Blockchain-Enhanced NSGA-III GKM Framework for Transparent and Trustworthy E-Commerce Supply Chains

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This study focuses on improving transparency and trust in e-commerce supply chains through the integration of blockchain technology. This is very important in blockchain because, it is necessary to secure, record, verify and share the data throughout multiple parties to ensure the transparency and trust. To achieve this, we introduce the advanced combining technology called blockchain based NSGA III-GKM. Genetic K-means clustering (GKM) and the Non-Dominated Sorting Genetic Algorithm (NSGA-III) are two advanced algorithms combined with the advanced blockchain technology that are used in a novel way to achieve this. Blockchain systems produce huge volumes of complex data, therefore it is important to identify meaningful patterns and trends. These problems of blockchain are solved by NSGA III and GKM. The present study used NSGA III to solve problems with multiple objectives such as, improving trust, transparency and transport cost reduction. By using NSGA, the best solutions are effectively identified that can balance these challenging goals. At the same time, GKM improves the grouping process by fine tuning the data points which are classified into similar clusters. This helps to identify the specific trends in blockchain based supply chain data. By combining these methods, we can able to improve the trends and actions mechanisms in e-commerce supply chains. These combined method assists companies in identifying effective supply chain strategies, which helps to minimizing risks, and also able to adapt the continuously changing blockchain systems. Real-world data from e-commerce supply chains was used to test the method's efficacy. According to the findings, it was successfully showed the balance between various goals and provide suggestions for improving supply chain networks driven by blockchain. Overall, by combining blockchain with NSGA III and GKM, it not only ensures the security and trust but also it leverages advanced analytics to improve transparency and operational efficiency. Therefore, it will help organizations to achieve the resilient and efficient supply chain management.

Keywords: Blockchain; NSGA-III; Genetic K-means Clustering; Supply Chain Resilience; Trust and Transparency; Multi-Objective Optimization; Supply Chain Management.

1. Introduction

Transparency and trust are the important elements in e-commerce supply chains which helps to guarantee effective operations and promote stakeholder confidence [1,2]. Transparency is also known as the ability of all parties in the supply chain to access accurate and real-time information about the flow of goods, transactions, and processes [3,4]. It allows stakeholders, like suppliers, distributors, and customers, to trace the journey of a product from its original place to its final destination. This visibility reduces the chances of fraud, errors, and inefficiencies and also encourages transparency at every stage. Similarly, trust ensures that the shared information is reliable and secure, which means the information cannot be accessed by other third parties [5,6]. It builds confidence among stakeholders that the processes and data within the supply chain are true and fair. In the e-commerce supply chain sector, blockchain technology is considered as one of the innovative forces which addresses the issues related to trust and transparency [7,8].

To guarantee data consistency and to encourage stakeholder trust, this study uses advanced blockchain mechanisms, which include secure, immutable, and decentralized features. Large volumes of advanced data, such as operating logs, real-time tracking data, and historical shipment records, are produced by blockchain-powered systems [9,10]. This data holds valuable information that can help to predict demand, identify patterns, and improve processes like scheduling and routing. These improvements can make supply chains more effective and reliable. However, working with large datasets is not easy. It needs advanced tools and methods to analyse the data, mainly to deal with uncertainties and challenges of supply chain operations; this study focuses on using blockchain technology combined with advanced analytical techniques to overcome these challenges and helps to increase the benefits for e-commerce supply chains [11,12].

Due to the pressing need for blockchain-powered solutions in the supply chain domain, this study uses innovative fusion techniques, which involve Non-Dominated Sorting Genetic Algorithm (NSGA III) with Genetic K means clustering algorithm (GKM) [13- 15]. Combining these methods improves the effectiveness of multi-objective optimization in supply chain management and transportation logistics. The NSGA-III is well known for its effective ability to use Pareto-optimal solutions, which allows the decision-makers to evaluate trade-offs between competing objectives such as improving trust and transparency, reducing transportation costs, and maximizing service levels. On the other hand, Genetic K-Means improves clustering and allows meaningful patterns and trends to be involved in large datasets generated by blockchain systems. In this work, NSGA III-GKM is being used for two purposes. First, it provides a strong and adaptable optimization framework to deal with the complexities and uncertainties related to the supply chain management of e-commerce. Secondly, the model acts as an effective tool for scenario analysis and decision support, which allows stakeholders to assess the impact of operational strategies, blockchain policies, and the overall efficiency of supply chains. By combining these advantages, the model provides higher convergence rates, various solutions, and increased effectiveness in detecting high-quality results that can balance various goals. Throughout the supply chain network, the NSGA-III-GKM model helps decision-makers to make well-informed decisions that improve trust, and transparency. It makes it possible to create strategies consistent with the complex features of modern e-commerce supply chains by producing a variety of Pareto-optimal solutions. Overall, this integrated model denotes a notable breakthrough in blockchain-driven supply chain optimization and provides useful insights and advantages for improving operational effectiveness and confidence.

The main contribution of the paper as follows

- Proposed an advanced technique for evaluating transparency and trust mechanisms in e-commerce supply chains by combining the advantages of blockchain technology and analytical methods.
- The proposed novel model combined two effective techniques: NSGA III and GKM.
- By combining these techniques with an advanced blockchain mechanism, the model improves diversity and provides strong tactics for tackling uncertainties in supply chain operations and helping to improve fluctuations in blockchain-powered e-commerce.

2. Related Work

By analysing some of the previous studies we found some common risks associated with supply chain disturbance. Natural disasters, delays in transit, and the spread of infectious diseases are a few causes of these disturbances. The main issue is preserving the strength and continuity of supply networks through risk reduction. Setting the ways to do so, resilience abilities and systemic risk backgrounds are just a few risk management techniques that must be combined to respond to these disturbances. The basic concept of supply chain resilience in disruptions remains a major worry for many business sectors. The technological limitations are also the main drawback of some of the studies, which are analysed and listed below. Considering this as a background, we proposed this present study as a new solution. Table 1 shows the literature discussion in detail.

Table 1. Literature discussion analysis.

Citation	Source	SC Resilience	Transportation Trends	Fluctuation Analysis	Results

[16]	Supplier Retailer relationship	Examine the new options	High demand instability	Service level constraint	Put options reduce losses from demand instability. Retailers benefit in high demand. Supplier gains vary under constraints. Wholesale prices coordinate supply chains similarly.
[17]	Global Supply chains	Mediating Role of Resilience Capability	Diverse Reducing Strategies	Supply Chain Risks	1) Reducing strategies and improve supply chain resilience. 2) Resilience capability mediates supply chain risks. 3) Practical guidance for uncertain events.
[18]	Global Supply chains	Integrated Cost and Risk Management Approach .	Trade Facilitators Disruptions	Systemic Risks	1) Transport disruptions challenge supply chains. 2) Combined approach boosts resilience, overcomes limitations. 3) Practical insights for risk management
[19]	Port Networks and Supply Chains	Systemic Risk Framework	Natural risks and disturbances	PortRisk Layering	1) Ports at risk from hazards. 2) Framework quantifies systemic risk. 3) Layering boosts resilience against risks.
[20]	Population Mobility and Transportation	Commercial Driver Networks	Long-Haul Truck Dri ver Interactions	Disease Transmiss ion Risks	1) Truck drivers key in disease spread. 2) Policymakers balance health and supply. 3) Commercial networks vital for prevention.

3. Methodology

3.1. *General Outline of the methodology*

To improve transparency and trust mechanisms in e-commerce supply chains, the proposed methodology combines blockchain technology with two advanced analytical approaches such as, GKM and NSGA-III. Initially it combines the strength of GKM, a clustering method designed for effective data partitioning, with the abilities of NSGA-III. By combining these methods, it addresses the challenges in achieving transparency and trust by reducing the complexities of blockchain powered supply chains. NSGA-III is one of the diversity-preserving method who able to study a wide range of Pareto-optimal solutions. Similarly, GKM uses genetic algorithms to improve the K-means clustering parameters and allowing the identification of clusters that related to blockchain driven e-commerce trends and patterns. This combination makes is easier to identify transparent and trusted supply chain methods that can adapt to changing blockchain dynamics, which is important for risk reduction and decision making. Through the combination of effective data clustering and multi objective optimization, the proposed technique provides a complete approach for analysing trends and variations in supply chain operations. This strengthens the model by providing information to make e-commerce supply chain networks' as adaptive, particularly in the changing conditions. Therefore, the suggested blockchain based analytical model provides the strong foundation for decision making in supply chain management which support the transparency, trust and sustainability.

3.2. *Review of Blockchain based E-Commerce Supply Chain Process to Promote Trust and Transparency*

The transparency and trust mechanism based on blockchain technology is designed to address the important challenges in modern e-commerce supply chains. Here we adapt the blockchain mechanism particularly to safeguard the e-commerce supply chain based confidential information's. The ability of all parties like suppliers, manufacturers, distributors, and consumers to obtain accurate, real-time information regarding supply chain operations and transactions is referred to as transparency. This is made possible by blockchain, which provides a decentralized ledger in which each transaction is safely recorded and unbreakable. This ability removes inconsistencies and promotes transparency by guaranteeing that the all parties involved in this process can view the same information. Similarly, trust is generated through the security functions was created by the features of blockchain. Blockchain increases stakeholder trust where the data is maintained safely without the need for central authorities. Some of the studies which focused on this same objective are effectively analysed through [21] [22] [23] and [24].

3.3. *Proposed Analytical Methods to Ensure Blockchain Ability*

3.3.1. *NSGA III*

NSGA-III is an effective multi-objective optimisation technique that is an extension of NSGAII. By effectively distributing and preserving a variety of solutions along with the Pareto front, it aims to provide decision-makers with various possibilities for decisions. NSGA-III combines parent and offspring populations in each generation, using non-dominated sorting to classify people into various levels. It guarantees a fair representation of solutions by repeatedly choosing and creating new populations from these levels. New ideas, including objective value normalization using ideal and extreme points, systematic beginning reference point generation, and niche preservation to preserve variety, are presented in NSGA-III. NSGA-III achieves stability and convergence by using these methods, providing an extensive collection of Pareto optimal solutions for difficult optimization issues. The general form of NSGA III is described in the step-wise procedures below.

Table 2. Normalization tasks.

Ideal Point Calculation	Translated Objective Values	ASF	Objective Normalization
$Zmin = (Zmin1, Zmin2, \dots . Z\min m)$	$F'_i = (x_j) = f_i(x_j) - Zmini$	$\min ASF(x_j, w) = \max_{i=1}^{m} F'_i(x_j) / w_i$	$Fin(xj) = \frac{F'i(xj)}{ai - Zi} min$

Step 1: Normalize the objective values to prove consistency and comparability, table 2 shows normalization tasks.

Step 2: Generate the initial reference points systematically for evaluation.

$$h = \left\lceil \frac{p+m-1}{p} \right\rceil \tag{4}$$

Step 3: Compute the distances between solutions and reference points.

Step 4: Preserve diversity among solutions to capture a range of Pareto-optimal solutions.

Niche count P_i represents the number of solutions associated with the $i - th$ reference point.

Minimum niche count $j_{min} = \min p_i$

Random selection: If $j_{min} > 1$ reference point is chosen randomly.

Solution Selection: Solutions associated with the chosen reference point are selected into the next generation; the niche count for each selected solution is incremented.

3.3.2. *Proposed GKM*

To improve the identification of cluster centers in the objective space, we provide an innovative method in our study called GKM clustering algorithm. The GKM is used in this combination to cluster the initial reference points, which classifies the goal space into several subspaces $s_1, s_2, \dots, s_k$. The proceedings of this techniques are inspired from [13].

Where k is the number of clusters. For a given subspace, each cluster center acts as the direction vector. Through this division of the objective space, we aim to remove the limitation that only solutions closest to reference points are considered during the niche preservation operation phase, by improving convergence. Then, we replace the parallel distance metric with the Penalty-Based Boundary Intersection (PBI) aggregation function, which improves the NSGA-III convergence even more. Using metrics like the Inverted Generational Distance (IGD) and Hypervolume (HV), we assess the performance of the NSGA-III-GKM hybrid technique. These metrics assess the methods ability to balance the convergence and diversity solutions which is important for achieving transparency and trust in blockchain driven e-commerce supply chains. The proposed blockchain driven NSGA III and GKM process is described below.

Algorithm 2

Step 1: Define the n of the population p_t and set the maximum number tm of function evaluation fe.

Step 2: Create the initial population by randomly applying genetic operations for each individual subspace.

Step 3: Perform non-dominated sorting for the parent and offspring populations within each subspace which is denoted as $p_s{}^t{}_i$ and $q_{s_i}^t$ combine these population to obtain r_t.

Step 4: Normalize the objective values of the populations using the same procedures as the basic NSGA III scheme.

Clustering of the reference point

Step 5: Initialize k clusters randomly and assign each reference point to its nearest cluster center, the cluster center recalculated to reduce the squared error E using

$$E = \sum_{j=1}^{k} \sum_{p \in c_j} ||p - m_j||^2 \quad (5)$$

Step 6: Use the real number encoding to denote cluster center as genes on chromosome for genetic operations.

Step 7: Apply Fitness function to balance tightness and separability, improving the number of clusters k based on g_b

$$fit_D = \frac{g_b}{b + a_E} \quad (6)$$

$$g_b = \frac{2}{k(k-1)} \sum_{i=1}^{k} \sum_{j=i+1}^{k} ||m_i - m_j||^2 \quad (7)$$

Step 8: Evaluate the PBI aggregation function $D(x_j)$ for each solution to measure its distance from the cluster centers which is expressed as

$$D(x_j) = Di, 1(x_j) + \theta Di, 2(x_j) \quad (8)$$

Step 9: Calculate the projection $Di, 1(x_j)$ and vertical $Di, 2(x_j)$ distances of each solution to the $i\,th$ cluster centers using the direction vector $s\ i$.

The distance is expressed as

$$Di, 1(x_j) = ||(f^n(x_j))\ s\ i||\ /||s\ i|| \quad (10)$$

$$Di, 2(x_j) = ||(f^n(x_j)) - Di, 1(x_j)(s\ i/||s\ i||)|| \quad (11)$$

Step 10: Select solutions with small $D(x_j)$ values indicating strong convergence, and add them to the next generation until reaching the target population size.

Step 11: Check if the maximum number of function evaluations tm is reached.

Step 12: If tm is reached, output the current solutions and terminate the program.

Step 13: If tm is not reached, repeat steps 2-6 to further refine solutions and improve supply chain resilience against blockchain-driven dynamics and e-commerce trends.

To set the stage for further actions, the algorithm starts by initialising parameters such the maximum number of function evaluations tm and the population size p_t. Once these parameters have been set, the algorithm uses random genetic processes to create an initial population. This produces a wide range of possible solutions that represent different approaches to improving supply chain resilience against changes and trends in the transportation industry. Figure 1 shows the proposed architecture of this research in detail.

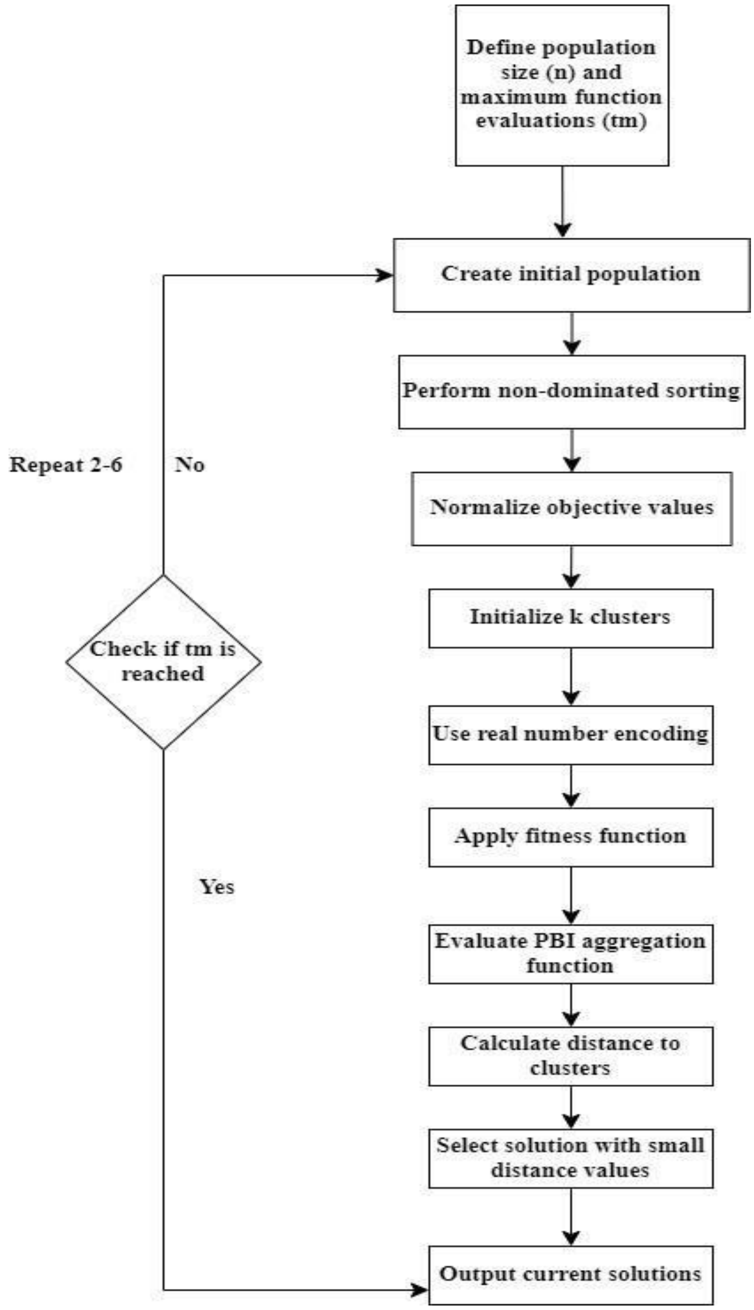

Fig 1: NSGA III-GKM Structure

After population creation, non-dominated sorting is carried out inside each subspace to find

Pareto-optimal solutions that strike a balance between several goals regarding to e-commerce supply chain transparency, trust and resilience dynamics and supply chain ability. The populations' objective values are then adjusted to guarantee balanced comparison and assessment. After randomly developing k clusters, the process of clustering reference points begins, with reference points being assigned to the closest cluster centers. By recalculating cluster centers iteratively to reduce the squared error a_E, the objective space is effectively divided into multiple subspaces that correspond to different features of supply chain resilience. Cluster centers are modeled as genes on chromosomes using real number encoding, which makes genetic optimization easier. By balancing the tightness and separability of clusters, the fitness function is used to improve the quality of clustering based on the sum of distances G_b between various clusters. The PBI aggregation function is then used to calculate each solution's distance from cluster centres. This calculation accounts for both projection and vertical distances, and it continues until the goal population size is reached. Solutions that show significant convergence, as indicated by modest values of the PBI aggregation function, are selected and added to the next generation. The algorithm then determines whether the maximum number of function evaluations tm has been reached. In that case, the software outputs the existing solutions and ends. Otherwise, the algorithm repeats steps 2-6 to improve transparency and trust mechanisms by continually improving and refining solutions within blockchain-driven e-commerce trends and transparency demands. Figure 1 shows the proposed architecture of this research in detail.

3.4. *Performance of NSGA-III-GKM in Transparency and Trust Mechanism for Blockchain-driven E-Commerce Supply Chains*

Table 3 likely presents an evaluation framework for analysing transparency and trust mechanisms in a system or model using NSGA-III (Non-dominated Sorting Genetic Algorithm III) optimized parameters combined with GKM (Generalized Knowledge Management) principles.

Table 3. Transparency and Trust Mechanism Analysis using NSGA-III-GKM Parameters.

Blockchain-driven E-commerce Transparency and trust analysis	**NSGA III-GKM Parameters**
IGD: Measures the average distance from the obtained Pareto front to the true Pareto front. Lower values show better convergence.	($\boldsymbol{n}$): Defines the number of solutions in each generation. Larger populations can provide better coverage of the solution space.
HV: Measures the volume of the objective space dominated by the obtained Pareto front. Higher values show better coverage of the objective space.	$\boldsymbol{tm}$: Limits the number of function evaluations allowed during optimization. Higher values may lead to better exploration of the solution space.
Trend Analysis: Examines long-term patterns or trends in e-commerce data, helping to find out potential risks.	**Genetic Operations:** Randomly apply genetic operations such as selection, crossover and mutation to create diverse solutions and explore the solution space effectively.
Transparency Analysis: Evaluated data consistency and accuracy in blockchain driven supply chain activities to addressing immediate needs for reliable insights.	**Clustering:** Using the GKM clustering algorithm to partition the objective space into subspaces, improving convergence by considering solutions from diverse regions of the solution space.
($\boldsymbol{k}$): Determines the number of clusters in the GKM clustering algorithm. Optimal cluster count improves the quality of clustering and solution diversity.	**Fitness Function:** Balances tightness and separability in clustering using the fitness function, guaranteed that solutions within clusters are similar while solutions between clusters are dissimilar.

Distance Metrics: Measure the distances between solutions and cluster centers to evaluate clustering quality and convergence.	**PBI:** Evaluates the distance of each solution from cluster centers, guiding the selection of solutions with strong convergence for the next generation.
$(\boldsymbol{Di}, \mathbf{1})$: Measures the distance of a solution to the cluster center along the direction vector.	$(\boldsymbol{Di}, \mathbf{2})$**:** Measures the vertical distance of a solution to the cluster center, aiding in solution selection based on convergence strength.
$\boldsymbol{E}$**:** Minimizes the squared error criterion in cluster center recalibration, improving the quality of clustering.	**Mutation Operation:** Facilitates automatic learning of the optimal number of clusters by adjusting the cluster count based on the fitness landscape.

4. Results and Experiments

Here, the suggested model is evaluated using two methods: blockchain-based evaluation and analytical model-based evaluation. The experimental features are adapted from two distinct datasets [25] and [26]. Table 4 provides blockchain-based evaluation methods.

4.1 Blockchain based Evaluation

Table 4. presents the blockchain based evaluation details.

	Drip: Industry database for product category and sales distribution.
Trends Analysis	Machine (work-centre) control
	E-commerce growth trends analyzed over specified years.
	Fraud patterns and percentages studied to identify risks.
	Product category trends assessed based on market insights.
Transparency Analysis	Data from semi-structured interviews with 190 stakeholders, including consumers, e-commerce representatives, and blockchain experts.
	Insights into blockchain's potential for reducing fraud and increasing traceability.
Schedule	Capacity
Dataset	E-commerce growth statistics.
	Fraudulent activity reports.
	Product category distribution figures.
Databases	ECDB: Industry-specific e-commerce data repository.
	Ekata: Fraud detection and e-commerce insights database.

Figure 2 shows the efficacy of the suggested in terms of traceability index for three databases called ECDB, Ekata, Drip. This highlights that how these databases support the transparency within the blockchain framework. Here we observed that the Ekata achieves the highest traceability score when compared with the other two databases. Similarly Figure 3 shows the data integrity scores of three databases.

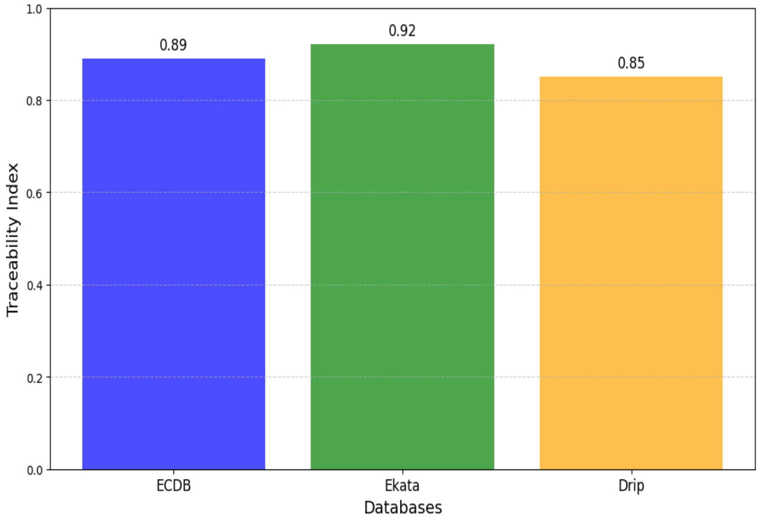

Fig. 2. Traceability index

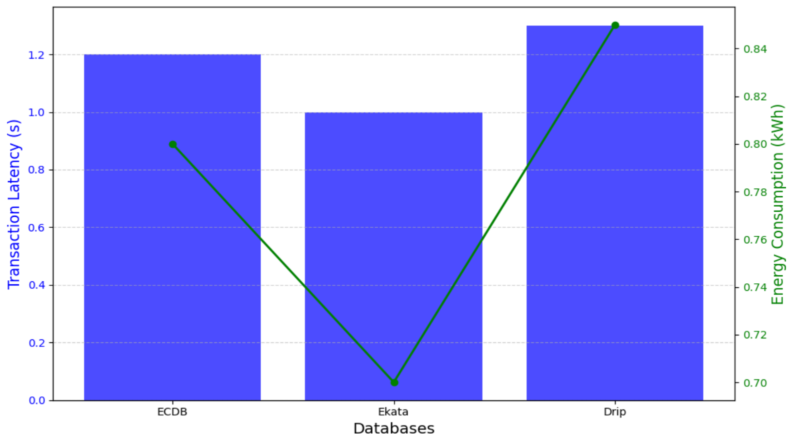

Fig. 3. Data Integrity Efficacy

Figure 4 shows the outcomes of each database in terms of consensus efficacy. The outcomes show how each database maintained effective consensus processes by

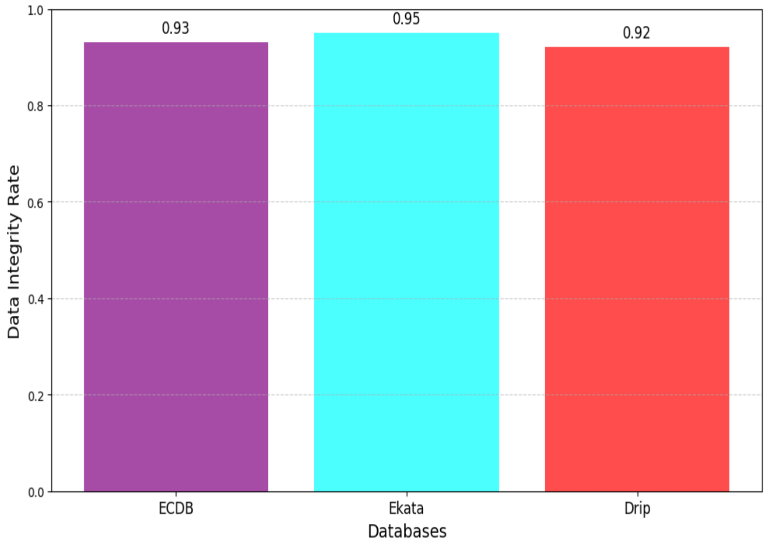

Fig. 4. Consensus Efficacy

maintaining a balance. With the lowest energy consumption (0.7 kWh) and transaction delay (1.0 seconds), Ekata shows the best consensus efficiency. These measurements highlight the suggested blockchain method's efficacy in guaranteeing quick, safe, and energy-efficient operations. Table 4 provides the simulation setup in detail.

Table 5. Simulation setup.

Data Features	Description
Lane	Single lane
Company	Fortune 100 multinational company in the FMCG industry
Source of data	Interviews with logistic sourcing managers, contract data, expert opinions, historical company data.
Input Variables	Annual shipment volume, transportation rate, lane length, schedule reliability of safety net carrier, safety net price, transportation option costs, the ongoing cost of spot market, historical data
Data Collection period	24 months from May 2013 to April 2015
Data Analysis Method	Monte Carlo simulation with 10,000 trials using @Risk software

4.2 Evaluation Criteria

This section evaluates the proposed NSGA III-GKM using various metrics such as convergence rate, robustness, computational efficiency and scalability. In this evaluation, the proposed model of NSGA III-GKM is compared with multiple effective techniques of NSGA III, NSGA II, MOEA/D, U-NSGA-III, DC-NSGA III, and B-NSGA III [13]. The suggested model is an advanced approach tested and shown in the earlier study of [13] to increase diversity and convergence rates in every scenario. We adapted the methodology based on the proceedings for our current investigation to examine the trends and transparency in the supply chain. Figure 5 shows the convergence rate analysis over iterations. Ten iterations were used to compare the convergence rates of different optimisation models, such as NSGA III, NSGA II, MOEA/D, U-NSGA III, DC-NSGA III, B-NSGA III, and the proposed NSGA III-GKM technique. An algorithm's convergence rate measures the speed at which it approaches a Pareto-optimal front and its effectiveness at solving problems. The proposed NSGA III- GKM constantly shows the highest convergence rates of all the models. The steady decrease in convergence rate over the iterations shows quick progress toward ideal solutions. However, other models show marginally slower convergence rates and show differences in performance over multiple iterations. NSGA III-GKM method is generally faster than other models, such as NSGA II, B-NSGA III, U-NSGA III, DC-NSGA III, and MOEA/D, even if these models also achieve decent convergence.

Figure 6 presents the effectiveness of the proposed NSGA III-GKM in terms of computational efficiency. Comparing the NSGA III-GKM model against other models, such as NSGA III, NSGA II, MOEA/D, U-NSGA III, DC-NSGA III, and B-NSGA III, the proposed NSGA IIIGKM shows lower computing times throughout the five transportation tasks. Compared to others, the proposed model requires less time and computer resources to run. Based on Figure 4, in 1, NSGA III-GKM takes 8 seconds to compute, but other models NSGA III, NSGA II, and MOEA/D take 10, 12, and 11 seconds to run, respectively. Similarly, in task 5, DCNSGA III and B-NSGA III require 24 and 18 seconds, but NSGA III-GKM needs 12 seconds. These comparisons show the proposed NSGA III-GKM model's effectiveness.

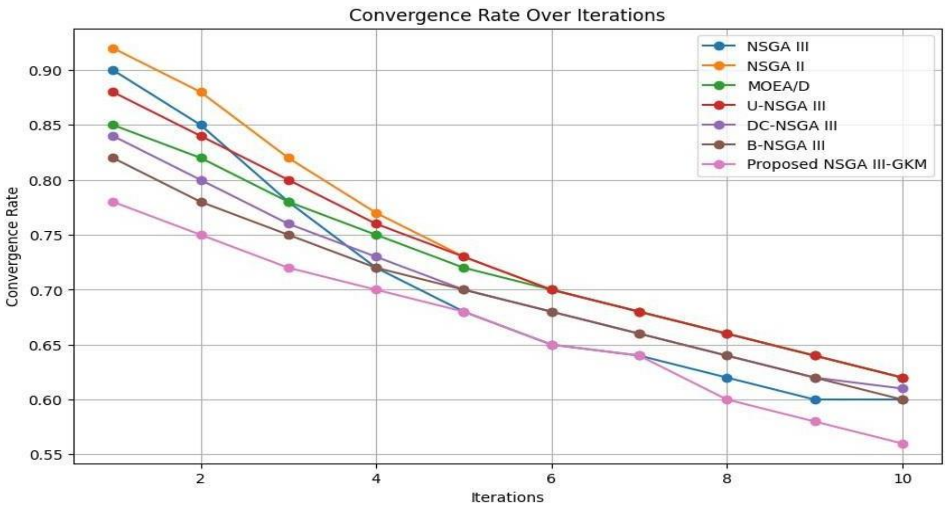

Fig. 5. Convergence Rate

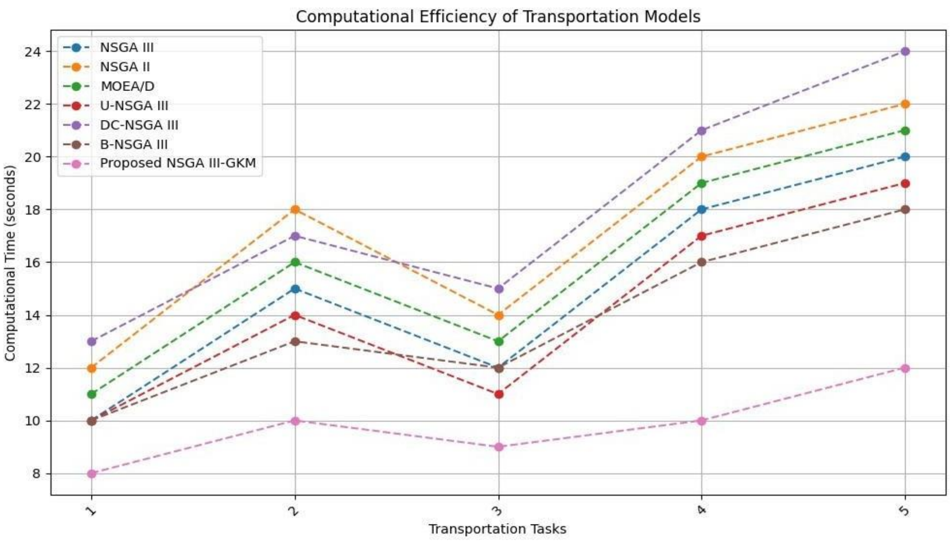

Fig. 6. Computational Efficiency

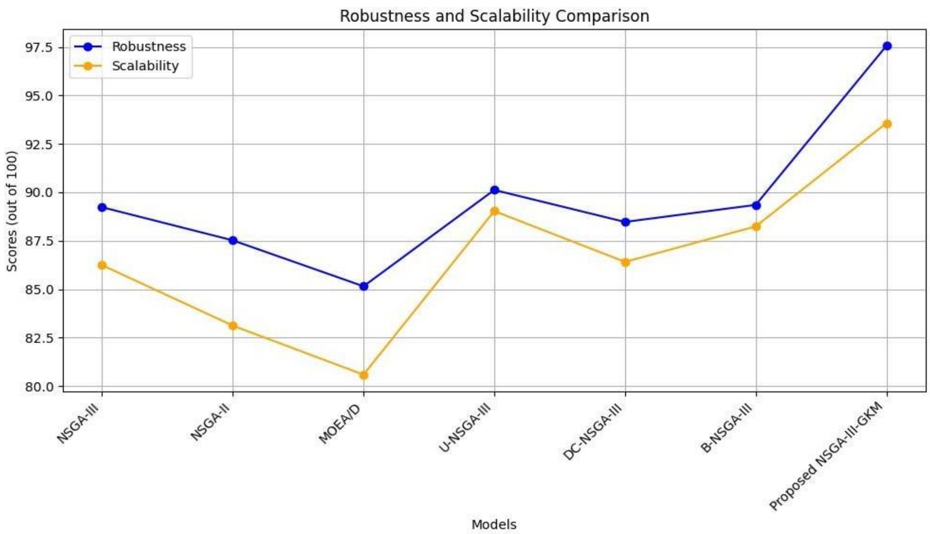

Fig. 7. Robustness and Scalability Comparison

In comparison to other models like NSGA-III, NSGA-II, MOEA/D, U-NSGA-III, DC-NSGA-III, and B-NSGA-III, Figure 7 shows the resilience and scalability of the proposed NSGA IIIGKM model. The suggested NSGA III-GKM has the most excellent robustness score among the compared models, outperforming all other models in terms of robustness. This shows that the proposed approach across various settings and datasets can maintain stability and efficacy. Furthermore, the NSGA III-GKM has better scalability than most other models, as evidenced by its much higher scalability score. This highlights that the proposed methodology may effectively manage bigger datasets and adapt to meet increasing computational needs without compromising effectiveness.

5 Conclusion

By using advanced analytical tools and blockchain mechanism, the proposed study provides a novel strategy for improving transparency and trust mechanisms in e-commerce supply chains. The suggested model effectively addresses important supply chain issues by combining the efficient techniques of blockchain mechanisms with advanced analytical models. Blockchain models generate huge volumes of data related to supply chain transactions. We use analytical methods to avoid the complexities in analysing the trends and transparency with these data. Here, NSGA-III makes it possible to generate a variety of Pareto-optimal solutions. Similarly, GKM finds clusters that correspond with trends and patterns associated with blockchain, which makes it easier to find useful information in supply chains for e-commerce. The simulations of this study are performed with two distinct datasets to assess the efficacy of models in two ways: blockchain-based evaluation and analytical methods-based evaluation. The efficacy of the suggested model is compared with various existing models. The model's outcomes show notable efficacy regarding analytical methods in terms of convergence rate, computational efficiency, and scalability. Similarly, traceability, data integrity and consensus efficiency are based on blockchain terms. Overall, this study shows the strongest foundation based on e-commerce supply chain management by addressing the dual objectives of transparency and trust.

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