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# A Data-Driven MINLP Approach for Enhancing Sustainability in Blockchain-Enabled e-Supply Chains

Afif Badawi[1], Syahril Efendi[2,*], Tulus[3], Herman Mawengkang[4]

[1]*Doctoral Program in Computer Science and Information, Universitas Sumatera Utara, Indonesia*

[2]*Department of Computer Science, Universitas Sumatera Utara, Indonesia*

[3,4]*Department of Mathematics, Universitas Sumatera Utara, Indonesia*

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**Abstract**

Modern e-supply chains face increasing complexity and a critical need for enhanced sustainability and traceability. Blockchain technology offers a promising infrastructure to support these goals through its decentralized, immutable ledgers and automated smart contracts, which can provide a foundation of trustworthy data for decision-making. Despite blockchain's potential, a notable gap exists in quantitative, data-driven optimization models that can rigorously assess the operational and sustainability impacts of its integration, particularly for systems with complex, non-linear interactions. This study aims to address this gap by presenting an in-depth analysis of a specific Mixed-Integer Non-Linear Programming (MINLP) model. The goal is to clarify the model's structure, evaluate its application for an e-supply chain that incorporates blockchain features and sustainability objectives (like carbon emission reduction), and derive practical insights from its application. The methodology involves a detailed exposition of the MINLP model, followed by its application to a defined e-supply chain scenario. The analytical approach includes computational experiments focusing on a base case analysis, benchmarking the model's performance against a conventional system, and conducting sensitivity analyses on key parameters to understand performance trade-offs. The initial base case analysis demonstrates the model's capability to optimize supplier selection and operational plans while adhering to sustainability constraints, such as maintaining carbon emissions at or below 300 kg $CO_2$ per period, and accounting for blockchain-specific costs like a per-supplier usage fee of 500. The model's structure and preliminary insights suggest its potential to achieve improved environmental impact compared to conventional systems, balanced against associated implementation costs. This research provides a detailed examination of a complex MINLP structure, offering a data-driven analytical approach for assessing blockchain's role in sustainable e-supply chains. It furnishes a foundational framework and insights that can guide managerial decisions and strategic planning for industries transitioning towards greener, more transparent, and digitally advanced supply chain operations.

*Keywords:* Blockchain Technology, E-Supply Chain, MINLP, Optimization, SSCM

## 1. Introduction

The rapid proliferation of e-commerce and the expansion of global digital markets have fundamentally reshaped supply chain dynamics, introducing heightened complexity in product flows, data management, and the coordination of stakeholders [1]. While this digitalization brings advantages such as increased speed and scalability, it concurrently intensifies challenges related to transparency, traceability, and trust within supply chain operations [2]. Digitalization can streamline information exchange and improve visibility to some extent; however, the sheer volume of data, the number of actors involved, and the pace of transactions in e-supply chains can also obscure origins, complicate compliance verification, and create new vulnerabilities. Against this backdrop, sustainability has emerged as a critical imperative in modern supply chain management, propelled by more stringent environmental regulations, growing consumer consciousness, and the urgent need to align business practices with global Sustainable Development Goals (SDGs) [3].

Conventional supply chains frequently operate in disconnected silos, characterized by fragmented data and restricted visibility across both upstream and downstream activities. This opacity makes it exceedingly difficult to verify

***Corresponding author: Syahril Efendi (syahril1@usu.ac.id)**
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adherence to environmental or social compliance standards. In the context of e-supply chains, where transactions are predominantly digital and geographically dispersed, these issues are magnified. Products often traverse through numerous intermediaries, rendering the tracking of origins, the monitoring of carbon emissions, and the assurance of ethical sourcing particularly challenging [4]. Consequently, traditional optimization models in supply chain design have often prioritized cost minimization or service level enhancement, frequently overlooking crucial sustainability trade-offs and the mechanisms for enforcing traceability [5].

Blockchain technology, distinguished by its decentralized architecture, immutable record-keeping, and transparent operational nature, presents a transformative approach to addressing these persistent challenges. By meticulously recording all transactions on a distributed, shared ledger and facilitating the execution of smart contracts, blockchain can automate compliance processes, ensure the provenance of data, and enforce sustainability protocols at every juncture of the supply chain [6]. The inherent features of blockchain thus provide a robust foundation for trustworthy and verifiable data, which is paramount for effective and responsible decision-making. For instance, empirical evidence shows blockchain's efficacy in enhancing food safety through improved traceability [7] and in mitigating the risks associated with counterfeit products in sectors such as pharmaceuticals and fashion [8].

Despite these promising attributes, the practical integration of blockchain into operational supply chain models, especially those designed to support sustainability objectives, remains an area requiring significant development. Much of the existing literature tends to explore conceptual applications or focuses on qualitative benefits, often without adequately addressing the quantifiable trade-offs and logistical complexities introduced by blockchain implementation. These complexities can include transaction processing delays, the costs associated with data verification, or penalties related to emissions [9], [10]. This results in a notable gap in the availability of comprehensive decision-support tools that can concurrently optimize for cost-efficiency, sustainability performance, and blockchain-enabled traceability. This paper addresses the specific problem of optimizing e-supply chains for enhanced sustainability by leveraging the capabilities of blockchain technology, focusing on the need for quantitative, data-driven optimization models to rigorously assess its operational and sustainability impacts, even when such models entail inherent complexities.

The main objective of this study is to present and analyze a specific MINLP optimization model for an e-supply chain network that incorporates blockchain features and sustainability objectives. This paper aims to contribute to the field by providing the following: 1) a detailed exposition and clarification of this specific MINLP model as it applies to blockchain-enabled sustainable e-supply chains; 2) a clear methodology for the practical application and solution of the model, including data considerations and solution approaches; 3) a quantitative evaluation of the model's performance through computational experiments that benchmark its outcomes against a conventional supply chain system; 4) a sensitivity analysis to assess the model's behavior and responsiveness to variations in key parameters, such as carbon costs and blockchain fees; and 5) the derivation of pertinent managerial insights that stem from this comprehensive analysis.

## 2. Literature Review

### 2.1. Sustainable Supply Chain Management (SSCM)

The transformation of traditional supply chains into Sustainable Supply Chains (SSCs) has become increasingly important in response to escalating environmental degradation, heightened ethical concerns, and mounting regulatory pressures. SSCM fundamentally integrates economic, social, and environmental goals, commonly referred to as the Triple Bottom Line (TBL) framework. As defined by Seuring and Müller, SSCM involves incorporating these three dimensions into comprehensive supply chain practices [11]. The TBL concept, first introduced by Elkington in 1994, necessitates businesses to weigh their operations against holistic sustainability criteria, thereby promoting a balance between economic growth, environmental stewardship, and social equity [11]. In operational terms, SSCM translates to minimizing waste, reducing carbon emissions, promoting ethical sourcing, and enhancing stakeholder collaboration [2]. Thus, in the context of SSCM, organizations must adjust their supply chain strategies to enhance overall sustainability while simultaneously maintaining or improving their competitive advantages [12], [13]. The objectives of SSCM extend beyond mere compliance with prevailing regulations; they are geared towards enhancing long-term organizational performance and ensuring stakeholder satisfaction [12], [14]. Research indicates that the successful implementation of SSCM practices can lead to more effective risk management and optimized resource utilization, thereby addressing critical global challenges such as resource scarcity and environmental degradation. Specifically, firms that proactively adopt sustainable practices can significantly improve their resilience against market volatility and environmental shifts, which ultimately boosts their competitive edge in the marketplace [15]. However, the adoption of SSCM is not without its difficulties. Challenges typically arise from the inherent complexity involved in balancing these diverse economic, environmental, and social objectives. Organizations often grapple with the intricacies of integrating sustainability principles into long-standing traditional supply chain practices, particularly while managing varied and sometimes conflicting stakeholder expectations [16], [17].

Optimization models play an integral role in advancing SSCM by providing robust quantitative frameworks to address the multidimensional challenges intrinsically associated with achieving sustainability. These models are diverse and can generally be classified into linear, non-linear, and multi-objective optimization models. Linear optimization techniques are frequently employed for more straightforward supply chain problems where the relationships between decision variables are assumed to be proportionate and additive [18]. In contrast, non-linear models are designed to account for more complex system dynamics where inputs and outputs are not directly proportional; such complexities often arise from the interdependencies associated with environmental regulations or the non-linear cost structures of sustainable technologies [18]. Furthermore, advanced multi-objective optimization models empower decision-makers to simultaneously address multiple, often conflicting, objectives inherent in SSCM. These can include concurrent goals such as operational cost reductions, the minimization of adverse environmental impacts, and the maximization of positive social benefits [18]. Such sophisticated models facilitate more informed and holistic decision-making processes, helping organizations to effectively navigate the intricate trade-offs between competing sustainability objectives [17].

## 2.2. Blockchain Technology in Supply Chain Management

Blockchain technology is increasingly recognized as a transformative solution in SCM, particularly in enhancing traceability, anti-counterfeiting measures, transparency, and compliance through smart contracts. The adoption of blockchain in supply chains aligns closely with efforts to improve sustainability, fostering transparency and trust among stakeholders while combating inefficiencies and unethical practices. Applications of Blockchain in SCM include traceability, which is arguably one of the most significant applications in industries such as food and pharmaceuticals where meticulous tracking of products is paramount for safety and compliance. In food supply chains, blockchain enables detailed tracking from farm to table, allowing stakeholders to trace products back through each stage of the supply chain, thus ensuring quality, safety, and potentially verifying sustainable farming practices or reduced food waste [19]. Similarly, in pharmaceuticals, blockchain can mitigate risks related to counterfeit drugs by providing immutable records that trace products back to their origins, ensuring patient safety and compliance with regulatory standards [20]. These capabilities help build consumer trust, as customers can verify the authenticity and quality of their products. Anti-counterfeiting measures benefit profoundly from blockchain's unique characteristics of immutability and transparency. By documenting every transaction and change of custody on a blockchain, entities involved in the supply chain can ensure that only legitimate products reach the consumer, which is crucial for sustainability by preventing resource waste on illicit goods [21]. This is especially critical in sectors vulnerable to counterfeit goods, where trust and safety are significantly jeopardized. Smart contracts enhance compliance by automating agreements based on predetermined conditions, which can include verifiable sustainability metrics such as emission thresholds or ethical sourcing certifications. These contracts execute automatically upon verification, reducing intermediaries and disputes, and enabling the direct incorporation of quantifiable sustainability achievements or penalties into optimization models [22], [23].

The benefits of Blockchain Adoption in SCM are numerous, mainly in terms of enhanced transparency and trust. Blockchain fosters a higher level of transparency, allowing all participants in the supply chain to access real-time data and documentation. This visibility can result in improved collaboration and reduced friction between partners [24]. Furthermore, the permanent and immutable nature of blockchain records significantly enhances trust among stakeholders, as each participant can validate transactions without reliance on a central authority [24]. Additionally, the potential for cost savings is notable, some of which can be linked to sustainability improvements. Blockchain can reduce inefficiencies related to administrative tasks, fraud, and error-prone processes, leading to improved operational efficiencies. These efficiencies can translate to reduced resource consumption, lower waste, and fewer penalties for non-compliance with environmental standards, thereby contributing to both economic and environmental sustainability objectives [25]. Crucially, for quantitative modeling and data-driven decision-making, blockchain provides enhanced data integrity and verifiability. This ensures that the data inputs for optimization models aiming to improve sustainability are more reliable and auditable, leading to more robust and trustworthy outputs. Despite its numerous advantages, the transition to blockchain technology within supply chains is not without challenges. A significant barrier is the lack of standardization and understanding of blockchain's capabilities across various sectors. There exists a broader uncertainty among supply chain professionals about the practical implications and risks associated with blockchain, reflecting a critical need for education and awareness [26]. There are also concerns regarding the integration of blockchain with existing systems. The fragmented nature of supply chains, characterized by varied technological capabilities among partners, can complicate the implementation of a unified blockchain system [27]. Moreover, the energy consumption associated with some blockchain technologies, particularly Proof of Work systems, raises sustainability concerns, echoing the very objectives the technology seeks to advance [26]. This is a particularly important consideration when focusing on studies that discuss blockchain for sustainability aspects, as the environmental footprint of the blockchain solution itself must be weighed against its benefits in promoting broader supply chain sustainability. However, it is important to note that alternative consensus mechanisms, such as Proof-of-Stake (PoS), offer significantly lower energy footprints, and the selection of an appropriate blockchain architecture itself can be a critical decision factor, and thus a modeling parameter, when designing sustainable, blockchain-enabled supply chains.

## 2.3. Quantitative Models Integrating Blockchain and Sustainability in SCM

The fusion of blockchain technology and sustainability objectives within SCM is an emerging area of academic inquiry, with a growing focus on quantitative models designed to integrate these distinct yet complementary features. Research in this domain explores a variety of mathematical approaches, including Mixed-Integer Linear Programming (MILP), MINLP, simulation methods, and other analytical techniques such as Structural Equation Modeling (SEM) and fuzzy inference systems, to understand and optimize the role of blockchain in fostering sustainable supply chains. Several studies highlight how blockchain can serve as a foundational technology for enhancing supply chain performance and sustainability through improved data management and stakeholder coordination. For instance, [28] utilize SEM alongside an Analysis of Fuzzy Inference Systems (ANFIS) to demonstrate blockchain's potential in facilitating data sharing and improving coordination, thereby promoting sustainable practices. Their work underscores blockchain's capability to integrate sustainability metrics directly into the decision-making fabric of supply chains. Similarly, [29] propose an innovative blockchain-based architecture specifically designed to support sustainable supply chains. While their paper focuses more on the architectural framework, it introduces the concept of a quantitative model to assess sustainability impacts, laying groundwork for future quantitative analyses.

The impact assessment of blockchain on sustainability performance is a recurring theme. Research [20], while acknowledging the potential benefits, emphasize the critical need for empirical studies that quantitatively establish the relationship between blockchain adoption and tangible sustainability outcomes. They advocate for future research to incorporate rigorous quantitative analyses, potentially using MILP or simulation, to establish causal links. Other research provides a contextual understanding of the interplay between blockchain and green supply chain practices. Study [30] underscore the importance of a firm's technological orientation in conjunction with blockchain adoption to enhance pro-environmental behaviors, suggesting that systemic changes are key and that quantitative modeling is a necessary future step for rigorous analysis. The integration of blockchain with existing enterprise systems for enhanced sustainability is also explored. Research [31] investigate how blockchain can complement Enterprise Resource Planning (ERP) systems to boost sustainable performance, proposing the integration of blockchain with quantitative modeling approaches already used in ERP systems. This suggests opportunities for developing sophisticated optimization models, potentially MILP or MINLP, that can balance operational efficiency with sustainability metrics. Furthermore, the role of blockchain in enhancing supply chain visibility and its implications for sustainability are discussed by [32]. Their work implies a strong potential for employing simulation models to demonstrate how increased visibility through blockchain affects decision-making in sustainability contexts, which could evolve into quantitative studies using stochastic modeling to analyze diverse sustainability scenarios. Despite these promising advancements, the literature reveals notable challenges in fully embedding blockchain features into quantitative optimization models for sustainable SCM. A significant obstacle is the current lack of standardized mathematical frameworks that can accurately represent the operational complexities of supply chains while simultaneously accounting for the specific dynamics and costs associated with blockchain technology [33]. As indicated by several studies, including those by [20], [29], there remains a considerable gap in comprehensive investigations that directly apply detailed MILP or MINLP models to these interactions, particularly models that quantify aspects like transaction validation times, immutability constraints, or the nuanced costs of smart contract execution.

This study contributes to the identified gap by presenting an in-depth analysis of a specific MINLP model tailored for an e-supply chain. This model explicitly incorporates blockchain features, such as transaction costs and conceptual smart contract enforcement for sustainability compliance, alongside traditional operational and sustainability objectives. The primary contribution of this paper, however, lies not in the formulation of a new model, but in the rigorous computational investigation of this complex MINLP structure. Our approach is critical because understanding the practical performance, sensitivities, and scalability of existing complex non-linear models under diverse operational and cost scenarios provides crucial, data-driven insights for real-world adoption. This analytical step is often bypassed in literature that may favor the proposal of new conceptual models over the deep empirical validation of existing complex ones. This paper aims to fill that void by offering a granular analysis of this particular MINLP model, achieved through a comprehensive methodology that includes detailed clarification of the model's components, benchmarking against a conventional system, and extensive sensitivity testing. By focusing on this in-depth empirical evaluation, this study provides tangible insights into the practical implications and performance trade-offs involved in applying such a model for blockchain-enabled sustainable e-supply chains. The detailed computational analysis and the subsequent derivation of managerial insights from this specific model structure represent a focused contribution to the applied data science aspect of this research domain, demonstrating a replicable workflow for evaluating emerging technologies within complex operational systems.

## 3. Methodology

### 3.1.Problem Description

This study considers a multi-echelon e-supply chain network operating within a digitally-driven ecosystem where blockchain technology is integrated to enhance traceability, security, and sustainability. The supply chain comprises several key echelons: suppliers (S) providing raw materials or components (Product I), manufacturing centers (M) that process these inputs into refined products (Product P), and distribution centers or warehouses (W) which, in an e-supply chain context, manage inventory and fulfill orders to end consumers or e-retailers. The product flow is sequential: raw materials move from suppliers to manufacturers, and finished products flow from manufacturers to distribution centers, ultimately reaching consumers whose demands are considered at the distribution center level. The planning horizon for operational decisions spans multiple time periods.

The core of the problem lies in optimizing a range of key supply chain decisions. These encompass procurement decisions, such as determining which suppliers to engage and the quantity of raw materials to source from each. They also include production decisions, which involve deciding which manufacturing facilities to operate, the quantity of each product to produce (considering both regular and overtime options), and effectively managing production capacities. Finally, the optimization extends to distribution and inventory decisions, covering the management of product flow to distribution centers, the determination of optimal inventory levels (including necessary safety stock) to meet stochastic consumer demand at a desired service level, and the planning of logistics routes.

A primary sustainability goal integrated into the model is the minimization of environmental impact, specifically by accounting for and penalizing carbon emissions generated at various nodes and during transportation activities. The model aims to reduce overall carbon emissions as part of its cost optimization objective. While not explicitly modeled as separate waste minimization variables, efficient resource utilization and inventory management inherent in the optimization contribute to reducing potential waste.

Blockchain technology is envisioned to operate as an underlying infrastructure for this e-supply chain, providing trustworthy data for the planning model. Each significant transaction, such as procurement orders, shipment dispatches,

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and processing activities, is recorded on an immutable, distributed ledger, ensuring an end-to-end verifiable audit trail. Smart contracts are conceptualized to automate the monitoring and enforcement of compliance with predefined sustainability parameters. For instance, a smart contract could be designed with the conditional logic: IF (node_m_emissions_period_t > emission_threshold_m) THEN trigger_alert() AND apply_penalty(). This alert would signal a deviation for managerial review, and the penalty could be a financial cost automatically factored into the system. This blockchain-verified data, including emission levels and transaction records, then informs the optimization process. The model explicitly incorporates blockchain-related costs, such as transaction fees, and implicitly accounts for aspects like computational delays through the overall system design. The objective is to minimize total operational costs—which include procurement, production, transportation, inventory holding, carbon emission penalties, and blockchain transaction fees—while satisfying demand, adhering to capacity limitations, and meeting sustainability constraints verified through the blockchain.

## 3.2. Mathematical Model Formulation (MINLP)

The optimization model analyzed in this study is formulated as a MINLP model. This classification arises from the presence of both continuous and integer decision variables, coupled with non-linear terms within the objective function, particularly those related to inventory management and emission cost calculations which involve products of variables or non-linear functions (as will be detailed in the objective function description). The MINLP approach is adopted to capture the complex interdependencies and trade-offs inherent in optimizing a blockchain-enabled sustainable e-supply chain. To facilitate a clear understanding of the MINLP model, table 1 defines the sets, indices, parameters, and decision variables used throughout the formulation.

**Table 1.** Nomenclature of Sets, Indices, Parameters and Decision Variables

| Category | Symbol | Description |
|---|---|---|
| Sets and Indices | S | Set of suppliers, indexed by s. |
| | M | Set of manufacturing facilities/plants, indexed by m. |
| | W | Set of distribution centers/warehouses, indexed by w. |
| | I | Set of raw materials/input items, indexed by i. |
| | P | Set of finished products, indexed by p. |
| | T | Set of time periods, indexed by t. |
| Parameter | $MF_M$ | Fixed operational cost to open/operate manufacturing facility m (currency/period). |
| | $EF_M$ | Fixed (constant) emission factor for operating manufacturing facility m (kg $CO_2$/period). |
| | $\tau$ | Carbon tax or cost coefficient (currency/kg $CO_2$). |
| | $O_{MI}$ | Ordering cost for item i at manufacturing facility m (currency/order). |
| | $D_{MI}$ | Demand for item i at manufacturing facility m (units/period). |
| | $H_{MI}$ | Holding cost for item i at manufacturing facility m (currency/unit/period). |
| | $EIP_{Mt}$ | Emission impact of holding one unit of item i at plant m during period t (kg $CO_2$/unit/period). |
| | $L_{MI}$ | Lead time for item i at manufacturing facility m (periods). |
| | $V_{MI}$ | Variance of demand for item i at manufacturing facility m during lead time (units$^2$). |
| | $Z_1-\alpha$ | Standard normal variate for service level $(1-\alpha)$ (dimensionless). |
| | $CP_t$ | Cost parameter related to warehouse operations or product p in period t (currency/unit). |
| | $\mu_{WM}$ | Mean demand of product p at warehouse w (units/period). |
| | $H_{WP}$ | Holding cost for product p at warehouse w (currency/unit/period). |
| | $EIP_W$ | Emission impact of holding one unit of product p at warehouse w (kg $CO_2$/unit/period). |
| | $CM_{Pt}$ | Manufacturing cost for product p during regular time in period t (currency/unit). |

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| Category | Symbol | Description |
|---|---|---|
| | $CW_{PMt}$ | Manufacturing cost for product p during overtime at plant m in period t (currency/unit). |
| | EVM | Emission factor for manufacturing one unit of product (kg $CO_2$/unit). |
| | $T_{MSI}$ | Transportation cost per unit of item i from supplier s to manufacturer m (currency/unit). |
| | $TEFIS_{ZMSI}$ | Fixed transportation emission from supplier s to manufacturer m if link ZMSI is used (kg $CO_2$/shipment). |
| | $TEVIS_{DMI}$ | Variable transportation emission per unit of item i from supplier s to manufacturer m (kg $CO_2$/unit). |
| | $T_{WMP}$ | Transportation cost per unit of product p from manufacturer m to warehouse w (currency/unit). |
| | $TEFPM_{YWMP}$ | Fixed transportation emission from manufacturer m to warehouse w if link YWMP is used (kg $CO_2$/shipment). |
| | $TEVPM_{\mu WM}$ | Variable transportation emission per unit of product p from manufacturer m to warehouse w (kg $CO_2$/unit). |
| | $S_{capM}$ | Supply or production capacity of manufacturer m (units/period). |
| | $P_{capMP}$ | Production capacity for product p at manufacturer m (units/period). |
| | $b_{PI}$ | Bill of materials coefficient: units of item i required for one unit of product p (units/unit). |
| | $T_P$ | Production time per unit of product p (hours/unit or time units/unit). |
| | $TR_{Mt}$ | Total available regular production time at manufacturer m in period t (hours or time units). |
| | $TO_{Mt}$ | Total available overtime production time at manufacturer m in period t (hours or time units). |
| | $U_p$ | Storage space required per unit of product p (space units/unit). |
| | $S_{capW}$ | Storage capacity of warehouse w (space units). |
| | S | Binary parameter: 1 if smart contract system is active, 0 otherwise (dimensionless). Assumed 1 in case study. |
| Decision Variables | $X_M$ | Binary variable: 1 if manufacturing facility m is open; 0 otherwise. |
| | $Y_{WMP}$ | Binary variable: 1 if product p is shipped from manufacturer m to warehouse w; 0 otherwise. |
| | $Z_{MSI}$ | Binary variable: 1 if item i is supplied by supplier s to manufacturer m; 0 otherwise. |
| | $Q_{MI}$ | Economic Order Quantity for item i at manufacturer m (units). |
| | $r_{MI}$ | Reorder point for item i at manufacturer m (units). |
| | $QR_{WMPt}$ | Quantity of product p produced during regular time at manufacturer m for warehouse w in period t (units/period). |
| | $QOW_{PMt}$ | Quantity of product p produced during overtime at manufacturer m for warehouse w in period t (units/period). |
| | $Ln_{WPt}$ | Inventory level of product p at warehouse w at the end of period t (units). |

The proposed algorithm is presented in (1) and consists of several components. The first part of the objective function represents fixed costs and constant emissions. The second refers to ordering and storage costs at each production site based on Economic Order Quantity (EOQ). The third part deals with reorder point calculations including buffer or safety stock. The fourth explains inventory holding costs and emission costs (emission cost is the product of emission volume and carbon tax). The fifth part refers to total manufacturing costs and associated emissions. The sixth represents transportation costs from S to M and their emissions. The seventh covers transportation from M to W and related emissions. Minimize Z, where

$$\begin{aligned} Z = S * \Bigg\{ & \sum_{M}\big[(F_M * X_M) + [(E_{FM} * X_M) * \tau]\big] + \sum_{M}\sum_{I}\sqrt{2(H_{MI} + EI_{PMt} * \tau) * O_{MI}} * \sqrt{D_{MI}} \\ & + \sum_{M}\sum_{I}(H_{MI} + EI_{PMt} * \tau) * Z_{1-\alpha} * \sqrt{L_{MI}} * \sqrt{V_{MI}} \\ & + \sum_{C}\sum_{P}\sum_{t}\mu_{WM} * (H_{WP} + EI_{PW} * \tau) \\ & + \sum_{W}\sum_{M}\sum_{P}\sum_{t}[QR_{WMPt} * C_{MPt} + QO_{WPMt} * C_{WPMt}] \\ & + \sum_{M=1}^{n}[E_{VM}(QR_{WPMt} + QO_{WPMt}) * \tau] \\ & + \sum_{M}\sum_{S}\sum_{I}[T_{MSI} * D_{MI} * Z_{MSI} + (TE_{FIS}Z_{MSI} + TE_{VIS}D_{MI}) * \tau] \\ & + \sum_{W}\sum_{M}\sum_{P}[T_{WMP} * \mu_{WM} * Y_{WMP} + (TE_{FPM}Y_{WMP} + TE_{VPM}\mu_{WM}) * \tau]\Bigg\} \end{aligned} \tag{1}$$

The goal is to minimize the total optimal cost and carbon emissions of the entire system. The model considers inventory, transportation, ordering, and manufacturing costs. Both regular and overtime production costs are taken into account, as are safety stock and emissions. Inventory is stocked at distribution centers to meet customer demand with a desired service level during the lead time period. Based on the desired service level, the probability function is defined as in (2):

$$Pr(D(L_{MI}) \le r_{MI}) = 1 - \alpha \tag{2}$$

D represents the demand for product I during the lead time L at outlet M.

The reorder point is calculated considering safety stock and assuming a normal distribution, as reflected in (3):

$$r_{MI} = E(D_{MI}) * E(L_{MI}) + Z_{1-\alpha}\sqrt{E(L_{MI} * V_{MI}) + E(D_{MI})^2\sigma_{LT}^2} \tag{3}$$

$\sigma_{LT}$ is the variance of demand over the lead time. Assuming constant lead time, we can omit the variance and reorder point, yielding:

$$r_{MI} = D_{MI} * L_{MI} + Z_{1-\alpha}\sqrt{V_{MI} * L_{MI}} \tag{4}$$

Here, Z indicates the value from the standard normal distribution, which is uniform across the network. Based on (4), inventory holding costs are computed with (5), including average holding cost, EOQ, and safety stock costs:

$$H_{MI} * Q_{MI}/2 + H_{MI} * Z_{1-\alpha} * \sqrt{L_{MI}} * \sqrt{V_{MI}} \tag{5}$$

Thus, the total holding and ordering cost is expressed as:

$$\sum_{M}\sum_{I} O_{MI} * D_{MI}/Q_{MI} + H_{MI} * Q_{MI}/2 + \sum_{M}\sum_{I} H_{MI} * Z_{1-\alpha} * \sqrt{L_{MI}} * \sqrt{V_{MI}} \tag{6}$$

According to the third assumption, capacity constraints are not considered. Setting (6) to zero yields an equation in Q, leading to (7):

$$Q_{MI} = \sqrt{\left[\frac{(2 * O_{MI} * D_{MI})}{(H_{MI})}\right]} \tag{7}$$

Combining (6) and (7), the aggregate production allocation model is formulated to reduce the total optimal cost of the supply chain system. Equation (8) ensures that supplier facility S is opened such that it supplies product I to meet the demand at manufacturing unit M:

$$\sum_{S} Z_{MSI} = X_M \quad \forall I = 1,\dots,I \quad \forall M = 1,\dots,M \tag{8}$$

Equation (9) ensures that all demands from distribution centers (warehouses) are fulfilled for all products by a single operating plant. It also states that product P is shipped from production facility M to warehouse W:

$$\sum_{M} Y_{WMP} = 1 \quad \forall W = 1,\dots,W \quad \forall P = 1,\dots,P \tag{9}$$

Constraints (10) and (11) represent capacity shortages and production limitations at manufacturing facility M. Here, Csup represents the supply limit and Cprod the production capacity of product P at M:

$$\sum_{S}\sum_{I} D_{MI} * S_I * Z_{MSI} \le S_{capM} * X_M \quad \forall M = 1,\dots,M \tag{10}$$

$$\sum_{W}\sum_{P} \mu_{WP} * T_P * Y_{WMP} \le P_{capMP} \quad \forall M = 1,\dots,M \tag{11}$$

Equations (12) and (13) yield the mean and variance, respectively, for product P produced at plant M:

$$\sum_{W}\sum_{I} \mu_{WP} * Y_{WMP} * b_{PI} \le D_{MI} \quad \forall M = 1,\dots,M \quad \forall P = 1,\dots,P \tag{12}$$

$$\sum_{W}\sum_{I} \sigma_{WP} * Y_{VMP} * b_{PI}^2 = V_{MI} \quad \forall M = 1,\dots,M \quad \forall P = 1,\dots,P \tag{13}$$

In (14), X, Y, and Z are binary variables taking values of 0 or 1:

$$X_M, Y_{WMP}, Z_{MSI} \in \{0,1\} \quad \forall I = 1,\dots,I \quad \forall W = 1,\dots,W \quad \forall P = 1,\dots,P \quad \forall M = 1,\dots,M \quad \forall S = 1,\dots,S \tag{14}$$

Constraint (15) balances demand at each distribution center by considering inventory from the current and previous periods, and aligns the production quantity of product P:

$$L_{nWP(t-1)} + QR_{WMPt} = L_{nPt} \quad \forall W, M, P \tag{15}$$

Equations (16) and (17) specify the production quantity constraints for regular and overtime hours:

$$\sum_{W}\sum_{P} QR_{WMPt} * T_P \le T_{RMt} \quad \forall M \tag{16}$$

$$\sum_{W}\sum_{P} QO_{WMPt} * T_P \le T_{OMt} \quad \forall M \tag{17}$$

Equation (18) reflects warehouse storage capacity:

$$\sum_{W} L_{nWPt} * U_p \le S_{capW} \quad \forall W, t \tag{18}$$

Constraint (19) ensures that product P is only produced at open plant M:

$$\sum_{t} [QR_{WMPt} + QO_{WMPt}] \le Y_{WMPt} \quad \forall W, M, P \sum_{W} L_{nWPt} * U_p \le S_{capW} \quad \forall W, t \tag{19}$$

Constraint (20) asserts that both regular and overtime production are always positive:

$$QR_{WMPt}, QO_{WMPt} \geq 0 \quad \forall W, M, P, t \tag{20}$$

The functionality of supplier-related facilities S is validated by Constraint (8). All distribution center demands for final products are met by one opened plant, validated by Constraint (9). Production and storage limitations for plant M are authenticated by Constraints (10) and (11). The validation of variance and mean for produced products at plant M is established by Equations (12) and (13). To ensure these units operate continuously, the binary variables X, Y, Z are always set to 1 as per Constraint (14). Demand balancing for distribution centers in relation to prior and current inventories and production quantities of product P is confirmed by Constraint (15). Production quantity restrictions for regular and overtime work are reflected in Equations (16) and (17). Equation (18) reflects warehouse storage capacity, and Constraint (19) ensures effective production of product P at open plant M.

## 3.3. Data Sourcing and Parameter Estimation

The numerical values for the parameters required by the MINLP model (Equation 1 and constraints 8-20) were established for the computational study primarily through the generation of synthetic data, designed to represent a plausible multi-echelon e-supply chain. This approach was adopted due to the common challenges in obtaining comprehensive, real-world datasets that span all echelons and incorporate novel aspects like blockchain fees and granular sustainability metrics for an initial model analysis. The case study considers a network structure with two suppliers, three manufacturers, and four distributors.

The generation process for this synthetic data involved defining parameters based on plausible operational ranges. For this study's analysis, demand for products at the distribution centers (related to μWM and VMI) was conceptualized considering variability, potentially drawing from a normal distribution with a specified mean and standard deviation. Cost parameters, including fixed operational costs (MFM), ordering costs (OMI), holding costs (HMI, HWP), manufacturing costs (CMPt,CWPMt), and transportation costs (TMSI,TWMP), were assigned values within ranges deemed representative for a generic manufacturing and distribution environment. Emission factors (e.g., EFM, EIPMt,EV M) were adapted from publicly available environmental. The carbon cost coefficient (τ) was established at 50 currency units per kg $CO_2$, a value reflecting potential carbon pricing scenarios. The blockchain transaction fee was explicitly set at 500 currency units per active supplier per period. Other structural and operational parameters, such as lead times (LMI), facility capacities (ScapM, PcapMP, ScapW), production rates (related to TP), and bill-of-material coefficients (bPI), were defined to ensure an internally consistent and solvable model instance. The overarching goal in parameterizing the model was to create a coherent testbed that, while synthetic, enables a meaningful exploration of the MINLP model's behavior and the trade-offs associated with integrating blockchain for sustainability.

## 3.4. Experimental Design

To rigorously evaluate the performance characteristics of the MINLP model and understand the impact of blockchain integration, a structured experimental design was implemented. This design centered on establishing a base case scenario, defining a comparable "conventional system" for benchmarking, and conducting a series of sensitivity analyses on critical parameters. A three-period planning horizon was chosen for the experiments. This timeframe is sufficiently long to demonstrate the model's multi-period dynamics, such as inventory carryover and evolving supplier engagement, while remaining computationally manageable for the purposes of this initial, detailed analysis. The base case scenario was formulated using the specific set of synthetic parameter values. This scenario serves as the primary reference point, providing a foundational understanding of the model's optimal solution, including total costs, emission levels, and operational decisions, under a standard, predefined set of conditions for the blockchain-enabled e-supply chain.

For effective benchmarking, a "conventional system" model was defined. This conventional system mirrors the structure of the fixed MINLP model described but is modified to represent an e-supply chain operating without blockchain-specific functionalities or their associated direct costs. Specifically, in the conventional system model, blockchain transaction fees (e.g., the "blockchain fee of 500" per active supplier) were set to zero. Furthermore, any constraints within the model that are uniquely enabled or enforced by blockchain technology (e.g., stricter emission compliance verified by smart contracts beyond standard regulations) would be relaxed to reflect a non-blockchain environment. Solving this conventional model under the same input data (for demand, core operational costs, etc.) as the blockchain-enabled model allows for a direct, quantitative comparison of key performance indicators such as total system cost and total carbon emissions.

Sensitivity analysis was subsequently performed to assess the robustness of the model's solutions and to identify which parameters exert the most significant influence on operational decisions, costs, and sustainability outcomes. Key parameters selected for this analysis included the carbon cost coefficient ($\tau$), the blockchain transaction fee, and overall market demand levels. These parameters were chosen due to their representation of significant external economic pressures (carbon pricing), direct technology adoption costs (blockchain fees), and fundamental market dynamics (demand fluctuations). Each selected parameter was systematically varied across a defined range: the carbon cost ($\tau$) was varied from -50% to +100% of its base value in increments of 25%; the blockchain fee was tested at values of 0, 250, 500, 750, and 1000 currency units; and demand levels were scaled by factors of 0.75, 1.0, and 1.25. The results from these analyses are intended to reveal the conditions under which the blockchain-integrated sustainable supply chain model offers the most significant advantages or incurs notable trade-offs, thereby providing valuable insights for decision-makers.

**4. Results and Discussion**

## 4.1. Base Case Results

The base case scenario, formulated with the parameter values, was solved to obtain an optimal operational plan. Key operational decisions from the base case are exemplified presented in table 2.

**Table 2.** Results from Base Case

| Supplier | Period | Units Supplied | Blockchain Used |
|---|---|---|---|
| S1 | 1 | 0 | 0 |
| S2 | 1 | 60 | 1 |
| S3 | 1 | 40 | 1 |
| S1 | 2 | 30 | 1 |
| S2 | 2 | 70 | 1 |
| S3 | 2 | 20 | 1 |
| S1 | 3 | 40 | 1 |
| S2 | 3 | 60 | 1 |
| S3 | 3 | 10 | 1 |

The core output, presented in table 2, details the optimal procurement plan determined by the MINLP model. This plan is not a static set of choices but rather a dynamic operational strategy that evolves over the three-period planning horizon. The most important insight from this plan is the model's strategic and adaptive decision-making regarding supplier selection. For instance, in Period 1, the model determines it is optimal to source materials only from Suppliers S2 (60 units) and S3 (40 units), while completely avoiding Supplier S1. This is a calculated decision, implying that the combined costs—including procurement, transportation, and emissions—for this specific combination are lower than any plan that would involve S1. In subsequent periods, as demand fluctuates, the model's strategy shifts, engaging all three suppliers but allocating different procurement quantities to each, demonstrating a sophisticated ability to adapt the supply plan over time to maintain efficiency and compliance.

The procurement decisions are directly linked to the model's handling of blockchain integration and its associated costs. The stipulation that every supplier used in a period incurs a blockchain fee of 500 is a critical factor in the optimization. By choosing not to use Supplier S1 in Period 1, the model successfully avoids this 500-unit fee, indicating that the cost savings from avoiding S1 outweighed any potential benefits it might have offered in that specific period. Conversely, in Periods 2 and 3, the model finds it optimal to engage all three suppliers, willingly incurring a total of 1500 in blockchain fees per period. This implies that the operational advantages or lower costs provided by using all three suppliers in those periods were significant enough to justify the technology-related expenditure. This highlights the model's capacity to perform a nuanced cost-benefit analysis of technology adoption, making dynamic trade-offs on a per-supplier, per-period basis.

From a sustainability perspective, the base case results confirm that the model successfully achieves its environmental objectives. The explicit outcome that all emission constraints were satisfied (emissions ≤ 300 kg $CO_2$ per period) is a crucial validation point, proving that the model operates effectively within the established environmental rules. The graph visualizing the relationship between demand and emissions (figure 1) further illustrates this optimization in action. As demand rises from Period 1 to Period 2, emissions logically increase due to higher production and transport needs. However, the key insight is that even with this increase, emissions remain below the 300 kg cap. This demonstrates the model making intelligent trade-offs; to accommodate higher demand without violating the emission limit, it may have strategically selected more expensive but cleaner suppliers or logistics routes. The model is constantly balancing the monetized "cost" of emissions (as defined by the carbon tax parameter, $\tau$) against all other operational costs to find an economically viable and environmentally compliant solution. In essence, the base case experiment successfully produces a clear, multi-period operational plan that dynamically manages suppliers, accounts for technology costs, and adheres to sustainability constraints, providing a solid foundation for the further analyses presented in this paper.

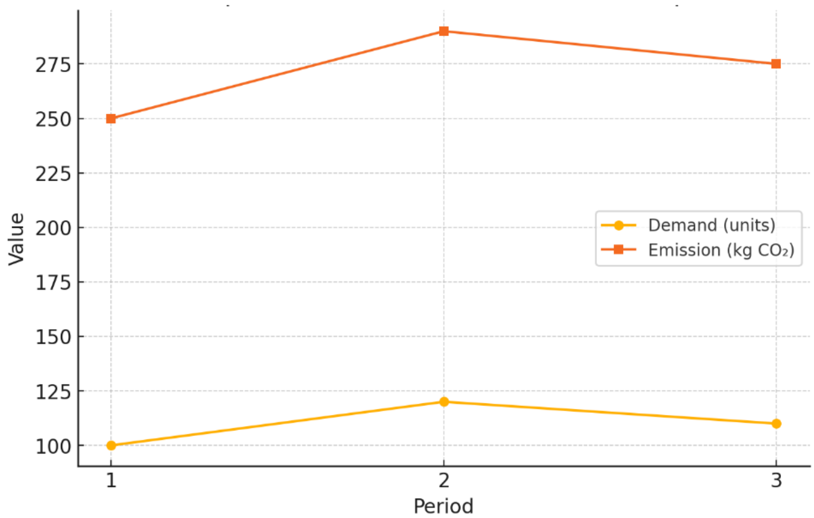


**Figure 1.** Relationship Between Demand And Emission Across The Three Periods

## 4.2. Interpretation of Key Findings

The computational results from the base case scenario offer initial insights into the operational dynamics of the blockchain-enabled e-supply chain. The optimal supply plan per period indicates a selective utilization of suppliers across the three periods. For instance, Supplier S1 was not utilized in Period 1, a period where its blockchain involvement was also nil, while Suppliers S2 and S3 handled the demand with active blockchain usage. This pattern shifted in subsequent periods where all three suppliers contributed, albeit with varying quantities, suggesting the model optimizes procurement by considering factors such as the explicit blockchain fee of 500 incurred per active supplier per period alongside other operational costs and constraints. The model successfully maintained emissions at or below the stipulated 300 kg $CO_2$ per period for all three periods, satisfying all emission constraints. The relationship depicted between demand and emissions shows a correlation where emissions tend to rise with increased demand and fall as demand lessens. This suggests that while higher throughput generally corresponds to increased emissions, the optimization framework operates within the environmental limits by making necessary trade-offs, influenced by the carbon cost structure embedded in the objective function.

Even with the currently presented base case results, several managerial and practical implications can be inferred. The model's ability to select suppliers based on an optimal plan that includes both operational costs and explicit blockchain usage fees can guide managers in strategic sourcing and in evaluating the cost-benefit of onboarding suppliers onto a blockchain platform. Understanding that each active supplier incurs a fixed blockchain fee, for example, might lead to strategies aimed at consolidating sourcing or negotiating tiered fee structures with blockchain providers, especially if sensitivity analysis (once performed) were to show high sensitivity to these fees. The model's adherence to emission caps demonstrates its utility as a tool for sustainability officers in planning operations that meet environmental targets. The inclusion of carbon costs within the objective function means the model can help quantify the financial implications of emissions and guide decisions on investments in cleaner technologies or processes. If further results from sensitivity analysis were available, understanding how changes in carbon pricing affect the optimal supply chain configuration could inform lobbying efforts or long-term strategic planning in anticipation of evolving environmental regulations. Policymakers could also find such a model (and its extended analyses) useful for assessing the impact of different carbon tax levels or for understanding the infrastructure needed to support blockchain-enabled sustainable practices.

Based on the model's structure, which incorporates blockchain transaction costs and conceptualizes smart contracts for enforcing sustainability compliance (like emission caps), the primary value of blockchain integrated into this fixed model appears to be its potential to enhance sustainability outcomes. The model suggests that by making emissions a monitored and costed factor, and by associating fees with blockchain use, decisions can be steered towards more environmentally conscious operations. The advantage lies in the potential for improved emission control, as evidenced by the satisfaction of emission constraints, and the implied benefits of traceability inherent in blockchain. The costs associated with this integration are explicitly modeled, through the blockchain fee per supplier. The current base case results alone show blockchain being utilized for most supplier activities despite the fee, suggesting the model finds this viable under the base parameters.

### 4.3. Limitations and Future Research Directions

While this study presents an analysis of an optimization model for blockchain-enabled sustainable e-supply chains, it is important to acknowledge its limitations. Firstly, the model is a MINLP model, which inherently involves greater computational complexity compared to linear models. Solving MINLPs, especially for large-scale instances, can be time-consuming and may not always guarantee global optimality, potentially yielding local optima depending on the solver and solution techniques employed. Secondly, an internal inconsistency arises from the model's structure: the objective function incorporates inventory cost components derived from EOQ principles, which traditionally assume uncapacitated systems. However, the model also includes explicit capacity constraints for manufacturing and warehousing. This juxtaposition means the EOQ-based costings are an approximation within a capacitated system, a characteristic of the fixed model structure being analyzed. This specific limitation directly motivates future research into alternative inventory modeling approaches, such as dynamic lot-sizing, within such MINLP frameworks for sustainable supply chains.

Based on the analysis and the identified limitations of the model structure, several avenues for future research emerge. A primary direction is the exploration of alternative mathematical formulations. This could involve developing linearized versions of the model to reduce computational complexity, or different non-linear approaches, particularly for representing inventory costs more dynamically within capacitated systems, moving away from the classical EOQ assumptions. Incorporating stochasticity into the model represents another significant area for enhancement. Real-world supply chains are subject to considerable uncertainty in demand, costs, lead times, and even blockchain performance metrics. Developing stochastic optimization or robust optimization versions of the model would improve its realism and the reliability of its recommendations. Furthermore, applying the current MINLP model, or a revised version, to a real-world industry case study using actual company data would be invaluable. This would not only help in validating its practical applicability and refining its parameters but also in uncovering unforeseen challenges and opportunities in implementing blockchain for sustainable e-supply chains.

## 5. Conclusion

This paper presented an analysis of a MINLP optimization framework for blockchain-enabled e-supply chains, focusing on balancing operational costs with environmental impact, particularly carbon emissions. The study detailed an existing model that integrates blockchain features, such as traceability concepts and decentralized validation implied through transaction costs and smart contract-enforced compliance (like emission caps). The application of this model to a base case scenario demonstrated its capability to generate optimal supply plans, manage supplier engagement considering blockchain fees, and ensure adherence to sustainability constraints, such as maintaining emissions at or below 300 kg $CO_2$ per period, while showing a correlation between operational demand and emission levels. While detailed comparative data was not presented in the

The analyzed MINLP model, despite its inherent complexities and specific structural assumptions (such as the EOQ-based inventory costing within a capacitated system), provides a valuable foundation for bridging digital supply chain transformation with sustainable operational practices. The insights gained from examining its structure and base case outputs underscore the potential of quantitative modeling to explore the intricate trade-offs in blockchain adoption for sustainability. Future work should focus on enhancing such frameworks through real-time data integration, the incorporation of dynamic pricing mechanisms, and rigorous testing on diverse industry datasets to further validate and refine their practical applicability in achieving greener and more transparent supply chains.

## 6. Declarations

### 6.1. Author Contributions

Conceptualization: A.B., S.E., T., H.M.; Methodology: A.B., T.; Software: A.B.; Validation: S.E., H.M.; Formal Analysis: A.B.; Investigation: A.B.; Resources: S.E., T., H.M.; Data Curation: A.B.; Writing – Original Draft Preparation: A.B.; Writing – Review and Editing: S.E., T., H.M.; Visualization: A.B.; All authors have read and agreed to the published version of the manuscript.

### 6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

### 6.4. Institutional Review Board Statement

Not applicable.

### 6.5. Informed Consent Statement

Not applicable.

### 6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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