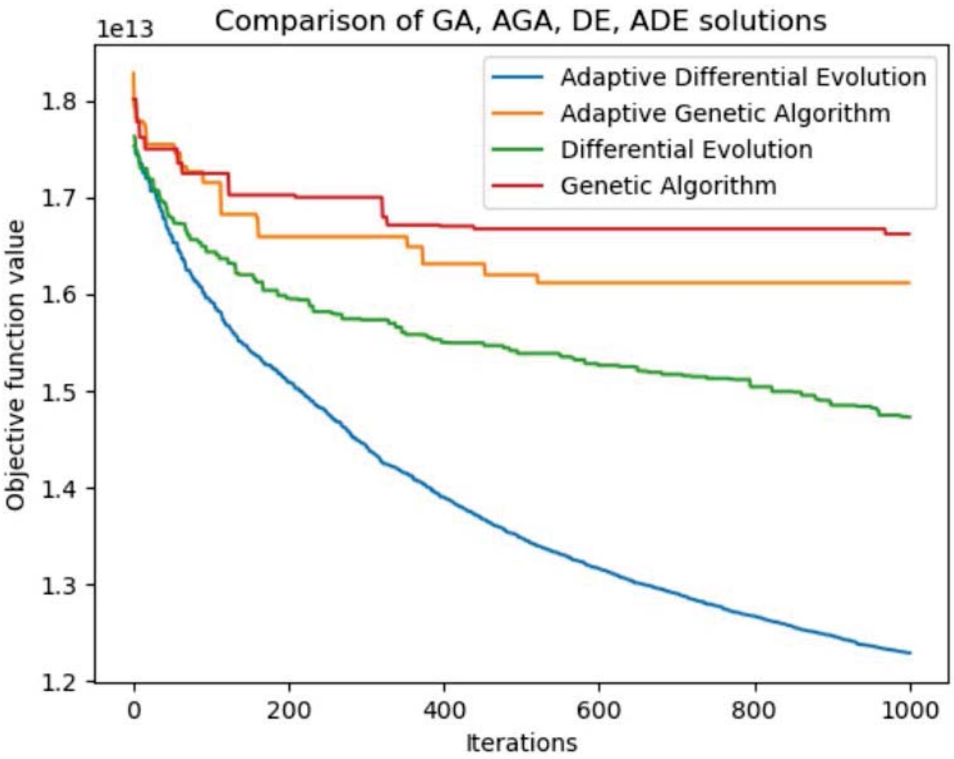

Figure 29: Large test case performance comparison of algorithms

The performance comparison of a large test case consisting of 70 suppliers, 37 manufacturing facilities, 112 distribution centers, and 42 products is shown in Figure 29.

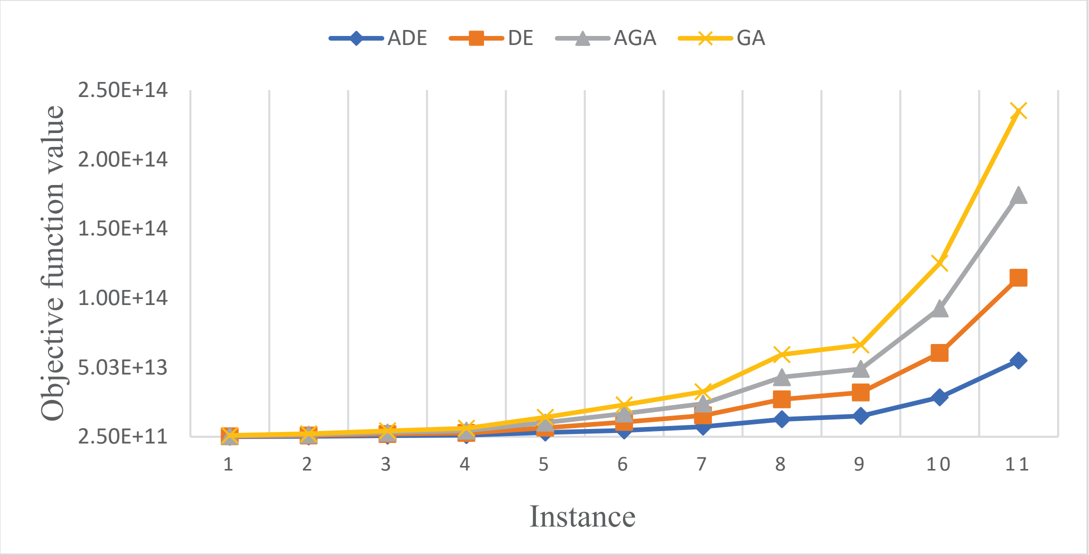

Figure 30: Comparison of solutions obtained from algorithms

ADE outperforms all others with the best (ADE) to worst (GA) performance difference of 30.53%. The performance difference between GA and AGA is 3.63%, while the difference between DE and ADE is 18.07%.%. ADE's performance has improved than DEs compared to small and medium-size instances. DE's scalability and capacity for handling high-dimensional search spaces enabled it to traverse complex landscapes and converge on optimal or near-optimal solutions better than AGA. In addition, when DE is modified with dynamic adaptability into ADE it outperformed all others in all test sizes. Figure 30 shows the comparison of solutions obtained from GA, AGA, DE, and ADE algorithms and Table 45 presents the comparative summary of computational results.

*Table 45**:** Summary of results.*

Size	Code (S, M, D, P)	DE	ADE	GA	AGA	Total number of variables
		Total Cost (In Rs.) $\times 10^{12}$		Total Cost (In Rs.) $\times 10^{12}$		
Small	(15, 5, 20, 5)	2.753	2.718	3.758	3.049	2430
	(20, 7, 25, 8)	5.671	5.408	6.340	6.294	4357
	(25, 10, 44, 10)	11.123	10.370	12.007	11.881	8993
Medium	(35, 15, 60, 15)	15.093	13.787	17.502	17.461	18320
	(40, 20, 70, 20)	34.528	32.764	38.061	37.819	28410
	(45, 25, 80, 25)	60.447	48.089	62.695	61.335	40550
	(60, 30, 95, 34)	80.504	75.376	85.751	85.603	61735
Large	(70, 37, 112, 42)	147.248	122.849	167.111	161.141	89134
	(85, 48, 135, 52)	169.359	152.350	172.350	170.350	139124
	(100, 61,167, 65)	318.825	287.154	326.079	321.978	214546
	(150,82,200,100)	595.982	552.390	608.343	598.203	391034

9.6 Sensitivity analysis

Sensitivity analysis is performed on technology adoption costs, stakeholder capacity for levels of technology adoption, and impact of technology adoption on cost and emission as shown in Table 46. The sensitivity analysis shows the robustness of the model as the changes in input parameter values have minimum effect on objective function value. The analysis also shows that in the case of no technology adoption (also no impact on cost and emission) there are noticeable increases in the objective function value.

Table 46: Sensitivity analysis

	Percentage change	Total Cost (In Rs.) $\times 10^{11}$			
		DE	ADE	GA	AGA
Parameters	OFV	56.545	54.373	63.559	62.958
Technology adoption cost	No TA	79.017	77.187	87.298	86.185
	-10%	57.066	54.672	63.822	61.717
	-5%	57.194	54.842	63.270	63.085
	5%	56.828	54.640	62.522	62.289
	10%	57.249	54.575	63.028	62.526
Stakeholder capacity for levels of technology adoption	-10%	57.547	54.914	63.580	62.931
	-5%	56.976	54.831	62.260	61.644
	5%	56.182	54.382	63.610	63.472
	10%	57.245	54.207	64.027	63.471
Technology impact on cost and emission	-10%	62.035	59.612	68.801	68.654
	-5%	59.973	57.328	66.646	65.603
	5%	54.214	52.243	60.572	60.058
	10%	51.805	49.903	57.425	56.592

*No TA- no technology adoption, OFV- Original objective function value