

**OPTIMIZING A BATIK MANUFACTURING SUPPLY CHAIN UNDER
CARBON TAX REGULATIONS USING EVOLUTIONARY
ALGORITHMS**

UNDERGRADUATE THESIS

**Submitted to the International Undergraduate Program in Industrial Engineering in
Partial Fulfilment of Requirement for the Degree of Sarjana Teknik at the Faculty of
Industrial Technology
Universitas Islam Indonesia**



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Yogyakarta, *July 24, 2025*



A handwritten signature in blue ink, consisting of several loops and a long horizontal stroke.

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Demikian surat keterangan penelitian ini kami buat. Atas perhatiannya dan kerja samanya kami mengucapkan terima kasih.

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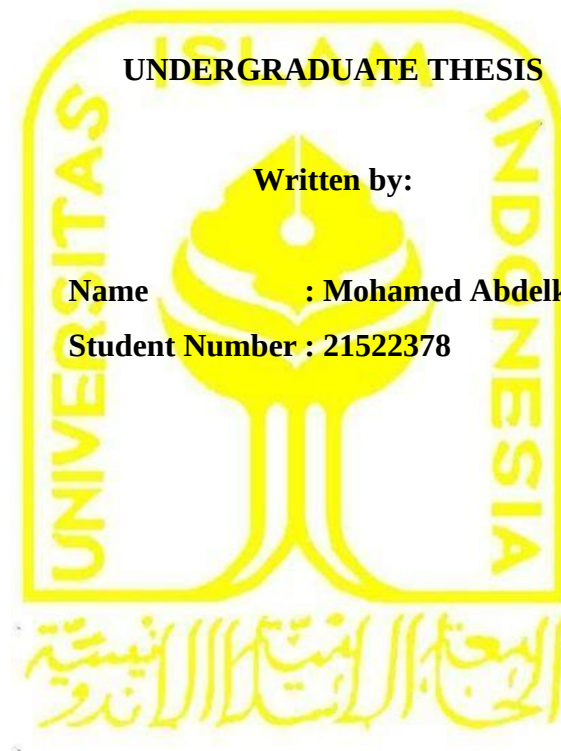
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TAX REGULATIONS USING EVOLUTIONARY ALGORITHMS**



UNDERGRADUATE THESIS

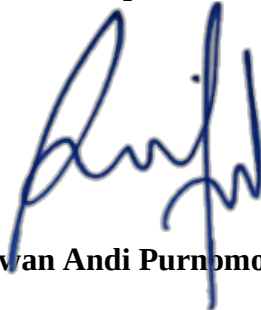
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EXAMINERS' APPROVAL PAGE

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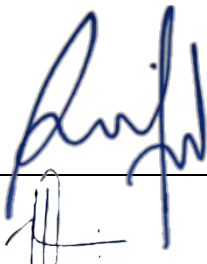
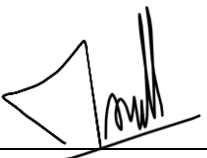
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DEDICATION PAGE

This work is dedicated to my beloved mother, whose unwavering support, sacrifices, and prayers made it possible for me to pursue an education in the first place. To my family, for their love, support, and encouragement, and to all who have supported me financially and emotionally throughout my academic journey.

MOTTO

"So verily, with hardship comes ease."
(Qur'an, Surah Al-Inshirah 94:6)

"And He found you lost and guided [you]."
(Qur'an, Surah Ad-Duha 93:7)

"Whoever does not thank people has not thanked Allah."
(Hadith, Sunan Abi Dawud 4811, authentic)

PREFACE

Bismillahirrahmanirrahim

Assalamu'alaikum Warahmatullahi Wabarakatuh

All praise and gratitude are due to Allah SWT, whose mercy, grace, and guidance made this journey possible. By His permission and blessings, the author was able to complete this undergraduate thesis, entitled “Optimizing a Batik Manufacturing Supply Chain Under Carbon Tax Regulations Using Evolutionary Algorithms.” The author would also like to extend heartfelt thanks to everyone who contributed to the completion of this thesis, namely:

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10. Everyone who played a part, big or small, in making this study possible—your contributions have truly made a difference, and the author is deeply grateful.

The author acknowledges that this undergraduate thesis is far from perfect and welcomes any suggestions or constructive criticism for its improvement. It is the author's hope that this report will not only be beneficial but also serve as a foundation for future development and research.

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ABSTRACT

Optimizing supply chains to be both cost-efficient and environmentally responsible has become essential in today's business landscape, especially with the introduction of carbon tax policies like Indonesia's Law No. 7 of 2021. The main goal of this research is to develop and implement an integrated supply chain model that brings together production, inventory, transportation, and carbon emission costs into a single decision-making framework. By combining these elements, the model provides a data-backed approach for companies that want to balance their financial objectives with environmental responsibility. To solve this complex challenge, the research applies evolutionary algorithms, to identify the most efficient solutions for order quantities, production batch sizes, and delivery routes. The model was tested using real operational data from a MSME batik manufacturer, serving as a practical example of how such a system can be put into action. The results show that with coordinated planning across all parts of the supply chain, companies can achieve significant cost savings while also reducing their carbon footprint and ensuring compliance with carbon tax regulations. Beyond the specific case, this approach offers valuable guidance for other small and medium-sized manufacturers in Indonesia and similar markets. The model is designed to be flexible and adaptable, making it suitable for businesses with varying production systems, product types, or market demands. By using this method, companies can more confidently navigate regulatory challenges and contribute to greener, more sustainable industrial practices. Ultimately, the research demonstrates the practical benefits and wider relevance of integrating sustainability into supply chain optimization.

Keywords: Carbon Tax, Supply Chain Optimization, Evolutionary Algorithm, Total Joint Cost.

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CHAPTER I

INTRODUCTION

1.1 Background

In an era of global eco-responsibility and economic uncertainty, supply chain management is crucial not only for reducing operational costs but also for meeting environmental and regulatory requirements. The modern business not only aims to deliver profits but also to be part of the climate solution. This double pressure has forced the embedding of sustainability into supply chain strategies to be not a source of competition but a condition for doing business (Zou, Gao, Zhang, & Tang, 2024). Specifically, sectors are being pressured to reconsider operations relative to issues of carbon taxes, consumer demand, and resource limitations.

One such regulation is the Indonesian carbon tax under Law No. 7 of 2021, mandating all sectors to factor carbon emission costs into their financial planning. This tax is applied at IDR 30 per kg CO₂ since April 2022, beginning with coal-fired power plants (Finance Ministers for Climate, 2023; ICAP, 202). The policy aims to reduce greenhouse gas emissions and stimulate greener practices (Parjiono, 2023), but presents fresh challenges for MSMEs rooted in conventional production and distribution.

The batik sector—deeply rooted in Indonesia’s cultural identity—exemplifies the tension between tradition and transformation. As small-scale, artisanal enterprises, many batik producers lack integrated systems, operating within fragmented vendor-to-retailer networks that lead to inefficiencies in inventory, fulfillment, and environmental performance (Gunawan et al., 2022; Novanty et al., 2023). These enterprises are commonly functioning in vendor-to-retailer contexts with little inter-agency alignment, yielding waste in inventory, fulfillment, and environmental performance (Zhang et al., 2021). These inefficiencies are even more costly under a carbon tax system as the value of a waste material being reused or converted largely depends on the kind and amount of carbon-based fuel that has been replaced – aggravating the loss of viability for small scale producers. Therefore, optimization-based methods are called for as a way to increase performance while still respecting the industry as usual.

This study uses a case study of PT. XYZ Batik Manufacturer in Yogyakarta, Indonesia. The manufacturer sells five different types of batik products to five regional buyers, with

different demand patterns. Manufacturing is heavily dependent on power-driven machinery (which gives rise to lots of carbon emissions), and distribution is marked by an inefficient, scattered supply chain. To allow the buyers to serve customers when faced with a stockout, the lateral transshipments between the five buyers take place during weekend, which are inter-buyer transfers. Although these measures exist, the company faces increasing operational costs, has not integrated its carbon tax liabilities into the production and transportation cost structures, and is plagued by a poorly coordinated supply chain--especially when it comes to determining optimal quantities and ordering frequencies for buyers' purchasers, which continue to drive total cost.

To mitigate these problems, this work model the supply chain network of PT. XYZ Batik Manufacturer and systematically determines CO₂ emissions from production processes and transportation. Based on this purpose, the research formulates an integrated model including carbon taxation, lateral transshipment in batik supply chain. The model aims to minimize cost through deciding several decision variables which include order quantity and frequency, for all the five products among all the buyers, and the manufacturer's daily production quantity for each product. The goal is to minimize the total joint costs by finding an optimal order and pricing strategy subject to the carbon tax policy.

To overcome this challenge, the present study employs Evolutionary Algorithms (EAs), which are a kind of population-based metaheuristic optimization algorithms by learning from natural evolution, e.g., selection, mutation, and crossover. With the ability to traverse large search spaces along complex, and often nonlinear, solution paths, they are well suited to the demands of today's supply chain optimization problems, which typically include multiple objectives, a mix of discrete and continuous variables, and a highly constrained environment. In recent years EAs have been adopted for different supply chain and logistics related domains with success.

For instance, advanced evolutionary algorithms have been used for dynamic e-procurement in supply chains which show capability to handle uncertainty and changing requirements (Raghul et al., 2024). In agriculture, GAs like Genetic Algorithms (GA) (Red Deer Algorithm) and Social Engineering Optimization Algorithm have been adopted to reduce operational costs of production, storage, transportation, and handling till the chain end that led to significant improvement in cost effectiveness and system efficiency (Aqib et al., 2020). Furthermore, GAs have been called as a solution for dynamic logistics transportation and

distribution problems, which later significantly reduced shipping cost, delivery distance, and time travel (Arifin, 2021).

Alternative optimization approaches, including linear programming (LP), simulated annealing (SA), and tabu search (TS), are also widely used for supply chain problems. While LP is effective for well-structured, linear optimization models, and SA and TS excel in specific combinatorial contexts, these methods can struggle with the high-dimensional, nonlinear, and multi-objective characteristics typical of real-world supply chains. In comparison, evolutionary algorithms offer greater flexibility, robustness, and the capacity to find high-quality solutions for problems with complex search spaces and diverse constraints. Their effectiveness is further supported by their adaptability to dynamic and uncertain environments, which is increasingly essential in modern supply chain management (Skitsko & Voinikov, 2024).

This study has important implications for an emerging new industrial system responding to the increasing reality of environmental reforms. It contributes not only to the improvement of supply chain performance; it also offers a scalable decision-making tool for MSMEs to sustain themselves in a regulated environment. The innovative aspect of the introduced model lies in the fusion of the carbon costing model, inventory optimization, and transshipment logistics; such an integration is not frequently studied in the domain of artisanal industries.

Finally, although not without limitations, this research has important implications for both academia and industry, proposing a model that can be transferred to other sectors with similar features. It creates an opportunity for small-scale producers, such as PT. XYZ Batik, to be competitive, to adhere to local environmental regulations, and to adopt sustainable supply chain practices in a rapidly changing world.

1.2 Problem Formulation

PT. XYZ Batik applying a batch production system, serves five types of batik products to its five types of reseller buyers. Moreover, the company is confronting the reality of operational costs that are both high and increasing, given that it has yet to adopt Indonesia's carbon tax regime set out in Law No. 7 of 2021. This legislation uses a market-based mechanism to include production and transportation emissions in business costs. Currently, PT. XYZ uses the traditional Economic Production Quantity (EPQ) for lot sizing, assuming the objective of minimizing setup and holding costs without considering the effect of the environment, as well as the benefit from total coordination in ordering across buyers and products. The distribution model also focuses on delivery efficiency, ignoring the carbon emissions released during

transportation. Accordingly, existing practices are problematic in terms of cost and sustainability, with the latter in relation to carbon tax liability.

PT.XYZ is forced to redesign its supply chain strategy to meet both financial (cost pressures and requirements) and regulatory requirements due to globalization and environmental challenges. The model and algorithm should also take into account the inconsistent demand of buyers, energy consumption, geographic dispersion, and the simultaneity of lateral transshipment; their work is not trying to solve the problem with optimization. Hence, the issues that we attempt to address in this study are:

1. How the current supply chain situation of PT. XYZ Batik can be represented as a holistic model in order to gain a better calculation of the joint total costs, which includes the carbon emissions costs.
2. How to use evolutionary algorithms to minimize total cost and emission cost in the modeled supply chain?

The goal of the model is to cover the following main decision areas:

- Best order quantities and intervals for each of the five batik types at five decentralized buyers,
- An optimal production lot sizes of the PT. XYZ Batik (supplier) for all five products,
- An optimal routing of transportation between the supplier and retailers with minimum emission cost.

1.3 Research Objectives

The main focus of this study is to design an integrated optimization model of PT. XYZ Batik's supply chain that integrates operational efficiency with the carbon tax policy adherence in Indonesia. For this purpose, the study intends to:

1. Build a detailed supply chain model to represent the on-going operations of PT. XYZ Batik To calculate total joint cost, which is including emissions cost among the costs that are derived from the considerations of both production and transportation.
2. Use evolutionary algorithms on the created model to optimize the total operating costs of the supply chain, focusing in reducing the emission related cost and to address with legal impositions.
3. Find the best order quantity and order interval amounts, for each batik product over all the buyers, the best production lot size values for the manufacturer and the optimal

routes and shipment plans such that the overall cost is minimized and the carbon emission is reduced.

By fulfilling these objectives, the research attempts to offer a pragmatic approach for PT. XYZ Batik so that it can improve its financial performance and environmental compliance in a more regulatory and competitive market.

1.4 Benefits of research

This research provides theoretical and actionable practical contributions that support academic development and industry's progress towards a greener supply chain practice, hence the benefits provided by this study are:

- Academic Benefits:
 1. Drives forward with the mainstreaming of environmental issues—particularly carbon cost modeling—into classical supply chain optimization models, closing the chasm between sustainability policy and optimized quantitative logistics frameworks.
 2. Broadens the application of evolutionary algorithms in multi-objective, multi-product, multi-echelon supply chain scenarios, particularly in the presence of regulatory and environmental considerations.
 3. Complements literature on lateral transshipment and carbon taxation by demonstrating how both can be strategically integrated to inventory, production, and transportation level decisions in traditional manufacturing industries.
- Practical Benefits:
 1. Allows PT. XYZ Batik to determine the appropriate production quantities, order lot size, a delivery schedule, and transshipment strategy, considering the Indonesian carbon tax law.
 2. Offers a modular, Excel-based decision model that other MSMEs in the batik industry or similar traditional sectors can customize to reconcile operational efficiency with environmental stewardship.
 3. Enables operationalization of Indonesia's Law No. 7 of 2021 by providing a realistic optimization framework that specifically connects supply chain choices with carbon emission results and financial impacts.

1.5 Research Limitations

Although the present research is intended to propose a rigorous and realistic model, it is limited by the following factors:

1. “The Perfect Production System” Assumption: It is assumed that the vendor’s production system has no failures, reworks, and breakdowns.
2. No Stochastic Disruptions: The effect of accidents, supply failure, or demand shocks is not considered.
3. Fixed mode of transport: All products are assumed to be transported by a 7-ton lorry with constant emission coefficients, regardless of the vehicle type and fuel efficiency.
4. Partial Emission Coverage for Lateral Transshipment: Carbon emissions associated with vendor-to-buyer delivery (excluding buyer-to-buyer or lateral transshipment moves) are considered in the model.

1.6 Systematic research

The research is structured into several chapters, and each chapter will be described as follows:

CHAPTER 1 INTRODUCTION

Provides an overview of the research background, formulates the central problem, states the research objectives, defines the scope and limitations, and explains the significance and expected contributions of the study.

CHAPTER II LITERATURE REVIEW

This chapter establishes an inductive connection to previous research, which adds useful references to the current study. The framework provides organized guidelines to resolve the research problems through its deductive analysis approach.

CHAPTER III RESEARCH METHODOLOGY

Describes the research design, methodology, and systematic procedures employed in the study. It outlines the data collection methods, research variables, and techniques used for data analysis and model development.

CHAPTER IV DATA COLLECTION AND PROCESSING

The chapter focuses on collecting and processing data in the research. The research data collection activities will be presented in this chapter ahead of processing through previously established methods. The next section analyzes information derived from data processing.

CHAPTER V ANALYSIS AND DISCUSSION

Presents the results of the study, interprets key findings, and discusses their implications in relation to the research objectives, theoretical context, and real-world applications.

CHAPTER VI CONCLUSIONS AND RECOMMENDATIONS

Summarizes the main findings, draws overall conclusions based on the analysis, and provides practical recommendations as well as suggestions for future research directions.

BIBLIOGRAPHY**APPENDIX**

CHAPTER II

LITERATURE REVIEW

2.1 Theoretical Basis

The theoretical basis section offers the concepts and dimensions which are pertinent to the research. It provides a structure for describing the variables, the relationships between them and the underlying concepts that leads the research. The key theories and literatures are defining for a theoretical development through which the research problem is viewed.

2.1.1 *Supply Chain Management*

The supply chain refers to the entire relationship network between end customers and suppliers, while supply chain management is defined as the strategic management of all activities necessary to convert raw materials into products, and deliver those products to the final customer, creating value and providing a sustained competitive advantage. Supply chain management is a sophisticated process, which would require that proper planning, execution and monitoring is carried out at the stages of sourcing, procurement, production, warehousing, transportation and distribution (Seyam et al., 2024). Effective supply chain management requires an end-to-end understanding of the roles played by the all the players in the supply chain (suppliers, manufacturers, retailers, wholesalers and customers) and emphasizes the need for information to flow freely across the supply chain and to promote synergy in overall operations (Nasution et al., 2018). The aim is to develop a responsive and flexible network that can respond to shifting market requirements, reduce costs, and increase customer satisfaction (Althaqafi, 2020).

Demand forecasting, inventory management, production planning and logistics optimization are some of the strategies and techniques used by supply chain management to achieve these objectives. There is now a growing understanding of the links between purchase and logistics activities so that purchasing and logistics can be viewed by companies as a linkage to enhancing quality, selling customer service and achieving competitive success (Li et al., 2004; Tan et al., 2002).

2.1.2 *Sustainable Production System*

Production systems are fundamentally viewed as a complicated web of processes, resources, and structures within an organization that are orchestrated to convert raw and intangible input material into tangible goods of value or essential services to consumers. These systems cover

the entire product life cycle, including the early phase of product design and development, but also manufacturing, assembly, and quality control, up to the efficient distribution of the final product to the consumers (Zarte et al., 2019). There is a fundamental concept at the core of all production systems – production efficiency, which aims to decrease waste and to increase efficiency and productivity (Früchtel et al., 2020). With the evolution of production systems, they are more complex today than needed in the past and usually incorporate advanced technologies (automation, robotics, data analysis) in order to improve their operability and to be more able to cope with dynamic market needs (Garetti et al., 2012).

Today, production systems not just form decisive parts of the contemporary supply chain but are also examined in increasing detail in terms of their economic and ecological effects, including sustainability (Paul et al., 2024). Nowadays, firms are taking into account environmental factors and social demands in their production processes, driven by a high level of competition and great awareness of environmental challenges (Lazrak & Amrani, 2023). This evolution involves the implementation of techniques that can simultaneously result in a cost decrease and significant environmental damage reduction (Pârv et al., 2021). In sustainable production systems, the logic of the traditional model of manufacturing has been turned upside down to support environmental, social and economic aspects in the long-term, and to the benefit of the environment, the health and safety of manufacturers, the wellbeing of communities and the economic viability of firms (Albano et al., 2019). Strategic management frameworks that provide a system-level perspective, defining a company's value in terms of its environmental, social, and governance (ESG) performance, should be applied for firms to become sustainable for the long term (YILDIZ et al., 2024).

Incorporating sustainability considerations into a production system requires a complete rethinking of all the phases of the product life cycle, including extraction of raw materials, manufacturing, product use, and end-of-life management (Zhu & Sarkis, 2005). Such a lifecycle approach encourages the production of greener products and cleaner production utilization, and consequently, economic benefits together with social and environmental performance are improved (Lukman et al., 2021). Sustainability practices enable manufacturing plants to optimize their resources and improve operational performance, that are important considering locations with emerging environmental standards (Meiryani et al., 2023). Cleaner production is essential in order to assess production processes and to limit the use of hazardous chemicals, and to minimize waste and emissions, and in the end, it serves as a requirement for future growth

in an environmentally sustainable manner (Fresner & Engelhardt, 2003). In addition, sustainable manufacturing drives operational cost savings through the use of energy-efficient equipment, reducing waste and emissions, and implementing circular economy practices to minimize energy, water, and raw material consumption (Meiryani et al., 2023).

2.1.3 Economic Production Quantity (EPQ)

The Economic Production Quantity (EPQ) model, a fundamental extension of the Economic Order Quantity (EOQ), is considered in the situation where production and demand take place simultaneously. Such a model is quite suitable for make-to-stock environments, where all the goods in a company are produced and not purchased from an external vendor (Salameh & Jaber, 2000). It improves inventory optimization over the production rate and the demand rate by taking into account the ordering and holding costs, resulting in a more realistic and practical model to minimize total inventory costs (Senthilnathan, 2019).

The strategic balance between ordering costs and storage costs, to determine the quantity to order in order to replenish items in stock, is the primordial logic of the EOQ model (Schwarz, 2008). This balance is critical inasmuch as it influences the degree of financial efficiency and operational effectiveness of an organization (Tungalag et al., 2017). At the other end, when a larger quantity is ordered infrequently, monthly ordering costs go down, but the average amount in stock (and hence, carrying costs) goes up due to higher storage costs each month. On the other hand, if orders are placed more often, then the storage costs will reduce with an increase in the costs corresponding to placing and processing the orders (Senthilnathan, 2019). The model's robustness is also advantageous when empirical information is only approximate or uncertain (Schwarz, 2008).

The EPQ model can be represented by the following equation:

$$EPQ = \sqrt{\frac{2DS}{H} \times \frac{P}{P-d}} \quad 2-1$$

Where:

D is the annual demand,

S is the setup cost per production run,

H is the holding cost per unit per year,

P is the daily production rate,

d is the daily demand rate.

By calculating the optimal lot size for production, EPQ helps manufacturing systems avoid excessive inventory levels and high costs associated with production runs. (Heizer et al., 2017)

2.1.4 *Inventory Theory*

Efficiently managing inventory is indispensable for the operations of any enterprise as it has a significant impact on cost-effectiveness and customer satisfaction. The key is to balance the tradeoff between keeping enough stock to produce smoothly and feeding the upstream to avoid the negative impact of overstocking and stockouts. A variety of approaches and techniques exist in the art for accomplishing these goals, each of which has particular advantages and challenges associated therewith. Based on recent research, this article focuses on the most important aspects of inventory management and its contribution to the development of sustainable businesses.

Good inventory management can help support businesses' green growth models by minimizing waste and maximizing resource usage." Establishing a complete closed-loop system from product design to resource recovery can allow businesses to enable a large-scale view of their inventory operations to synchronize with corporate sustainability goals (Ma, 2022). An important aspect of this alignment is mitigating the bullwhip effect, where distortions in demand information can cause inventory to inflate in supply chain tiers. Through coordinated controlling, the supply chain can suppress the bullwhip effect, promote waste elimination, and lower the inventory cost in the epoch of green transformation (Ma, 2022).

In addition, many analytical tools (EOQ, ABC analysis, and Inventory Turnover Ratio) are used by firms to increase the level of capital that is invested in inventory. These types of tools support decision making and lead towards operational efficiency that provides benefits (Jhansi et al., 2022). Advancements in inventory control techniques such as VMI and JIT systems have increased the analytical toolkit. VMI improves the performance of the supply chain due to inventory ownership being transferred to suppliers, lower levels of inventory, and increased responsiveness. However, JIT wishes to reduce the level of out-of-production material and subsequently encourages smoother material flow from the start to the end of the process of production process (Mohamed, 2024).

Beyond technical skills, effectively managing an inventory also requires consideration of the type of inventory held (i.e., anticipation and fluctuation) and the costs related to holding inventory (i.e., ordering costs and carrying costs) (Singh & Gupta, 2023). The regulation of these operational parameters is very important for production and cost reduction purposes. Poor inventory management, on the other hand, can lead to significant material losses, reduced sales, complaints and deficient inventory. Conversely, effective management of inventory and the

inventory system results in operational efficiency, high service level, and profits growth (Mohamed, 2024).

2.1.5 Periodic Review System

The Periodic Review System stem (also sometimes referred to as the fixed-interval or fixed-order-interval system) is the basis of the review and reorder inventory management, assuming that orders are reviewed and placed at roughly equal time intervals. In this mechanism of inventory control, the inventory status is reviewed after fixed regular periods: for example, every 3 days or week or month or quarter, and orders are placed so that the stock is up to a target level, often referred to as the “order-up-to” levels or target levels (Chiang, 2004).

This approach differs from continuous review systems, which track the inventory level and issue an order when the inventory level falls to a predetermined reorder point. The order-up-to policy is commonly used when it is financially or operationally more convenient or less expensive for buyers to periodically place orders (at fixed intervals), for example, when they combine orders from the same supplier in order to reduce ordering and transportation costs. To ensure the period review system functions properly, it is important to get the balance right in setting the order-up-to level, which is impacted by factors such as demand variability, lead time, and service level required (Silver & Bischak, 2010).

Decision on the length of the review period is another key decision in developing a periodic review system; it is affected by a number of factors such as demand pattern, the holding costs of inventory, and the cost of ordering items. A long review period incurs low ordering while carrying cost, and a possible stockout may increase. The order-up-to level should be calculated prudently to balance the risk of stockouts and the cost of excessive inventory. This includes the normal demand during the review period, plus the lead time and a safety stock provision to guard against demand uncertainty.

With its simplicity and practicality, the order-up-to policy is appealing for inventory management problems in general (Silver, 1991). For cases where demand is fairly stable and predictable, a periodic review policy can be a cost-efficient way of keeping the right level of stock and reducing overhead for administration. Yet, the performance of safety stock policy may deteriorate in the presence of high demand variability or long lead times, which leads to larger safety stock levels, to sustain the required service levels, and accordingly higher inventory holding costs.

In practice, the optimization of the order-up-to policy is frequently realized by statistical and forecasting techniques to forecast the future demand and to establish the right safety stock levels. Time series analysis, regression analysis, and simulation modeling are among the methods used to analyze historical demand data for trend, seasonality, and demand distributional parameters. The application of such techniques can enhance demand forecast accuracy and aid in inventory replenishment decision-making.

Also, the use of the order-up-to policy under supply chain modes in conjunction with them, e.g., VMI and CPFR, can lead to the improvement of the coordination for the supply chain and the performance of the entire system. Backlogging works well; however, stockouts and order-up-to policies need much deeper investigation (Pinçe, 2020).

2.1.6 Lateral Transshipment

The transshipments between stocking locations of the same echelon in a supply chain, referred to as lateral transshipments, offer an attractive way to improve responsiveness and robustness to demand variability and disruptions (Ekwall, 2012). Facility stock consolidation, by which companies are able to divert stock from one facility to another, can help avoid stockouts at some locations while reducing over inventory at others, and therefore enable improved service levels and reduced holding costs (Bullinger et al., 2002).

The level of benefit from lateral transshipment depends on the nature of the network, transportation costs, the degree of demand correlation across the locations, and how fast information can be exchanged (Glock, 2011). Well-developed logistics infrastructure between organizations is necessary to execute lateral transshipment, along with enabling and efficient inventory management, and effective transportation machinery (Zinn & Goldsby, 2020). The strategic location of distribution centers, as presented in some studies, can also magnify the gain from lateral transshipment when distribution centers serve as concentrated spots for inventory consolidation and redistribution (Chidozie et al., 2024).

Additionally, incorporating innovative solutions, such as real-time visibility and predictive analytics, can equip executives with the means to make informed decisions concerning transshipment, inventory allocation, and reduce transportation costs.

Lateral transshipment policies, however, require a careful trade-off analysis of transportation costs, costs of holding inventory, and potential service level improvements. Although transshipping can help avoid out-of-stock conditions and better capitalize on demanded units, its transportation costs may diminish profits if not adequately controlled.

Thus, it becomes necessary for companies to create refined optimization models that take the aforementioned issues into account and, as such, determine the optimal transshipment policies that lead to the best rates of global supply chain efficiency. Moreover, the benefit of lateral transshipment is contingent upon the level of the demand correlation between stocking locations; highly correlated demand patterns attenuate the impact of transshipment as all locations would tend to stock out concurrently.

On the other hand, if demand and patterns are negatively related or independent, lateral transshipment is extremely helpful in dealing with demand variability. Furthermore, lateral transshipment requires transparency; hence, the transfer of information must be unfettered throughout the supply chain processes.

2.1.7 Evolutionary Algorithm Optimization

Evolutionary algorithms (EAs) are a class of stochastic optimization methods that mimic the natural mechanisms of biological evolution. In this paradigm, well-known algorithms such as Genetic Algorithms, Evolution Strategies, Evolutionary Programming, and Differential Evolution have shown great flexibility in a wide variety of problem domains (Rao & Babu, 2014). These methods mimic the mechanism of natural selection, progressively evolving a population of candidate solutions over generations, and improving their performance concerning a given constrained objective function (Iacca et al., 2020). Generally, an evolutionary algorithm originates from an initial population in a random manner that is improved by means of central operators—selection, crossover (also called recombination), and mutation (Manuel et al., 2023). The individuals in the population having the best fitness are preferred to be propagated forward and ensure that promising features are preserved and magnified inside the population (Dasgupta & Michalewicz, 1997). Crossover allows the exchange of attributes between the selected parents, enabling exploration of the solution space as well as exploitation of good quality areas, and mutation on the other hand, injects random changes in the population to prevent excessive convergence and premature convergence (Louati et al., 2023; Xiao et al., 2020).

Evolutionary algorithms (EAs) have gained much popularity due to their inherent flexibility and ability to perform well for a wide range of problems, which include engineering design, operations research, finance, and recently, for machine learning. In the latter domain, evolutionary algorithms have had a significant impact on making the search for neural architecture automated by the discovery of novel network architectures that achieve state-of-

the-art performance (Louati et al., 2023). They also apply to finding optimal hyperparameters, in which the model's parameters are optimized to achieve higher accuracy and generalization (Xiao et al., 2020). Ranked among metaheuristic methods, GAs have the advantage of operating in the domain of a target problem as a "black box," without an explicit mathematical model or detailed information on the problem structure (Mohammad et al., 2020). This flexibility and ease of use have made the EA technique a useful tool for solving genuine, extensive optimization problems.

2.1.8 Carbon Tax

The introduction of a carbon tax in Indonesia is a key milestone toward realizing Indonesia's ambitious climate objectives and a more sustainable economic development under the Paris Agreement. Indonesia's pledge to address the issue of climate change is evidenced by its ratification of the Paris Agreement pursuant to Law No. 16/2016 in October 2016, and it has positioned a strong commitment to reduce the adverse effects of climate change (Muhammad & Aryani, 2021). This is echoed by the formation of Nationally Determined Contributions on reducing emissions in some key sectors such as forestry, industry, energy, waste, and agriculture, which adds strength to Indonesia's commitment and proactive role in participating in climate actions (Sugiarto et al., 2023). Indonesia, the second-largest archipelagic state in the world, has a significant economic stake in climate change, as the world's fourth most populous nation potentially experienced losses of up to 544 trillion rupiahs (approximately \$54 billion) between 2020 and 2024 to various environmental hazards which potentially shrinking its GDP by 16.7% to 30.2% with a 2–2.6°C temperature increase (Sugiarto et al., 2023). However, a carbon tax, an important revenue generator, may change the game, possibly bringing economic and environmental takeaways. This tax money could be spent on national development and employee expenses, significantly decrease carbon emissions, and move towards a cleaner, greener future (Alifah & Bawono, 2020).

There are several key considerations for Indonesia in implementing a carbon tax: how the structure of the tax will be, the default tax rates, and the use of the revenue. Economic modelling and analysis are also necessary to understand the impacts of the introduction of a carbon tax on the various sectors of the Indonesian economy. For example, companies with heavy dependence on fossil fuels as raw materials of production could incur higher costs, which in turn may affect the firms' competitiveness in the international market. Conversely, it may also drive investment in clean technologies and generate jobs in the renewable-energy sector

(Malerba et al., 2024). Thoughtful design is essential for the tax to match Indonesia's economic underpinnings, development aspirations, and social priorities. It has widely been reported that the pattern of economic growth of a country is its carbon emissions, especially in relation to a country that has a pretty large population, such as Indonesia, where economic activities are dependent heavily on the use of coal (Yanto et al., 2019).

The introduction of the carbon tax in Indonesia is a difficult policy, environmentally friendly yet economically resilient, with many obstacles in between. The carbon tax enacted by the 2021 Harmonization of Tax Regulations Law is also intended to decrease CO₂ emissions from fossil fuel sources and to support a shift to clean energy (Ardhimansyah & Khaddafi, 2024; Olpah et al., 2023). However, regulations are incomplete, and digital infrastructure and industry opposed to fossil fuel are weak (Harefa et al., 2024). The effectiveness of the policy is also constrained by bureaucratic complexities, inaccurate emission data, and underdeveloped monitoring systems (Ardhimansyah & Khaddafi, 2024; Hukum et al., 2023). Above all, an integrated, holistic approach regarding the economic, political, and social dimensions is indispensable for the effective and efficient implementation of a carbon tax in Indonesia (Adyana, 2023).

2.2 Literature Study

As opposed to the earlier theoretical Basis part that provided theoretical foundations of this study through reviewing seminal models and concepts such as EPQ, carbon taxation, and lateral transshipment that explain the forces behind the proposed model, the motive of this part is to present the literature study.

In this section, the attention is directed to finding out patterns, similarities, and limitations among the previously conducted research that is similar to the research developed in this dissertation. This approach facilitates the identification of unexplored regions, thus being conducive to a more directed and impactful research contribution.

2.2.1 Prior Research on Related Themes

To contextualize the present study, Table 2.1 summarizes selected research articles that cover one or more relevant dimensions: supply chain configuration (One to Many, Many to One, Many to Many), product types (single or multi), optimization methodology (e.g., MILP, GA, EA), lateral transshipment usage, focus on the batik industry, and treatment of carbon emissions policies.

Each of these studies has been selected based on its thematic alignment with the scope of this research, particularly with respect to inventory control, environmental sustainability, traditional industry application, and algorithmic implementation.

2.2.2 Literature Synthesis and Research Gap Discussion

The discipline of sustainable supply chain management has advanced significantly and environmental issues, including carbon emissions, have increasingly been incorporated into strategic and operational considerations. Recent literature shows an upward trend in the sophistication of models that optimize the economic and environmental constraints simultaneously (Nie et al., 2020; Li et al., 2020, 2022). These studies highlight the importance of supply chains, particularly in energy-intensive industries, to integrate logistics efficiency with carbon reduction requirements like carbon taxes and cap-and-trade systems.

Another stream on cooperative inventory management through lateral transshipment has also attracted special focus, with contributions that develop policies to mitigate demand uncertainty and/or improve service levels (Donjuk et al., 2025; Ekren & Arslan, 2020; Yan et al., 2019). Nonetheless, a systemic embeddedness of the environment as well as retail-related emissions linked both to the transport of buyer-to-buyer logistics transshipment operations are still generally missing in such analytical frameworks.

The MSME-dominated traditional Indonesian batik industry encounters specific sustainability issues. Some early research has underscored operational inefficiencies and conceptual dialogues on green certificates, as well as partial production systems (Zhang et al., 2021; Purnomo, 2024). However, such activities are not yet associated with a quantitative optimization modeling with disparate consideration of carbon emission and national carbon tax bounds. Furthermore, current supply chain optimization for batik MSMEs has hardly considered the production variability and collaborative logistics with an explicit environmental regulation.

Drawing on Miles's (2017) taxonomy of research gaps, which includes evidence, knowledge, methodological, theoretical, empirical, population, and practical-knowledge conflict gaps, this review identifies multiple deficiencies in the literature relevant to this study's (Adu & Miles, 2023):

- **Population gap:** Limited focus on MSMEs in traditional industries like batik, which differ significantly from large-scale industrial contexts primarily dominating current research.

- **Empirical and methodological gaps:** Scarce quantitative models addressing operational variability and the intricacies of lateral transshipment alongside carbon policies tailored to MSMEs.
- **Knowledge and theoretical gaps:** Insufficient integration of carbon emissions in cooperative inventory frameworks, and the absence of models contextualized to Indonesia's carbon tax policy.
- **Practical-knowledge conflict gap:** A dearth of user-friendly, accessible decision-support tools leveraging evolutionary algorithms for MSME practitioners, despite advances in such algorithms for large-scale supply chains.

In filling these overlapping gaps, this study structures a multiple-product batik MSME supply chain model, where its distinctive feature is the amalgamation of machine-energy and transportation carbon emission incorporated within Indonesia's carbon taxation system. The decision to encase an evolutionary algorithm in Excel Solver has the potential to lay a bridge that connects academia innovations and the MSME reality, making it more accessible and applicable. Therefore, this study not only integrates the scattered streams of literature but also provides a cohesive framework for the advancement of environmental solutions and operational performances towards the traditional sector.

As shown in Table 2.1, the review provides a comparative perspective of distribution configurations, diversity of products, optimization approaches, lateral transshipment practice, focus on MSME/batik industry, and carbon policy linkages, hence clarifying the gaps of existing research as well as positioning the current study as a new and essential academic contribution.

Table 2.1 Comparative Review of Relevant Literature

No.	Author (Year)	Distribution Model	Product Type	Optimization Model	LT	Batik/MSME Industry	Carbon Emission Policy	Contribution / Focus
1	Nie et al. (2020)	OM	Multi	MINLP + Dynamic Programming	X	✓	✓	Proposes a multi-echelon model integrating low-carbon emission constraints under a cap-and-trade system, emphasizing trade-offs

								between logistics cost and environmental impact.
2	Donjuk et al. (2025)	MM, LT	Multi	Spreadsheet Simulation	✓	✗	✗	Investigates stochastic demand management using a hybrid ordering and lateral transshipments policy, providing strategic insights for multi-item inventory coordination.
3	Zhang et al. (2021)	OM	Single	Optimization	✗	✓	✓	Analyze the operational and emission efficiency trade-offs in traditional batik industries under carbon tax regulation using quantitative modelling.
4	Ekren & Arslan (2020)	OM, LT	Single	Simulation (ARENA)	✓	✗	✗	Uses simulation modelling to analyze the effect of lateral transshipment policies on inventory performance in a continuous review system.
5	Yan et al. (2019)	MO, LT	Multi	Genetic Algorithm (GA)	✓	✗	✗	Presents a priority-based lateral transshipment optimization strategy for inventory systems serving heterogeneous customer groups with differing urgency.
6	Zhou et al. (2021)	—	—	—	✗	✗	✓	Conducts a broad literature review evaluating how various carbon pricing mechanisms (taxes, cap-and-trade) influence

								supply chain design and operations.
7	Li et al. (2020)	OM	Single	Differential Evolution + Sine SSA	✗	✗	✓	Compares the cost and emission outcomes of implementing carbon tax vs. emission cap strategies in coal-based supply chains using hybrid algorithms.
8	Li et al. (2022)	OM	Multi	Linear Programming	✗	✗	✓	Integrates carbon cost explicitly into a linear SCND model to evaluate the trade-off between emission control and distribution efficiency.
9	Xu & Szmerekovsky (2023)	MO, LT	Multi	Multi-stage Stochastic Programming	✓	✗	✗	Models transshipment-based coordination in a perishable supply chain (blood platelets) under probabilistic demand and location constraints.
10	Purnomo (2024)	OM, LT	Multi	Genetic Algorithm (Simulation-in-the-loop)	✓	✓	✗	Develops a GA-based model for a single-vendor, multi-buyer, multi-product batik supply chain, considering random imperfect production, rework cycles, and reactive lateral transshipment. Though it simulates realistic buyer interactions and EPQ logic, it does not incorporate carbon emissions or tax policies.
11	Raghul et al. (2024)	OM	Multi	Differential Evolution (DE),	✗	✓	✗	Proposes a dynamic e-procurement framework

			Genetic Algorithm (GA), Hybrid Multipopulational Reinitialization Strategy (HMRS)				for two-echelon supply chains, leveraging evolutionary algorithms— particularly DE variants and a novel hybrid strategy—for adaptive supplier selection and order allocation under fluctuating real-world parameters.	
12	Aqib & Ullah (2023)	OM	Multi	Genetic Algorithm (GA), Red Deer Algorithm (RDA), Social Engineering Optimizer (SEO)	✗	✓	✗	Applies multiple evolutionary algorithms to agricultural supply chain network design, optimizing production, inventory, and transportation across all stages.
13	Arifin (2021)	OM	Single	Genetic Algorithm (GA)	✗	✓	✗	Focuses on optimizing parcel delivery logistics in Yogyakarta, Indonesia, by applying GA to determine the most efficient delivery routes and fleet allocation, thus minimizing transportation cost, travel distance, and delivery time.
14	This Study	OM, LT	Multi	Evolutionary Algorithm (Excel Solver)	✓	✓	✓	This study integrates carbon emissions, production optimization, and lateral transshipment in the context of a multi- product batik manufacturer’s supply chain. It fills the research gap by modeling both

machine energy-based emissions and transportation emissions, under Indonesia's carbon tax policy. The model is using an evolutionary algorithm embedded in Excel Solver, making it accessible, replicable, and directly applicable to real-world MSMEs.

| **LT**: Lateral Transshipment, **OM**: One to Many, **MO**: Many to One, **MM**: Many to One

The following observations have been also due to the comparative study in Table 2.1. While there are increasing the attempts to model supply chain complexity and environmental impacts in the literature, substantial gaps also remain, especially with respect to MSMEs in traditional industries such as batik. Few contributions addressing production variability and collaborative logistics have been made, and none have done so in the context of the specific features of new carbon policies. Interestingly, the most sophisticated models proposed to date in addressing the batik sector either fail to include quantitative emissions modeling or overlook the mainstream implications of Indonesia's carbon tax regulation.

In addition, in spite of the increasing use of evolutionary algorithms – as Genetic Algorithms, Differential Evolution, and its hybrids -to enhance the optimization in a wide range of supply chain environments, the majority of the applications are still restricted to large-scaled industrial networks, and general test problems. The possibilities to enable MSMEs with pragmatic, user-friendly tools for decision, are still not sufficiently explored.

Given these limitations, this study seeks the ways for responding to the intersection of those research gaps by devising a supply chain model representing a batik MSME. It is the only system to combine carbon emission costs of the production energy and transportation based on national policy parameters, according to the Indonesian law. By incorporating an Evolutionary Algorithm within Excel Solver, the method remains accessible and reproducible to practitioners and extends academic discussions around sustainable ultra-collaborative and context-specific supply chain optimization. In so doing, this paper not only combines the previously segregated

research streams but also provides a strong and practically relevant framework for promoting sustainability in traditional industry clusters.

CHAPTER III

RESEARCH METHOD

3.1 Research Design

The research is designed using a quantitative case study approach in developing and testing an integrated supply chain optimization model for PT. XYZ Batik manufacturer, is categorized as an MSME operating in Yogyakarta, Indonesia. The study is designed to develop a systematic approach to derive the actual business practices of the manufacturer throughout its supply chain system into an integrated mathematical model using Excel. This provides a mode for the precise determination of joint total costs, including both conventional operation costs and carbon emissions generated by manufacture and transportation.

The research is pursued in phases. The benchmark processes and cost of the present supply chain are identified through secondary data provided by PT.XYZ Batik includes volume produced, demand patterns, inventory policy, energy consumption of machines, and the manufacturer's location coordination alongside all five buyers. After that, a mathematical model for the supply chain is developed by considering carbon tax policy and the dynamic lateral transshipment between buyers.

For dealing with complexity and multi-objectivity in the problem, the work uses an evolutionary algorithm as the primary optimization tool. The aforementioned algorithms are applied in an iterative process to find optimal sequencing policy, production lot, and transportation routes, which result in minimizing the total costs and carbon emissions simultaneously. The model is validated through simulation and sensitivity analysis, providing insights into how well the optimization model performs under different levels of demand and policy.

By setting the research design on empirical evidence and an advanced optimization algorithm, we can produce valuable insights for the PT. XYZ Batik and also to the sustainable supply chain management literature in the traditional manufacturing context.

3.2 Research Flow

The following research flow diagram outlines a structured and systematic approach to problem identification, model development, and solution implementation. Each step is carefully designed to ensure scientific rigor and practical relevance.

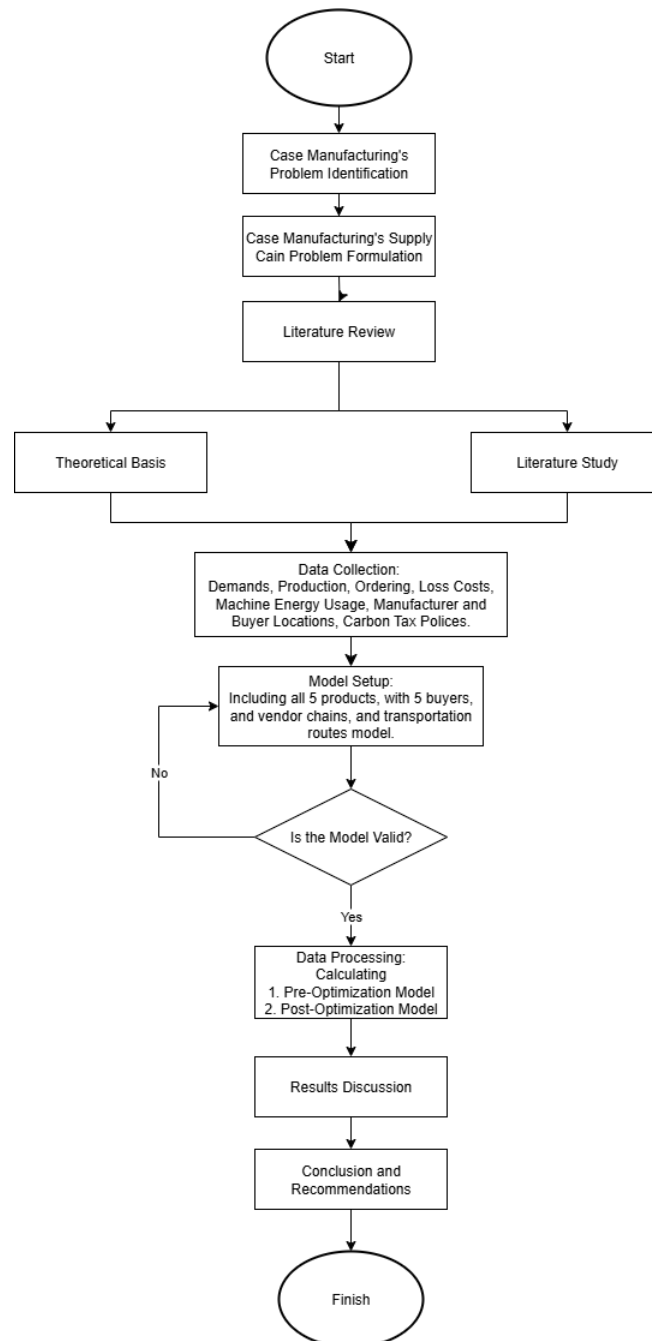


Figure 3.1 Research Flow

The research in this study is arranged in a systematic way to guarantee the establishment of a powerful optimization model for PT. XYZ Batik. The implemented flow is as follows:

1. Start

2. Case Manufacturing's Problem Identification:

Start by making a list of the key issues that PT XYZ Batik is encountering, like inefficiencies in the operations, high costs, and pressures brought on by new regulations and carbon taxes. This is the bedrock of the entire research as it stipulates what is to be addressed.

3. Case Manufacturing's Supply Chain Problem Formulation:

Translate found challenges into specific research problems and questions. Here, you describe what specifically is wrong with the supply chain — lack of coordination, unaccounted-for carbon emissions, suboptimal ordering, for example — and what your research is intending to fix.

4. Literature Review:

Performing a thorough literature review and positioning the study within both the theoretical and empirical frameworks:

- Theoretical Basis: To carry out a study on the theoretical aspect of the thesis and review the relevant theories and principles of supply-chain optimization, environmental legislations, and the implementation of carbon tax. This way, the research is based on existing knowledge.
- Literature Study: Review empirical studies and/or cases that address similar problems or methodologies. This can help to identify best practices, areas for research, and methodologies relevant to your work.

5. Data Collection:

Collect all the data needed to construct a realistic model. These data include product demand, production levels, ordering and loss costs, machine energy consumption, the locations of the manufacturer and buyers as well as the specifics of a carbon tax policy. This is done to ensure that the model applies to real-world circumstances.

6. Model Setup:

Develop an integrated supply chain model that incorporates each of the following components: five types of products, five buyers, the vendor operation, and the

transportation network. This step maps the physical supply chain into a model that can be analyzed and optimized. The following are the steps for conducting the model set up for buyers' simulation:

Table 3.1 Step by Step Buyers Model Simulation Setup

Step	Description
1	<p>Parameter Initialization: For each buyer and product, initialize all necessary parameters. This involves specifying the ordering cost from vendor (A_{vendor}), ordering cost from buyers (Transshipments) (A_{buyer}), holding cost (h), lost sales penalty (C_{lost}), lead time (L), review period (P), reorder point (R), and initial inventory (I_0).</p>
2	<p>Parameter Table Construction: Present the above parameters in a summary table above each simulation, serving as a structured reference. This table ensures transparency and reproducibility by clearly outlining the parameters for each scenario, such as buyer, product, cost values, and time-based variables.</p>
3	<p>Simulation Table Design: Develop a time-indexed simulation table for each buyer-product combination, covering each day $t = 1, 2, \dots, 60$. For instance, in product 1 buyer 1, the columns include: Simulation Day (t), Beginning Inventory (I_t), Customer Demand (D_t), Lateral Demand from other buyers (D_{B2}, D_{B3}), Ending Inventory (I'_t), Lost Sales (L_t), Order Status (O_t), Orders Received (OR_t), and cost calculations.</p>
4	<p>Column-by-Column Definition and Logic: Starting with the</p> <ol style="list-style-type: none"> simulation day (t), hence at each day t, calculate beginning inventory (I_t) by referencing the previous day's ending inventory, updated with any incoming orders: $I_t = I'_{t-1} + OR_t$. Customer demand (D_t) is generated using a normal distribution (e.g., for product 1 buyer 1, $D_t \sim N(10, 1.17)$ with Excel: $=\text{ROUND}(\text{NORM.INV}(\text{RAND}(); 10; 1.17); 0)$.

-
4. Lateral transshipment demands from other buyers (D_{B2}, D_{B3}) are simulated with uniform distributions and Excel formulas based on day of the week. After accounting for all demand,
 5. compute ending inventory: $I'_t = \max(0, I_t - D_t - D_{B2} - D_{B3})$,
(=MAX(0; (B8+I8) -SUM(C8:E8)),
 6. Then, calculating lost sales: $L_t = \max(0, D_t + D_{B2} + D_{B3} - I_t)$,
(=MAX(0; SUM(C8:E8) - (B8+I8))), reflecting any demand unmet due to insufficient stock.
 7. Order Placement Logic: Orders are placed periodically according to the review period (P). At every P days ($t \bmod P = 0$), set order status: $O_t = 1$, if ($t \bmod P = 0$), otherwise 0 (=IF(MOD(A8;4)=0;1;0).
 8. Orders arrive after a lead time (L) as: $OR_t = O_{t-L} \cdot \max(0, R - I_{t-L})$, represented in Excel as =IF(OFFSET(H8;4;0)=1;MAX(31-OFFSET(F8;-4;0);0);0).
 9. Integrate lateral transshipment logic, allowing emergency supply from designated buyers (e.g., B5), with linkage to the relevant cell or simulation rule (=BB10). This mimics collaborative inventory support across the network.
 10. **Next**, for each period, compute: **Ordering Cost** ($C_{ij,t}^{order}$) if an order is placed, **Holding Cost** ($C_{ij,t}^{hold} = h \cdot I'_t$), and **Lost Sales Cost** ($C_{ij,t}^{lost} = C_{lost} \cdot L_t$). Example Excel formulas: = (H8 * MAX(ROUNDUP((K\$3-F8)/4;0);0) * \$E\$3) + IF(J8>0;\$H\$5;0) for ordering cost, =F8*2000 for holding cost, =G8*20000 for lost sales cost.
 11. **Lastly, Grand Total Cost (GTC):** Aggregate all costs over the simulation horizon:

$$GTC_{j,i} = \sum_t (C_{ij,t}^{order} + C_{ij,t}^{hold} + C_{ij,t}^{lost}), \quad \text{In Excel:}$$

$$=\text{SUM}(K8:K67) + \text{SUM}(L8:L67) + \text{SUM}(M8:M67).$$
-

systematic approach allows for consistent analysis and ensures that the model can be easily extended to different scenarios or policy interventions.

Following that:

Step-by-Step Model Setup for Vendor Simulation

Table 3.2 Step-by-Step Model Setup for Vendor Simulation

Step	Description
1	Parameter Initialization: Begin by defining all core parameters for the vendor's simulation. For each product, set the setup cost (S), holding cost (h), Lost Sales Cost (LS), , carbon emission setup cost ($EmSetup$), daily carbon emission cost ($EmDaily$), initial inventory (I_0), and daily production quantity (PQ).
2	Parameter Table Construction: Clearly present these parameters in a summary table above each simulation, ensuring transparency. The table lists the vendor, product, cost and emission values, production lot size, and starting inventory, as in your example above. This guarantees each scenario is fully specified for reproducibility.
3	Simulation Table Design: Construct a day-by-day simulation table spanning the full planning horizon ($t = 1, 2, \dots, 60$). Columns include: time period (t), beginning inventory (I_t^{begin}), orders from each buyer ($O_{j,t}$), ending inventory (I_t^{end}), lost sales (L_t) setup cost (C_t^{setup}), daily and setup carbon emission cost ($C_{i,t}^{em}$), inventory cost ($C_{i,t}^{inv}$), and lost sales cost ($C_{i,t}^{lost}$).
4	Inventory Dynamics: On each day, calculate the beginning inventory () as the sum of the prior day's ending inventory and production added daily: $I_t^{begin} = I_{t-1}^{end} + PQ.$
5	Order Fulfillment: Aggregate all buyer orders for day t as $O_{j,t}$ (for buyers $j = 1, \dots, 5$), which are determined by each buyer's simulation logic. The total fulfilled demand in period t is $\sum_{j=1}^5 O_{j,t}$
6	Ending Inventory and Lost Sales: Calculate ending inventory after all orders: $I_t^{end} = \max\left(0, I_t^{begin} - \sum_{j=1}^5 O_{j,t}\right) (=MAX(0, BL8 - SUM(BM8:BQ8))).$ Compute lost

sales for any excess buyer demand beyond inventory:

$$L_t = \max\left(0, \sum_{j=1}^5 O_{j,t} - (I_t^{begin} + PQ)\right).$$

Setup and Carbon Emission Costs: Every 3rd day ($t \bmod 3 = 1$), incur setup costs $C_t^{setup} = S$ and carbon setup emission cost $EmSetup$, while the daily carbon

7 emission cost ($EmDaily$) is applied each day. Formally, total emission cost for

day t: $C_{i,t}^{em} = EmDaily + EmSetup \cdot SetupIndicator_t$. Excel:

$$= \$BT\$5 + IF(MOD(BL8; 3) = 1; \$BR\$5; 0).$$

Cost Calculations: For each day, calculate:

- **Setup Cost:** $C_t^{setup} = S$ if setup occurs, else 0 ($=IF(MOD(BK8, 3)=1, \$BQ\$2, 0)$).

8 - **Inventory Cost:** $C_{i,t}^{inv} = h \cdot I_t^{end}$

- **Lost Sales Cost:** $C_{i,t}^{lost} = LS \cdot L_t$

- **Total Emission Cost** as above.

Grand Total Cost (GTC): Aggregate all daily costs for the planning horizon:

9 $GTC_{\text{vendor},i} = \sum_t (C_t^{setup} + C_{i,t}^{em} + C_{i,t}^{inv} + C_{i,t}^{lost})$ In Excel: $=SUM(BT8:BW67)$.

Joint Total Cost (JTC): To evaluate the overall system, sum the vendor's GTC with the GTCs from all five buyers for each product:

10 $JTC = GTC_{\text{vendor},i} + \sum_{j=1}^5 GTC_{\text{buyer}_j,i}$

For example, in Excel: $=BS4+BF3+AU3+AI3+V3+K4$.

Replication and Documentation: Repeat this logic for all products, clearly

11 documenting the calculation logic and any scenario-specific adjustments for each simulation sheet. This supports transparency and enables sensitivity analysis for different emission rates, costs, or policy changes.

7. Model Validation:

Test the model to ensure that it is correct and appropriate. This includes comparing model results to reality or expert opinion. Upon unsatisfactory validation, the model will have to be reviewed/changed, or input parameters should be re-edited and validated again, until the model can simulate the real system.

8. Data Processing:

Compute with the validated model for two scenarios:

- a. **Pre-Optimization Model:** Study existing (baseline) supply chain conditions, including costs, emissions, and performance, prior to any form of optimization.
- b. **Post-Optimization Model:** Use the proposed optimization strategy (evolutionary algorithms) to achieve an optimized cost and emission result, and recalculate the results.

9. Results Discussion:

Compare the results in the pre-and post-optimization phase. Analyze the optimization results, focusing on cost-effectiveness improvement, emission reduction, and the consistency with the carbon tax constraint.

10. Conclusion and Recommendations:

Summarize the most important points from the analysis. Suggest a practical decision for PT. XYZ Batik on how they could implement the optimization model to improve financial and environmental performance. Focus on implications for other MSMEs with similar issues.

11. Finish:

Conclude the research process, ensuring all objectives have been addressed and actionable outcomes are presented.

CHAPTER IV

DATA COLLECTION AND PROCESSING

This chapter describes the comprehensive collection and processing of data necessary to build, simulate, and validate the supply chain optimization model for PT. XYZ Batik. The following is an illustration of the supply chain of PT. XYZ Batik Manufacturer.

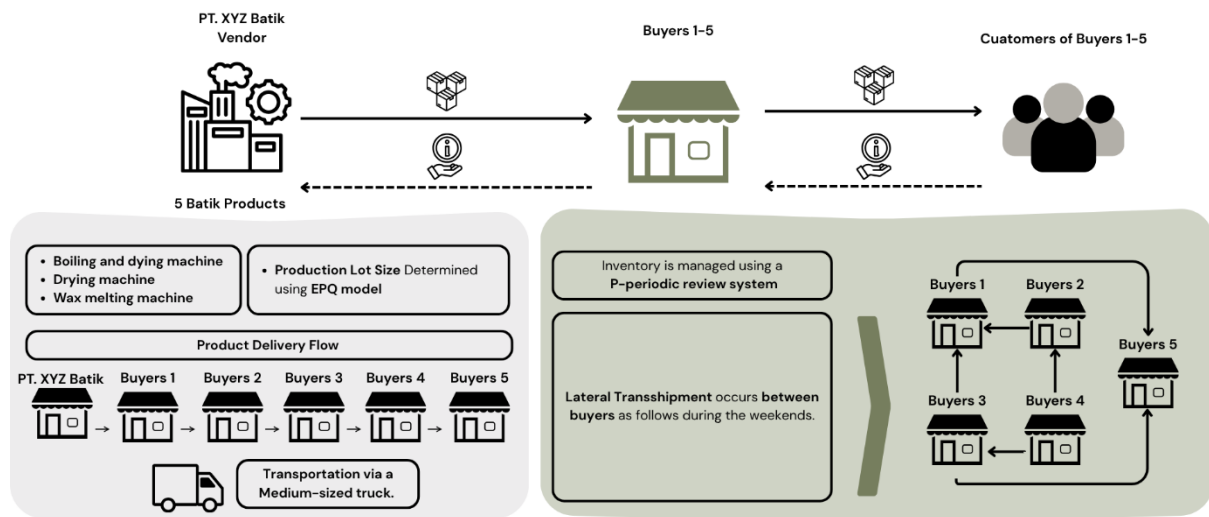


Figure 4.1 PT. XYZ Batik's Supply Chain Description

The data in this section includes operational cost metrics, emission parameters, detailed demand profiles, geolocation coordinates, and regulatory considerations like carbon taxation. These elements collectively support creating a robust optimization model utilizing an evolutionary algorithm.

4.1 Data collection

This section summarizes the data collected, outlining its relevance to the optimization model, reliability checks, and integration strategy.

4.1.1 Holding and Lost Sales Costs

A critical aspect of this study involves capturing financial details for inventory management. Data regarding holding costs and lost sale costs were obtained and the table below summarizes this information.

Table 4.1 Holding and Lost Sales Costs Data

Chain	Parameter	Value (IDR)	Chain	Parameter	Value (IDR)
Vendor	Setup Cost / 4 pcs	5.700	Buyer 1	Ordering Cost / 4 pcs	13.000

	Holding Cost (Product 1)	3.500		Holding Cost (Product 1)	2.000
	Lost Sale Cost (Product 1)	5.500		Lost Sale Cost (Product 1)	20.000
	Holding Cost (Product 2)	3.500		Holding Cost (Product 2)	2.000
	Lost Sale Cost (Product 2)	6.500		Lost Sale Cost (Product 2)	25.000
	Holding Cost (Product 3)	3.500		Holding Cost (Product 3)	2.000
	Lost Sale Cost (Product 3)	4.000		Lost Sale Cost (Product 3)	20.000
	Holding Cost (Product 4)	3.500		Holding Cost (Product 4)	2.000
	Lost Sale Cost (Product 4)	7.000		Lost Sale Cost (Product 4)	20.000
	Holding Cost (Product 5)	3.500		Holding Cost (Product 5)	2.000
	Lost Sale Cost (Product 5)	4.000		Lost Sale Cost (Product 5)	25.000
Chain	Parameter	Value (IDR)	Chain	Parameter	Value (IDR)
Buyer 2	Ordering Cost / 4 pcs	8.000	Buyer 3	Ordering Cost/ 4 pcs	10.000
	Holding Cost (Product 1)	2.000		Holding Cost (Product 1)	2.000
	Lost Sale Cost (Product 1)	25.000		Lost Sale Cost (Product 1)	25.000
	Holding Cost (Product 2)	2.000		Holding Cost (Product 2)	2.000
	Lost Sale Cost (Product 2)	25.000		Lost Sale Cost (Product 2)	30.000
	Holding Cost (Product 3)	2.000		Holding Cost (Product 3)	2.000
	Lost Sale Cost (Product 3)	25.000		Lost Sale Cost (Product 3)	25.000
	Holding Cost (Product 4)	2.000		Holding Cost (Product 4)	2.000
	Lost Sale Cost (Product 4)	25.000		Lost Sale Cost (Product 4)	30.000
	Holding Cost (Product 5)	2.000		Holding Cost (Product 5)	2.000
	Lost Sale Cost (Product 5)	25.000		Lost Sale Cost (Product 5)	25.000
Chain	Parameter	Value (IDR)	Chain	Parameter	Value (IDR)
Buyer 4	Ordering Cost / 4 pcs	8.000	Buyer 5	Ordering Cost / 4 pcs	13.000
	Holding Cost (Product 1)	2.000		Holding Cost (Product 1)	2.000
	Lost Sale Cost (Product 1)	35.000		Lost Sale Cost (Product 1)	25.000
	Holding Cost (Product 2)	2.000		Holding Cost (Product 2)	2.000
	Lost Sale Cost (Product 2)	25.000		Lost Sale Cost (Product 2)	25.000
	Holding Cost (Product 3)	2.000		Holding Cost (Product 3)	2.000
	Lost Sale Cost (Product 3)	25.000		Lost Sale Cost (Product 3)	25.000
	Holding Cost (Product 4)	2.000		Holding Cost (Product 4)	2.000
	Lost Sale Cost (Product 4)	25.000		Lost Sale Cost (Product 4)	35.000
	Holding Cost (Product 5)	2.000		Holding Cost (Product 5)	2.000
	Lost Sale Cost (Product 5)	25.000		Lost Sale Cost (Product 5)	30.000

These parameters form the foundation of the cost minimization model, informing inventory decisions by quantifying trade-offs between holding costs and potential profits across the vendor and buyer network.

4.1.2 Inventory Policy and Production Parameters

A core component of the supply chain optimization model is the set of decision variables that govern inventory review and replenishment behavior at both the buyer and vendor levels. These variables include the Review Period (P) and Order-Up-To Level (R) for each buyer, and the Production Quantity (PQ) for the vendor. For each product, every buyer is assigned a review period (the interval in days between inventory reviews and possible ordering events) and an order-up-to level (the stock threshold that triggers a new order when reached or breached). The vendor, in turn, establishes a daily production quantity for each product.

The table below, Table 4.2, summarizes the set points for these decision variables for all products and actors in the supply chain pre-optimization. The values were collected through direct data collection.

Table 4.2 Inventory Policy and Production Parameters

Vendor	Product 1	Product 2	Product 3	Product 4	Product 5
Production Quantity PQ	22	22	22	22	22
Product 1					
Buyer	1	2	3	4	5
Review Period P	3	3	3	3	3
Order-up-to inventory level R	20	20	10	10	20
Product 2					
Buyer	1	2	3	4	5
Review Period P	3	3	3	3	3
Order-up-to inventory level R	20	20	10	10	20
Product 3					
Buyer	1	2	3	4	5
Review Period P	3	3	3	3	3
Order-up-to inventory level R	15	20	20	25	30
Product 4					
Buyer	1	2	3	4	5

Review Period P	3	3	3	3	3
Order-up-to inventory level R	10	10	15	20	20
Product 5					
Buyer	1	2	3	4	5
Review Period P	3	3	3	3	3
Order-up-to inventory level R	15	10	20	20	20

This structured parameterization allows for the systematic simulation and optimization of inventory policies and production planning across the multi-echelon supply chain. By explicitly setting these decision variables for each actor and product, the model supports scenario analysis and facilitates targeted supply chain efficiency and cost minimization improvements and sets the comparison between and after optimization results.

4.1.3 Vendor to Buyers Demand Distribution

Historical sales records and expert consultation formed the basis for modeling buyer demand. Probability distributions (normal and uniform) were employed to accurately represent purchasing variability.

Table 4.3 Vendor to Buyers Demand Distribution

Product	Buyers				
	1	2	3	4	5
1	Normal(300, 35)	Normal(150, 20)	Uniform(130, 270)	Uniform(120, 155)	Normal(60, 25)
2	Normal(300, 70)	Normal(500, 130)	Normal(400, 100)	Uniform(300, 450)	Uniform(200, 350)
3	Uniform(220, 470)	Uniform(100, 130)	Uniform(128, 240)	Uniform(100, 125)	Uniform(180, 310)
4	Uniform(60, 170)	Uniform(100, 300)	Uniform(240, 393)	Uniform(100, 350)	Normal(500, 120)
5	Normal(287, 70)	Normal(380, 70)	Uniform(140, 330)	Uniform(100, 230)	Normal(290, 25)

These stochastic demand inputs facilitate a realistic representation of market behavior within the optimization model, enhancing decision-making under uncertainty.

4.1.4 Lateral Demand Distribution Data: Buyer-to-Buyer

In addition to vertical vendor-buyer relationships, lateral transshipment behaviors were incorporated using uniform distributions, reflecting informal but frequent inter-buyer transactions in PT. XYZ Batik's buyers supply chain network.

Table 4.4 Lateral Demand Distribution: Buyer-to-Buyer Data

Products	From Buyer	To Buyer	Demand Distribution
Product 1	1	2	Uniform(20, 100)

Product 1	1	3	Uniform(20, 150)
Product 1	2	4	Uniform(70, 130)
Product 1	5	1	Uniform(20, 50)
Product 2	1	2	Uniform(50, 80)
Product 2	1	3	Uniform(50, 70)
Product 2	2	4	Uniform(20, 50)
Product 2	5	1	Uniform(20, 50)
Product 3	1	2	Uniform(50, 150)
Product 3	1	3	Uniform(70, 90)
Product 3	2	4	Uniform(40, 110)
Product 3	5	1	Uniform(30, 40)
Product 4	1	2	Uniform(40, 70)
Product 4	1	3	Uniform(30, 110)
Product 4	2	4	Uniform(30, 90)
Product 4	5	1	Uniform(40, 50)
Product 5	1	2	Uniform(20, 100)
Product 5	1	3	Uniform(20, 70)
Product 5	2	4	Uniform(100, 300)
Product 5	5	1	Uniform(50, 80)
Product 5	5	3	Uniform(30, 60)

These data support the model's ability to optimize redistribution decisions and evaluate cooperative buyer strategies in minimizing overall costs and emissions.

4.1.5 Buyer-to-Buyer Ordering Costs Data

Direct interactions with retail partners provided data on buyer-to-buyer ordering costs, capturing the financial implications of lateral transshipment.

Table 4.5 Buyer-to-Buyer Ordering Costs Data

From Buyer	To Buyer 1	To Buyer 2	To Buyer 3	To Buyer 4	To Buyer 5
Buyer 1	–	Rp 8.000	Rp 8.000	–	–
Buyer 2	–	–	–	Rp 8.000	–
Buyer 3	–	–	–	–	–
Buyer 4	–	–	–	–	–
Buyer 5	Rp 13.000	–	Rp 8.000	–	–

These figures represent realistic constraints that guide decision-making within the optimization model, distinguishing economically viable transshipment routes.

4.1.6 Machine Energy Use and Emissions Data

Machine-specific energy consumption and emission intensity data were gathered from PT. XYZ Batik using nationally recognized standards for carbon taxation.

Table 4.6 Machine Energy Use and Emissions Data

Machine	Setup Energy (kWh per setup / 3 days)	Post-Setup Energy Consumption (kWh/Hour)
1. Boiling and dying machine	450 kWh	15 kWh
2. Drying machine	300 kWh	15 kWh
3. Wax melting machine	550 kWh	15 kWh

These emissions factors underpin the model's integration of environmental externalities into operational decision-making, aligning closely with national sustainability targets. These parameters are used to compute both the setup emission cost (incurred every three production days) and the daily operational emission cost, which are then integrated into the total cost minimization model.

4.1.7 Geographic Coordinates Data

Latitude and longitude coordinates were obtained for accurate distance calculations using the Haversine formula.

Table 4.7 Geographic Coordinates Data

Retailer	Latitude	Longitude
Vendor	-6,888,000	109,675,000
Buyer 1 (B1)	-6,839,361,622	1,096,828,248
Buyer 2 (B2)	-6,854,844,076	1,096,372,801
Buyer 3 (B3)	-6,878,038,531	1,097,241,524
Buyer 4 (B4)	-6,909,885,239	1,097,207,780
Buyer 5 (B5)	-6,932,159,781	1,097,165,063

This spatially precise data ensures accurate estimations of transportation-related carbon emissions and logistics optimization.

4.2 Model Components

This subsection defines the essential mathematical elements and notation that underpin the integrated supply chain optimization model developed for PT. XYZ Batik. All relevant indices, parameters, and decision variables are formally introduced to establish a rigorous foundation for the formulation of the objective function and constraints. By standardizing this notation, the subsequent mathematical model and simulation logic can be presented with clarity and precision.

4.2.1 Indices

Table 4.8 Indices

Symbol	Description
i	: Index of products, $i = 1, 2, \dots, 5$
j	: Index of buyers, $j = 1, 2, \dots, 5$
k	: Index of buyers for transshipment, $k \neq j$
m	: Index of delivery route segments, $m = 1, 2, \dots, M$, where each m represents a travel leg between two consecutive nodes in the transportation route
t	: period (day)

4.2.2 Parameters

Table 4.9 Parameters

Symbol	Description	Unit / Dimension
S_i	: Setup cost per lot for product i	IDR
H_{ij}	: Holding cost per unit of product i at buyer j	IDR/unit
h	: Holding cost per unit at vendor	IDR/unit
$A_{ij}^{(v)}$	: Fixed ordering cost per order for product i from vendor to buyer j	IDR/order
$A_{jk}^{(b2b)}$	: Fixed ordering cost per order from buyer j to buyer k (for product i).IDR	
LS_{ij}	: Lost sales cost per unit of product i at buyer j	IDR/unit
$L_{i,t}$	: Lost sales of product i at time t (unfulfilled demand)	Units
d_j	: Distance between vendor and buyer j , computed via Haversine	Km
d_{jk}	: Distance between buyer j and k , computed via Haversine	Km
D_{ij}	: Demand distribution of product i at buyer j	Units
W_i	: Weight per unit of product i	Kg
$C_{i,t}^{em}$	: Total emission cost for product i on day t (setup+daily).	kWh
CI	: Carbon intensity per kWh	kg CO ₂ / kWh
WorkingHours	: Operating hours per day	Hours/day
EF	: Emission factor for transportation (e.g., 0.00021 kg CO ₂ /kg·km)	kg CO ₂ / (kg·km)
CT	: Carbon tax per kg of CO ₂	IDR/kg CO ₂
CarbonCost _{setup,i}	: Carbon cost due to setup for product i	IDR
CarbonCost _{daily,i}	: Daily carbon emission cost from the production of product i	IDR/day
$I_{ij,t}^{begin}$	: Beginning inventory of product i at buyer j at the end of period t .	Units
$I_{ij,t}^{end}$	: Ending inventory of product i at buyer j at the end of period t .	Units
$x_{ij,t}^{(v)}$	: Binary variable, 1 if buyer j orders product i from the vendor in period t , 0 otherwise.	IDR

4.2.3 Decision Variables

Table 4.10 Decision Variables

Symbol	Description	Unit
PQ_i	: Daily production quantity for product i (decision variable)	Units
Q_{ij}	: Order quantity of product i by buyer j	Units
T_{ijk}	: Quantity of product i transshipped from buyer j to k	Units
x_{ij}	: Binary variable: 1 if product i is shipped to buyer j , 0 otherwise.	Binary
y_{ijk}	: Binary variable: 1 if product i is transshipped from buyer j to k , 0 otherwise	Binary
z_i	: Binary variable indicating whether a setup is done for product i	Binary

4.3 Mathematical Model Formulation

4.3.1 Objective Function

The final system objective is to minimize the sum of Joint Total Costs (JTC) for all chains, where each JTC captures the aggregate of vendor and buyer costs (including emissions and transport) for product i :

$$\min \sum_{i=1}^5 JTC_i \quad 4-1$$

Where, for each product i :

$$JTC_i = (GTC_{\text{vendor},i} + \sum_{j=1}^5 GTC_{\text{buyer}j,i}) + C_j^{\text{trans}} \quad 4-2$$

- $GTC_{\text{vendor},i}$: Vendor's Grand Total Cost for product i (includes setup, inventory, emissions, and any lost sales)
- $GTC_{\text{buyer}j,i}$: Buyer j 's Grand Total Cost for product i (includes ordering, holding, lost sales, and transshipment)
- C_j^{trans} : Total Transportation emission cost associated with buyer j 's delivery route.

Each of these components is, in turn, defined as follows:

Vendor Grand Total Cost (GTC_{vendor})

$$GTC_{\text{vendor},i} = \sum_t (C_{i,t}^{\text{setup}} + C_{i,t}^{\text{em}} + C_{i,t}^{\text{inv}} + C_{i,t}^{\text{lost}}) \quad 4-3$$

- Vendor Setup Cost :

$$C_{i,t}^{setup} = S_i \cdot z_{i,t} \quad 4-4$$

- Vendor Machines Emission Cost :

$$C_{(i,t)}^{em} = \begin{cases} \text{CarbonCost}_{(daily,i)} + \text{CarbonCost}_{(setup,i)}, & \text{if } t \bmod 3 = 1 \\ \text{CarbonCost}_{(daily,i)}, & \text{otherwise} \end{cases} \quad 4-5$$

- Vendor Inventory Holding :

$$C_{i,t}^{inv} = h \cdot I_{i,t}^{end} \quad 4-4$$

- Vendor Lost Sales :

$$C_{i,t}^{lost} = LS_i \cdot L_{i,t} \quad 4-5$$

Buyer Grand Total Cost ($GT C_{buyer}$)

$$GT C_{buyer,j,i} = \sum_t (C_{i,t}^{order,total} + C_{ij,t}^{hold} + C_{ij,t}^{lost}) \quad 4-8$$

- Total Ordering Cost :

$$C_{i,t}^{order,total} = C_{ij,t}^{order,vendor} + C_{ijk,t}^{order,trans} \quad 4-9$$

$$C_{(i,t)}^{(order, total)} = \sum_j \left[A_{ij}^{(v)} \cdot x_{(ij,t)}^{(v)} \right] + \sum_j \left\{ \sum_{k \neq j} \left[A_{jk}^{(b2b)} \cdot x_{(ijk,t)}^{(b2b)} \right] \right\} \quad 4-10$$

- Buyer Ordering from the vendor :

$$C_{ij,t}^{order,vendor} = A_{ij}^{(v)} \cdot x_{ij,t}^{(v)} \quad 4-11$$

- Buyer Ordering via transshipment :

$$C_{ijk,t}^{order,trans} = A_{jk}^{(b2b)} \cdot x_{ijk,t}^{(b2b)} \quad 4-12$$

- Buyer Holding :

$$C_{ij,t}^{hold} = H_{ij} \cdot I_{ij,t}^{end} \quad 4-13$$

- Buyer Lost Sales :

$$C_{ij,t}^{lost} = LS_{ij} \cdot L_{ij,t} \quad 4-14$$

Transportation Emission Cost

$$C_j^{trans} = \sum_{m=1}^M d_m \cdot w_m \cdot EF \cdot CT \quad 4-15$$

Where:

- d_m : Distance travelled in the segment m of the delivery route
- w_m : Weight of product i being transported in a segment m
- EF : Carbon emission factor (e.g., 0.2 kg CO₂/kg·km for medium lorry)
- CT : Carbon tax (IDR/kg CO₂)

Haversine Distance Calculation

$$d = 2r \cdot \arcsin \left(\sqrt{\sin^2 \left(\frac{\Delta\phi}{2} \right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2 \left(\frac{\Delta\lambda}{2} \right)} \right) \quad 4-16$$

Where:

- d Is the distance between two points (in kilometres).
- r Is the Earth's radius (average radius = 6,371 km).
- $\Delta\phi$ Is the difference in latitude between two points (in radians).
- $\Delta\lambda$ Is the difference in longitude between two points (in radians).
- ϕ_1, ϕ_2 Are the latitudes, and λ_1, λ_2 Are the longitudes of the two points (converted to radians).

4.3.2 Constraints

1. Inventory Balance (Buyer):

$$I_{ij,t}^{begin} + Q_{ij,t} + \sum_k T_{kji,t} - D_{ij,t} - \sum_k T_{ijk} = I_{ij,t}^{end}, \forall i, j, t \quad 4-17$$

2. Vendor Production Balance:

$$I_{i,t}^{begin} + PQ_i - \sum_j Q_{ij,t} = I_{i,t}^{end}, \forall i, t \quad 4-18$$

3. Lost Sales:

$$L_{ij,t} = \max (0, D_{ij,t} - (I_{ij,t}^{begin} + Q_{ij,t} + \sum_k T_{kji,t})) \quad 4-19$$

4. Capacity

$$Q_{ij,t} \leq M \cdot x_{ij,t}, \forall i, j, t \quad 4-20$$

5. Setup:

$$z_{i,t} \geq M \cdot x_{ij,t}, \forall i, j, t \quad 4-21$$

6. Transshipment Binary Logic:

$$T_{ijk,t} \leq M \cdot y_{ijk,t}, \forall i, j, k, t \quad 4-22$$

7. Transportation Route Assignment (for vehicle routing)

$$AllDifferent(route_j), \forall j \quad 4-23$$

8. Non-negativity and Binary:

$$Q_{ij,t}, T_{ijk,t}, I_{ij,t}^{end}, I_{i,t}^{end}, L_{ij,t} \geq 0; x_{ij,t}, y_{ijk,t}, z_{i,t} \in \{0,1\} \quad 4-24$$

4.4 Data Processing

The data processing stage is critical for transforming raw data into structured inputs essential for accurate simulation and subsequent optimization. This section details the systematic procedures used to prepare the data, ensuring a robust foundation for the optimization phase.

4.4.1 Pre-optimization Costs

This subsection presents the baseline (pre-optimization) supply chain costs and decision variable settings for each buyer and the vendor, illustrating the supply chain environment prior to optimization.

1. Buyer 1

The table below summarizes the review period (P), order-up-to level (R), and corresponding Grand Total Costs (GTC) for Buyer 1 across all products.

Table 4.11 Pre-Optimization Buyer 1 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	3	20	7.182.000
Product 2	3	20	9.104.000
Product 3	3	20	10.240.000
Product 4	3	20	2.874.000
Product 5	3	20	8.771.000

Joint Total Cost (JTC)	
Value	
JTC for Buyer 1:	Rp38.171.000

The calculated Joint Total Cost (JTC) aggregates all product costs for Buyer 1, providing a clear initial cost scenario before optimization.

2. Buyer 2

The following data illustrates the pre-optimization cost structure and inventory management parameters for Buyer 2, reflecting existing inventory practices and associated financial outcomes.

Table 4.12 Pre-Optimization Buyer 2 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	3	20	2.554.000
Product 2	3	20	17.348.000
Product 3	3	20	1.962.000
Product 4	3	10	6.778.000
Product 5	3	10	15.166.000

Joint Total Cost (JTC)	
Value	
JTC for Buyer 2:	Rp43.808.000

Similar to Buyer 1, the JTC value encapsulates the overall financial performance of Buyer 2's product management strategy before improvements through optimization.

3. Buyer 3

The baseline costs and inventory parameters for Buyer 3 are detailed below, revealing the specific economic impacts of their inventory decisions and practices.

Table 4.13 Pre-Optimization Buyer 3 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	3	10	6.061.000
Product 2	3	10	18.106.000
Product 3	3	20	4.111.000
Product 4	3	15	11.788.000
Product 5	3	20	5.769.000

Joint Total Cost (JTC)	
Value	
JTC for Buyer 3:	Rp45.835.000

The resulting JTC for Buyer 3 highlights the aggregate financial exposure under current supply chain policies.

4. Buyer 4

Buyer 4's pre-optimization data provides insight into the current financial management of their inventory levels and ordering decisions, demonstrating cost implications prior to system improvements.

Table 4.14 Pre-Optimization Buyer 4 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	3	10	4.720.000
Product 2	3	10	14.508.000
Product 3	3	25	1.724.000
Product 4	3	20	5.727.000
Product 5	3	20	3.299.000

Joint Total Cost (JTC)	
Value	
JTC for Buyer 4:	Rp29.978.000

The JTC calculation for Buyer 4 indicates areas where optimization might significantly reduce total supply chain costs.

5. Buyer 5

The table below outlines Buyer 5's existing supply chain parameters and costs, crucial for identifying initial conditions and potential opportunities for optimization.

Table 4.15 Pre-Optimization Buyer 5 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	3	20	1.854.000
Product 2	3	20	7.826.000
Product 3	3	30	5.161.000
Product 4	3	20	25.260.000
Product 5	3	20	10.586.000

Joint Total Cost (JTC)	
Value	
JTC for Buyer 5:	Rp50.687.000

The resulting JTC for Buyer 5 illustrates their financial standing within the pre-optimized system.

6. Vendor

For the vendor, the following table shows the pre-optimization production quantity (PQ) settings and associated GTC for each product, reflecting initial operational practices and financial outcomes.

Table 4.16 Pre-Optimization Vendor Results

Vendor		
Buyer	Production Quantity (PQ)	GTC (IDR)
Product 1	22	24.051.194
Product 2	22	5.840.694
Product 3	22	6.224.194
Product 4	22	12.683.194
Product 5	22	7.286.194
Joint Total Cost (JTC)		
GTC of Product 1-5	Transportation Route Emissions	Total
Vendor's Costs	Rp119.394.972	Rp119.544
		Rp56.205.016

With the following transportation route:

Vendor → Buyer 1 → Buyer 2 → Buyer 3 → Buyer 4 → Buyer 5 → Vendor

The provided transportation route cost calculation also emphasizes the current transportation-related emissions and costs based on initial logistic arrangements.

7. Total Joint Supply Chain Cost

Finally, the aggregated pre-optimization costs across all buyers and the vendor are summarized below, offering a holistic perspective of the overall financial performance of the supply chain prior to optimization.

Table 4.17 Pre-Optimization Total Joint Supply Chain Cost

	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Buyer 5	Vendor
Cost (IDR)	38.171.000	43.808.000	45.835.000	29.978.000	50.687.000	119.514.317
System's JTC	327.993.317					

This summary establishes a baseline to compare and evaluate the effectiveness of subsequent optimization measures, highlighting areas where significant cost reductions may be achieved.

4.4.2 Product-Level Optimization

Product-level optimization is central to this study's integrated supply chain model, aiming to minimize the Joint Total Cost (JTC) for each product while simultaneously ensuring service-level and sustainability goals. This optimization determines optimal values for three critical decision variables for each product:

- **Production Quantity (PQ):** Units produced daily by the vendor.
- **Review Period (P):** Frequency (days) at which inventory levels are reviewed for placing orders.
- **Order-Up-To Level (R):** Inventory threshold triggering replenishment orders.

Optimization Objective

The objective is clearly formulated as minimizing the Joint Total Cost (JTC) for each product:

$$\min JTC_i = GTC_{vendor,i} + \sum_{j=1}^5 GTC_{buyer,j} \quad 4-6$$

Where:

- $GTC_{vendor,i}$ = Grand Total Cost for the vendor of product i
- $GTC_{buyer,i,j}$ = Grand Total Cost for buyer j of product i

Step-by-Step Optimization Process Using Excel Solver Evolutionary Algorithm

Step 1: Model Preparation

The entire supply chain logic, inventory movements, and cost calculations were structured within an Excel simulation. Decision variables (PQ, P, R) were clearly marked and linked to corresponding cells for Solver manipulation.

For instance, parameters for Buyer 1 and Product 1, highlighting decision variables clearly,

were set as:

- **Buyer Parameters:**
 - Review Period (P): 3 days
 - Order-Up-To Level (R): 15 units
- **Vendor Parameters:**
 - Daily Production Quantity (PQ): initially 30 units

Step 2: Objective Function Definition

The Excel Solver objective function cell is set to minimize the total JTC:

$$JTC_i = \text{SUM of Vendor GTC and all Buyer GTCs for Product } i$$

An example Excel formulation:

=SUM([Vendor GTC Cell], [Buyer 1 GTC Cell], [Buyer 2 GTC Cell], [Buyer 3 GTC Cell], [Buyer 4 GTC Cell], [Buyer 5 GTC Cell])

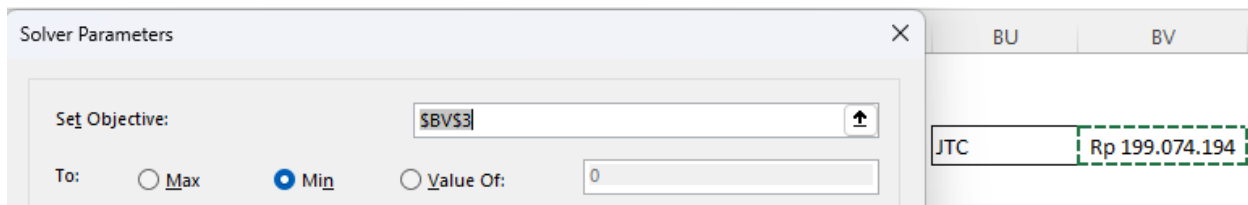


Figure 4.2 Objective Setting Product-Level Optimization

Step 3: Defining Decision Variables

Solver identifies decision variable cells explicitly marked:

- PQ (daily production quantity)
- P (inventory review frequency)
- R (inventory reorder threshold)

Example decision variable cell references for Product 1 are:

\$K\$2:\$K\$3; \$V\$1:\$V\$2; \$AI\$1:\$AI\$2; \$AU\$1:\$AU\$2; \$BF\$1:\$BF\$2; \$BS\$3

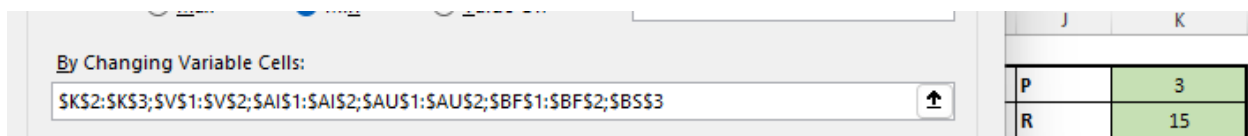


Figure 4.3 Solver Decision Variable Product-Level Optimization

Step 4: Variable Bounds and Constraints

To ensure realistic solutions, upper and lower bounds were imposed:

- **Production Quantity (PQ):**
 - Minimum: 1 unit/day
 - Maximum: 200 units/day (high limit capturing realistic production scope)

- **Review Period (P):**
 - Minimum: 1 day
 - Maximum: 50 days (covers practical review intervals)
- **Order-Up-To Level (R):**
 - Minimum: 1 unit
 - Maximum: 50 units (flexibility for practical inventory control)

Bounds are essential, preventing the Solver from exploring impractical solutions and ensuring a feasible operational space for optimization.

The screenshot shows the 'Solver Parameters' dialog box in Excel. The 'Set Objective' field is set to '\$BVS3'. The 'To' section has 'Min' selected. The 'By Changing Variable Cells' field is set to '\$KS2:\$KS3;\$VS1:\$VS2;\$AIS1:\$AIS2;\$AUS1:\$AUS2;\$BFS1:\$BFS2;\$BS53'. The 'Subject to the Constraints' list contains the following constraints:

- \$AIS1:\$AIS2 <= 50
- \$AIS1:\$AIS2 = integer
- \$AIS1:\$AIS2 >= 0
- \$AUS1:\$AUS2 <= 50
- \$AUS1:\$AUS2 = integer
- \$AUS1:\$AUS2 >= 0
- \$BFS1:\$BFS2 <= 50
- \$BFS1:\$BFS2 = integer
- \$BFS1:\$BFS2 >= 0
- \$BS53 <= 200
- \$BS53 = integer
- \$BS53 >= 0
- \$KS2:\$KS3 <= 50

 The 'Make Unconstrained Variables Non-Negative' checkbox is checked. The 'Select a Solving Method' dropdown is set to 'Evolutionary'. The 'Solving Method' section provides instructions: 'Select the GRG Nonlinear engine for Solver Problems that are smooth nonlinear. Select the LP Simplex engine for linear Solver Problems, and select the Evolutionary engine for Solver problems that are non-smooth.' Buttons for 'Add', 'Change', 'Delete', 'Reset All', 'Load/Save', 'Options', 'Help', 'Solve', and 'Close' are visible.

Figure 4.4 Solver Constraints Setup

Step 5: Solver Configuration and Evolutionary Algorithm Settings

The Excel Solver utilized the Evolutionary Algorithm, suitable for non-linear, complex, and stochastic optimization problems typically encountered in supply chain scenarios.

After selecting the Evolutionary algorithm, the following advanced Solver settings were applied for accuracy and efficiency:

- **Convergence:** 0.0001
 - Ensures precision by halting when minimal improvements are detected.
- **Mutation Rate:** 0.075
 - Balances exploration and convergence, preventing premature solution fixation.

- **Population Size: 100**
 - Provides adequate diversity for robust solution searching.
- **Random Seed: 0**
 - Ensures randomized initial search points to avoid solution bias.
- **Maximum Time Without Improvement: 30 seconds**
 - Enhances computational efficiency by terminating searches with prolonged stagnation.
- **Require Bounds on Variables: Enabled**
 - Guarantees adherence to set bounds, maintaining realistic operational scenarios.

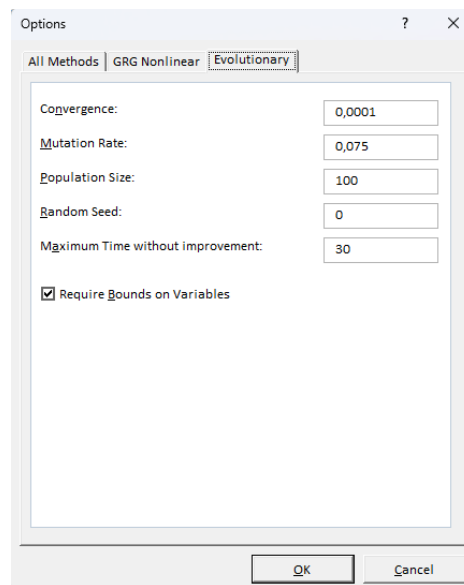


Figure 4.5 Evolutionary Algorithm Settings

Step 6: Optimization Execution and Results Interpretation

Upon finalizing all settings, Solver was executed. The optimal values for PQ, P, and R obtained were recorded along with their corresponding minimized JTC values, thus concluding product-level optimization.

This detailed and systematic optimization process ensures comprehensive operational and financial decision-making aligned with sustainability and efficiency goals.

4.4.3 Transportation Route Optimization

Optimizing the distribution route from the vendor to all buyers is a crucial stage in minimizing the total carbon emissions and associated costs of the supply chain. This section describes the methodology and practical steps employed to determine the most emission-efficient delivery

sequence using Excel Solver's Evolutionary Algorithm, based on the previously computed demand, weight, and distance data.

1. Objective Function and Mathematical Model

The goal of transportation route optimization is to minimize the total transportation carbon emission cost incurred in distributing products from the vendor to all buyers. This is mathematically represented as follows:

$$C_{trans} = \sum_{l=1}^n d_l \times w_l \times EF \times CT \quad 4-7$$

Where:

- d_l : Distance of segment l in the delivery route (km), determined by the route sequence.
- w_l : Weight transported on segment l (kg), reflecting the sum of all undelivered product weight at that point.
- EF : Emission factor for transportation (e.g., 0.2 kg CO₂/kg · km), representing the CO₂ emitted per unit weight per unit distance.
- CT : Carbon tax per kg CO₂ (e.g., Rp 30/kg CO₂), as stipulated by regulation.
- n : Total number of delivery segments in the route (including return to the vendor if a closed loop is required).

This model ensures the transportation cost reflects both the actual distances travelled and the dynamically changing payload at each segment, making the emission cost calculation robust and realistic.

For each segment in the delivery route, the carbon emission cost is calculated by multiplying the segment's distance by the transported weight, then by the emission factor and the applicable carbon tax rate. The sum across all route segments gives the total transportation emission cost, C_{trans} . This formulation incentivizes route sequences that reduce total kilometers traveled and minimize weight carried over longer distances—thus directly supporting both cost efficiency and environmental impact reduction.

2. Route Optimization Using Excel Solver

Once the data for all route permutations is structured in Excel (distance matrix, weights, emission factors), the following steps are taken to identify the optimal transportation route:

Step 1: Define the Objective Cell

The objective cell is set as the total transportation emission cost C_{trans} , calculated as the sum of all segment-wise emission costs according to the above formula. In Excel, this is typically represented as:

=SUM([Emission Cost Column])

Step 2: Identify Decision Variables

The route variable cells in Excel represent the delivery sequence (i.e., the order in which buyers are visited). Solver will optimize the values in these cells to minimize the objective cell.

Table 4.18 Delivery Route Sequence

	Solution	1	2	3	4	5	
Route	1	2	3	4	5	6	1
Distance		2,018413752	5,097353335	9,698731068	1,252547366	0,961239067	4,903022397
Weight		1660	1260	924,5	638,5	365,5	0
Em. Cost		Rp20.103	Rp38.536	Rp53.799	Rp4.799	Rp2.108	0
Total Cost							Rp119.345

Step 3: Impose Constraints

- Each buyer must be visited exactly once enforced via the Excel logic of AllDifferent constraint
- The route starts at the vendor and may optionally end at the vendor (closed loop).
- No buyer is visited more than once.

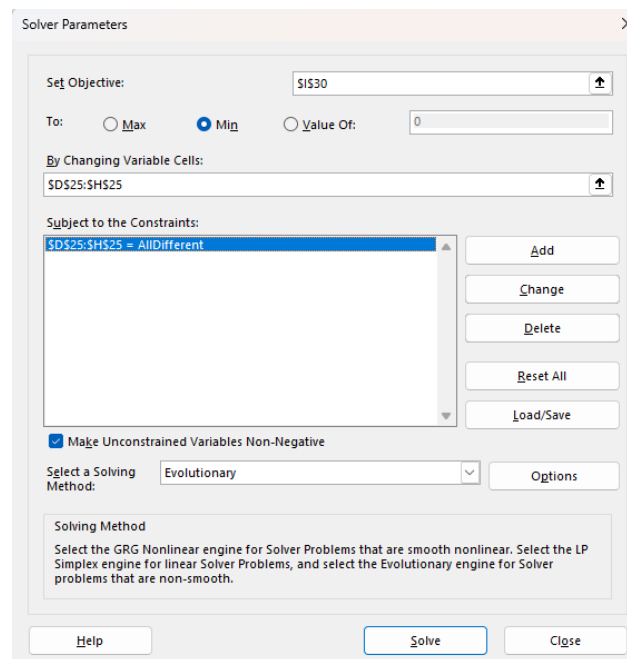


Figure 4.6 Delivery Route Sequence Optimization Constraints

Step 4: Solver Algorithm and Options

- **Algorithm:** Evolutionary Algorithm is selected due to the combinatorial (permutation-based) nature of the problem.
- **Options:** Solver's advanced settings are configured for efficient search:
 - *Mutation Rate* and *Population Size* are tuned to balance diversity and speed.
 - *Convergence* and *Time Without Improvement* are set to ensure sufficient search effort.
 - All variables are restricted to valid route numbers (buyer indices).

- Similar to the product-level optimization, mutation rate = 0.075, convergence = 0.0001, population size = 100, and random seed = 0, and the Maximum Time Without Improvement is 30 seconds.

Step 5: Optimization Execution

Solver is run, and the optimal delivery sequence that results in the minimum total transportation emission cost is recorded. The output includes:

- The optimal route (buyer visit sequence)
- Segment distances, weights, and individual emission costs
- The minimized total transportation emission cost C_{trans}

By employing this structured optimization approach, the model ensures that PT. XYZ Batik's transportation activities achieve the minimum possible carbon emissions and comply with environmental taxation. This step, together with product-level JTC optimization, completes the integrated cost and emission minimization strategy for the entire supply chain.

4.4.4 Post-optimization Costs

The following the flow of conducting the Evolutionary Algorithm in using Excel Solver.

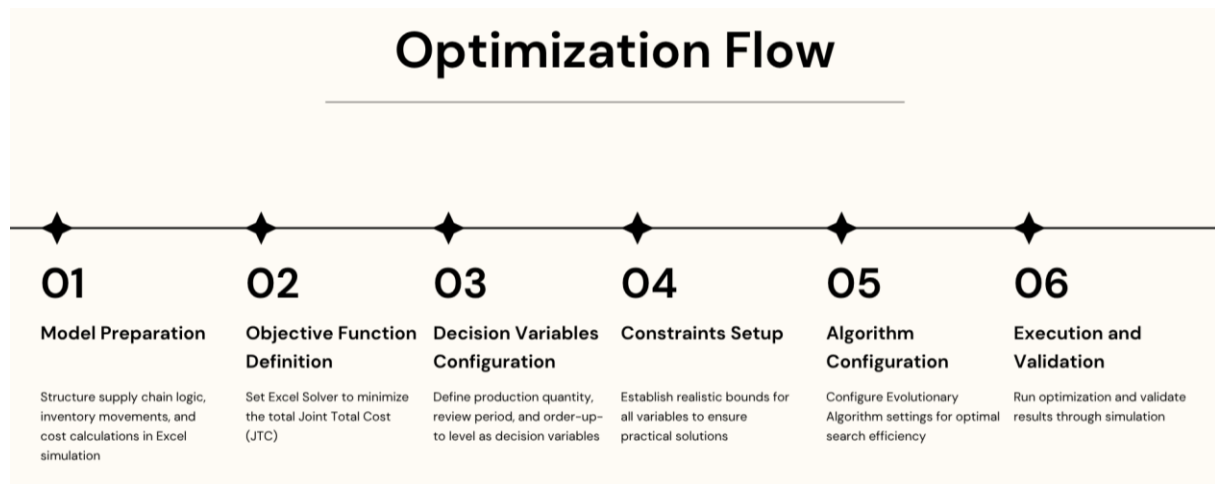


Figure 4.7 Evolutionary Algorithm Implementation Flow

This subsection details the optimized supply chain costs and decision variables following the implementation of the optimization model. It presents the refined parameters for each buyer and the vendor, reflecting significant improvements in cost efficiency across the supply chain.

1. Buyer 1

Table 4.19 Post-Optimization Buyer 1 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	2	31	5.690.000
Product 2	2	31	6.516.000
Product 3	2	31	6.267.000
Product 4	2	31	2.708.000
Product 5	2	31	5.609.000

Joint Total Cost (JTC)		
Value		
JTC for Buyer 1:	Rp	26.790.000

After optimization, Buyer 1's operational parameters have been refined, significantly reducing total costs across all products.

2. Buyer 2

Table 4.20 Post-Optimization Buyer 2 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	3	20	2.301.000
Product 2	2	35	7.351.000
Product 3	6	18	3.759.000
Product 4	2	19	3.521.000
Product 5	2	27	5.409.000

Joint Total Cost (JTC)		
Value		
JTC for Buyer 2:	Rp	22.341.000

Buyer 2's optimization resulted in adjusted ordering strategies, leading to enhanced cost management.

3. Buyer 3

Optimization for Buyer 3 introduced adjustments in review periods and order-up-to levels, achieving better cost outcomes.

Table 4.21 Post-Optimization Buyer 3 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	2	25	2.957.000
Product 2	1	16	5.924.000
Product 3	2	19	2.193.000
Product 4	1	11	3.678.000
Product 5	2	19	2.567.000

Joint Total Cost (JTC)		
Value		
JTC for Buyer 3:	Rp	17.319.000

These optimizations effectively minimized Buyer 3's overall costs.

4. Buyer 4

Buyer 4 benefited significantly from the optimization model, with improved inventory control parameters.

Table 4.22 Post-Optimization Buyer 4 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	3	24	1.494.000
Product 2	1	19	5.930.000
Product 3	3	18	1.298.000
Product 4	3	33	3.457.000
Product 5	3	22	2.363.000

Joint Total Cost (JTC)		
Value		
JTC for Buyer 4:	Rp	14.542.000

The optimized parameters markedly decreased Buyer 4's JTC.

5. Buyer 5

The adjustments made through optimization improved Buyer 5's inventory management and ordering efficiency.

Table 4.23 Post-Optimization Buyer 5 Results

Buyer	Review Period (P)	Order-Up-To Level (R)	GTC (IDR)
Product 1	10	17	1.660.000
Product 2	2	20	3.675.000
Product 3	2	17	3.586.000
Product 4	2	39	7.837.000
Product 5	2	20	4.072.000

Joint Total Cost (JTC)		
Value		
JTC for Buyer 5:	Rp	20.830.000

Buyer 5 realized notable cost savings due to the optimized parameters.

6. Vendor

Post-optimization parameters for the vendor were crucial in achieving overall supply chain cost efficiency.

Table 4.24 Post-Optimization Vendor Results

Buyer	Production Quantity (PQ)	GTC (IDR)
Product 1	9	5.897.694
Product 2	33	4.051.694
Product 3	15	3.306.194
Product 4	22	4.944.694
Product 5	26	4.581.694

Joint Total Cost (JTC)			
GTC of Product 1-5		Transportation Route Emissions	Total
Vendor's Costs	Rp 22.781.972	Rp 156.739	Rp 22.938.711

The vendor's costs were significantly reduced, notably influencing the overall supply chain performance.

The optimized transportation route,

Vendor → Buyer 1 → Buyer 3 → Buyer 4 → Buyer 5 → Buyer 2 → Vendor,
minimized transportation-related emissions and costs.

7. Total Joint Supply Chain Cost

The optimized parameters across the vendor and all buyers significantly reduced the Total Joint Supply Chain Cost.

Table 4.25 Post-Optimization Joint Supply Chain Total Cost

	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Buyer 5	Vendor
Cost (IDR)	26.790.000	22.341.000	17.319.000	14.542.000	20.830.000	22.938.711
System's JTC	124.760.711					

The collaborative optimization across buyers and vendor substantially improved the efficiency and sustainability of the entire supply chain, achieving a markedly lower System's Joint Total Cost.

CHAPTER V

ANALYSIS and DISCUSSION

This chapter includes a detailed explanation of the analysis and discussion of the result of batik supply chain optimization. The three major parts of the discussion are as follows. Section 5.1 presents a comparison between the total cost that each buyer pays before and after optimization. Section 5.2 continues considering the supplier and studies the variation in the total costs of the vendor due to the new optimization rules. Finally, the comparisons of the total joint costs of the entire supply chain in Section 5.3 gives a holistic view of the entire impact on and improvement of the proposed optimization approach. Across these three sections, the chapter tries to shed some light on the concrete advantages, performance improvements, and broader meanings that may be related to the proposed supply chain model.

5.1 Comparative Analysis of the Total Cost of Buyers

5.1.1 Buyer 1

Table 5.1 Comparative Total Cost Analysis for Buyer 1

Products	Pre-Optimization			Post-Optimization		
	P	R	GTC (IDR)	P*	R*	GTC* (IDR)
Product 1	3	20	7.182.000	2	31	5.690.000
Product 2	3	20	9.104.000	2	31	6.516.000
Product 3	3	20	10.240.000	2	31	6.267.000
Product 4	3	20	2.874.000	2	31	2.708.000
Product 5	3	20	8.771.000	2	31	5.609.000
Joint Total Cost						
Buyer 1 JTC			Buyer 1 JTC*			
Rp38.171.000			Rp26.790.000			

Before optimization Buyer 1 had a fixed review period (P) of three days and an order-up-to level (R) of 20 units in all products. The total joint cost (JTC) on the five products was Rp38,135,000. After optimization, the review period was reduced to two days whereas the order-up-to level was boosted greatly to 31 units per product. Such an adjustment resulted in significant savings of the total cost, whereby the total joint cost reduced to Rp26,790,000.

It is possible to explain this improvement by the fact that the periods of review were shorter, and the amount of inventory was larger, resulting in reduced stockout and the reduced variability of orders. The improved replenishment plan allowed it to be aligned more closely to the actual demand trends, and it maintained the optimum batch-ordering levels, which translated into reduced unit cost of ordering and cost of holding stocks. The fact that the cost

was reduced significantly in all products, especially for Product 3 and Product 5, emphasizes the importance of the adaptive approach to the inventory within the changing market.

5.1.2 Buyer 2

Table 5.2 Comparative Total Cost Analysis for Buyer 2

Products	Pre-Optimization			Post-Optimization		
	P	R	GTC (IDR)	P*	R*	GTC* (IDR)
Product 1	3	20	2.554.000	3	20	2.301.000
Product 2	3	20	17.348.000	2	35	7.351.000
Product 3	3	20	1.962.000	6	18	3.759.000
Product 4	3	10	6.778.000	2	19	3.521.000
Product 5	3	10	15.166.000	2	27	5.409.000
Joint Total Cost						
Buyer 2 JTC			Buyer 2 JTC*			
Rp43.808.000			Rp22.341.000			

The pre-optimization approach taken by buyer 2 was the same review time of 3 days and a moderate level of order-up-to making the total cost share Rp43,713,000. Once the optimization was done, Buyer 2 would have distinct review periods and order-up-to levels based on each product, with both Product 2 and Product 5 witnessing the most significant changes. The new total cost jointly generated as a result of these changes was Rp22,341,000-which is nearly half the amount.

Such a sharp drop in costs can be mostly attributed to the replenishment of the optimization model, which refines the replenishment frequency of products, as well as their batch size, cutting down on unnecessary inventory reserves, and decreasing the need to place an emergency order. Strategic changes in the order quantities and inspection rates noticed in Product 2 and Product 5 resulted in huge savings in terms of cost efficiency. The products produced such results and they show that product-specific inventory applications should be used instead of those that are standard.

5.1.3 Buyer 3

Table 5.3 Comparative Total Cost Analysis for Buyer 3

Products	Pre-Optimization			Post-Optimization		
	P	R	GTC (IDR)	P*	R*	GTC* (IDR)
Product 1	3	10	6.061.000	2	25	2.957.000
Product 2	3	10	18.106.000	1	16	5.924.000
Product 3	3	20	4.111.000	2	19	2.193.000
Product 4	3	15	11.788.000	1	11	3.678.000
Product 5	3	20	5.769.000	2	19	2.567.000

Joint Total Cost	
Buyer 3 JTC	Buyer 3 JTC*
Rp45.835.000	Rp17.319.000

In Buyer 3, all the pre-optimization costs were quite high and the total cost together was Rp45.835.000 under the traditional approach of three-day review intervals and the order-up-to amounts were varying. After optimization, Buyer 3 installed less lengthy and more changing time frames of review and order-up-to levels premises that were flexible with respect to the request of each product. The outcome was a new sum joint total cost of Rp17,319,000 which translates to a decrease of over 60 percent.

Such a drastic improvement was made easier by a transition to a differentiated review period as opposed to the one-size-fits-all review period, especially in Products 2 and 4. The maneuverability provided by the evolutionary algorithm enabled the buyer to react faster to demand changes, decreasing the need for and safety stock, as well as the danger of becoming obsolete. The extreme declines in cost also confirm that scenario-based optimization is effective when it comes to managing a variety of products with varied demand features.

5.1.4 Buyer 4

Table 5.4 Comparative Total Cost Analysis for Buyer 4

Products	Pre-Optimization			Post-Optimization		
	P	R	GTC (IDR)	P*	R*	GTC* (IDR)
Product 1	3	10	4.720.000	3	24	1.494.000
Product 2	3	10	14.508.000	1	19	5.930.000
Product 3	3	25	1.724.000	3	18	1.298.000
Product 4	3	20	5.727.000	3	33	3.457.000
Product 5	3	20	3.299.000	3	22	2.363.000
Joint Total Cost						
Buyer 4 JTC			Buyer 4 JTC*			
Rp29.978.000			Rp14.542.000			

The initial approach of the buyer 4 resulted in a total cost of Rp29.978.000 that was achieved by applying fixed, moderate inventory policies. After optimization, when alternative review periods and higher order-up-to levels were adopted (particularly those of Products 1 and 2), the total cost was joint, i.e. Rp14,542,000.

The considerable reduction in the costs especially of Products 1 and 2 was accomplished due to improved co-ordination of the replenishing cycles and demand spikes, hence curbing the dominance of both overstocking and of a panic order under shortage situations. Optimization process therefore allowed Buyer 4 to switch to the lighter inventory regime but not change the

service levels, which demonstrated that the model could produce context-sensitive policies on the balance of holding, ordering, and shortage costs.

5.1.5 Buyer 5

Table 5.5 Comparative Total Cost Analysis for Buyer 5

Products	Pre-Optimization			Post-Optimization		
	P	R	GTC (IDR)	P*	R*	GTC* (IDR)
Product 1	3	20	1.854.000	10	17	1.660.000
Product 2	3	20	7.826.000	2	20	3.675.000
Product 3	3	30	5.161.000	2	17	3.586.000
Product 4	3	20	25.260.000	2	39	7.837.000
Product 5	3	20	10.586.000	2	20	4.072.000
Joint Total Cost						
			Buyer 5 JTC	Buyer 5 JTC*		
			Rp50.687.000	Rp20.830.000		

The buyer 5 had the facility to incur the maximum pre-optimization joint total cost of Rp50,687,000. The optimization procedure resulted in an essentially longer time horizon of the review cycle of Product 1, and augmented order-up-to levels coupled with product-wise techniques for the rest of the products. This dictated that the total cost of the whole joint, after optimization needs, was cut down the system to Rp20, 830,000 which was around 57% lower.

Such a drastic change can be attributed to the embrace of product-specific ordering frequency and orders, which became instrumental in curbing both under-stocks and over-stocks. Flexibility of the new policy has allowed Buyer 5 to optimize its product range complex which has helped it to lower the operations cost and improve the usage of capital.

5.1.6 Cross-Buyer Insights

The relative comparison makes it clear that the evolutionary optimization of inventory policies results in substantial savings of costs to all the buyers irrespective of their initial cost structure and product mix. The shift across the board to dynamic, data-driven policy making helped each buyer to find a better balance between the flow of inventories and the real demands and provisions. This percentage of savings, which is shown to be between 48% to more than 60%, is not only a confirmation of the strength of the optimization developed in this thesis, but also a realization of the opportunities that are yet unexplored as far as efficiency in the conventional ways of functioning a supply chain in the batik industry.

In addition to this, it can be seen through the findings that such approach with each product and buyer being considered on an individual basis as opposed to having a standardized

system, provides better results. The findings support the case of moving to an alternative paradigm of adaptive, analytics-driven supply chain management in which optimization is a continuous activity that reflects market, environmental and operational dynamics.

Altogether, the post-optimization performance gives strong evidence that, the combination of optimized advanced optimization technique, including evolutionary algorithm and lateral transshipment, can significantly deliver improvement in cost efficiency and supply chain resilience in the Indonesian batik industry.

5.2 Comparative Analysis of Total Vendor Costs

Table 5.6 Comparative Total Vendor Cost Analysis

	Pre-Optimization			Post-Optimization		
Products	PQ	GTC (IDR)	Trans CO ₂ Cost (IDR)	PQ*	GTC* (IDR)	Trans CO ₂ Cost* (IDR)
Product 1	22	24.051.194	Rp119.544	9	5.797.694	Rp156.739
Product 2	22	5.840.694		33	4.464.194	
Product 3	22	6.224.194		15	3.334.194	
Product 4	22	12.683.194		22	5.193.194	
Product 5	22	7.286.194		26	4.418.194	
Joint Total Cost						
Total JTC			Total JTC			
Rp56.205.016			Rp23.364.211			

The vendor's role as an intermediary plays an anchoring role in efficiency and agility in the batik production system. As described in Table 5.6 we assume that the pre-solved situation is characterized by fixed production amounts of 22 of each product, regardless of the buyer-specific deviations in demand. This was very inflexible and extremely inefficient, with JTC (Joint Total Cost) of all items of Rp56,205,016. In this era the biggest cost drivers include overproduction, too much inventory carrying costs, and failure to link actual demand signals and production schedules.

The vendor adopted a dynamic production decision after the optimization model was used. In this case, the production volumes projected for each product were adjusted based on the specific needs of the buyers, by-products and amount of waste generated, ranging from 9 units for Product 1 to 33 units for Product 2. This pull-type model significantly improved resource utilization by minimizing over-production and overstock. Accordingly, the total JTC for the supplier decreased significantly to Rp23,364,211 or about 58+% cost savings.

Along with the consolidated savings, when drilling down, we see additional operational enhancements. Due to Product 1, the GTC (General Total Cost) was cut down, from

Rp24,051,194 to Rp5,797,694 although the transportation CO₂ cost grew from Rp119,544 to Rp156,739. This relatively small increase in transportation emission cost indicates the model is sensitive to subtle trade-off considerations between delivery frequency and inventory reduction. Nevertheless, the huge savings in production and inventory costs were more than the relatively small cost added by transport emissions.

Moreover, indirect environmental cost structure optimization was observed in addition to direct monetary gains; for example, in terms of carbon dioxide emissions related to transportation. Although your purchase followed the same path the thing was transported the same way (**Vendor** → **Buyer 1** → **Buyer 3** → **Buyer 4** → **Buyer 5** → **Buyer 2** → **Vendor**), the CO₂ emissions on transportation for Product 1 did increase, from Rp119,544 to Rp156,739. This modest increase is driven by an increased level of over-scheduling on the part of some products in response to the adjusted plant schedule. However, this increase was outweighed by the large cost reductions in both production and inventory, and distribution from these actions.

In conclusion, these results illustrate the principle of the tremendous impact of an orchestrated supply chain optimization. The vendor achieved large cost savings and environmental benefits from incorporating dynamic production planning combined with responsive inventory management without any additional routing. The research shows the need for supply chain management to be both adaptive and data-driven, allowing the development of more efficient balance between economic and environmental objectives.

5.3 Comparative Analysis of Joint Supply Chain Total Costs

The operation of the batik supply chain has been optimized at the vendor, PT. XYZ Batik, and buyer levels and a significant decrease in the Total Joint Supply Chain Cost of the system was achieved. As can be seen in Table 5.7, the Joint Total Cost (JTC) of the whole system before optimization, is Rp264,684,016. This value represents the combined impact of siloed decision making in which static non-coordinated supply is guided by both production and replenishment policies. These practices would often result in wastage in the form of overproduction, overstocking and over-transportation, which balloon the operating costs as a whole.

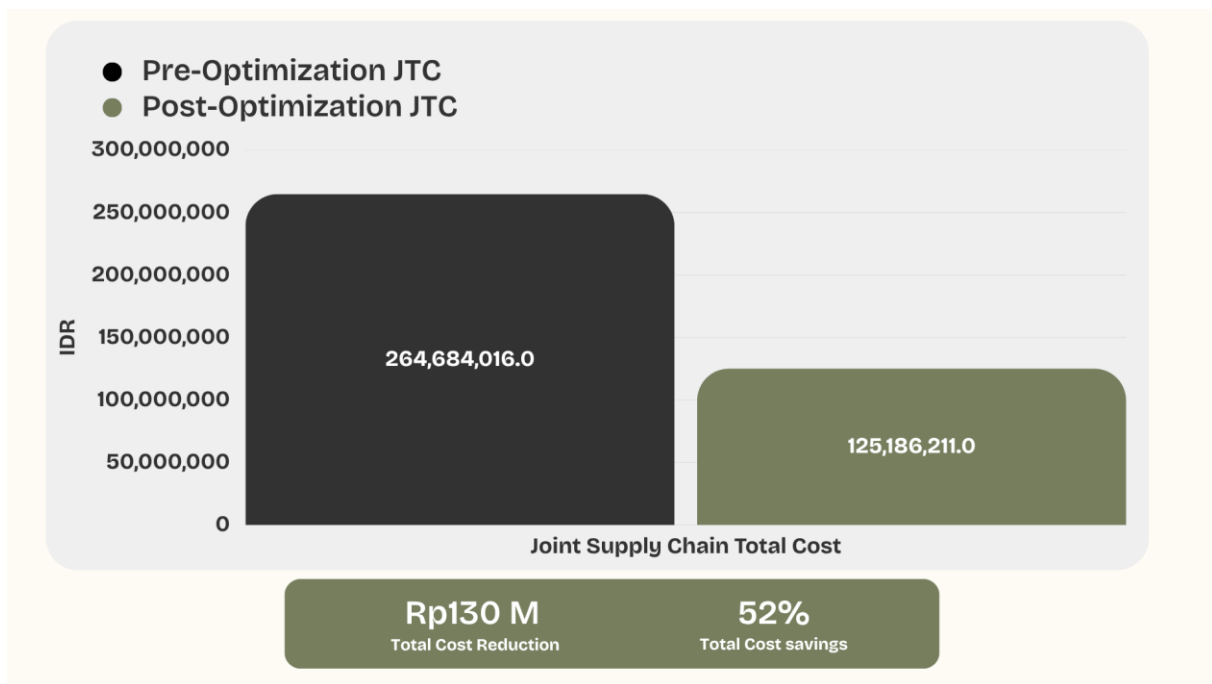


Figure 5.1 Comparative Analysis of Joint Supply Chain Total Cost

The integrated optimization strategies (led by evolutionary algorithms, flexible replenishment frequencies and coordinated production planning) enabled the JTC of the system to decrease significantly to Rp125,186,211. This 52% reduction represents almost a complete reduction of fragmentation-based practice through the use of a measurable and data-informed, error-free planning approach. The coordinated policy changes not only created direct cost savings, but also a nimbler method of deploying resources, and helped position the supply chain to respond more quickly to changes in market demand and regulatory changes.

Furthermore, these changes enabled enhancements over and above financial performance. Through the elimination of waste and the co-ordination of activities among all supply chain actors, the batik supply chain also moved closer to environmental sustainability, most notably within the framework of Indonesia's carbon tax regime. Comparison results highlight the strategic importance of the holistic collaborative optimization for conventional manufacturing industries, confirming that performance and environmental stewardship were not always antagonistic but are mutually reinforcing.

Ultimately, the shift from fragmented, static operations to an integrated, analytics-based supply chain results in substantial cost savings while also being sustainable and resilient. These are measures that not only make batik companies able to compete in the short term, but also to be long-term adaptable in the increasingly competitive business climate.

CHAPTER VI

CONCLUSIONS and SUGGESTIONS

6.1 Conclusion

The study was based on the fact that PT. XYZ Batik, a small and medium enterprise located in Yogyakarta, has urgent operational and regulatory issues in regards to its increasing operational cost and the carbon tax reality that it works within its multi-buyer, multi-product supply chain. Hence, Therefore, the following points are the conclusion made from this study:

1. This study developed a unified supply chain model of PT. XYZ Batik which considers production quantity, inventory policy, transportation route and carbon tax costs from machine operation and logistics was developed in this study. The model was implemented as an Excel spreadsheet and was capable of estimating the entire lifecycle cost based on efficiency and emissions among others. The result of the simulation showed that the supply chain cost amounted to Rp264,684,016 before optimization, and was reduced to Rp125,186,211 after optimization.
2. The use of an Evolutionary Algorithm on this model provided an optimal solution that minimized joint total costs. The model, which also considers order quantity, production lot size and best delivery route to buyers, assists PT. XYZ Batik in achieving compliance with Law No. 7 of 2021 and the pursuit of operational excellence and sustainability.

6.2 Suggestion

Based on the findings of this study, a number of recommendations are made for future academic investigations and practical application.

1. A key contribution of this research is the proof that factoring sustainability into supply chain optimization not only brings in environmental advantages but can actually amount to substantial cost reductions for MSMEs. Likewise, the model can be put in the direction that attends to how to bowknot the three aspects of sustainability economic, environmental and societal. This will help the reader to take a broader look at supply chain optimization within conventional industries.
2. Hence, future work could incorporate social considerations such as worker safety, fair labor practices, community engagement, and the company's broader contribution to social well-being.

3. Finally, the model developed in this research is a step towards integrating environmental policy into the classic supply chain optimization. Being modular, it should facilitate further adaptation and expansion, which may lead it to play a more useful reference for supporting the evolution towards sustainability of the batik industry in Indonesia or other countries.

APPENDIX

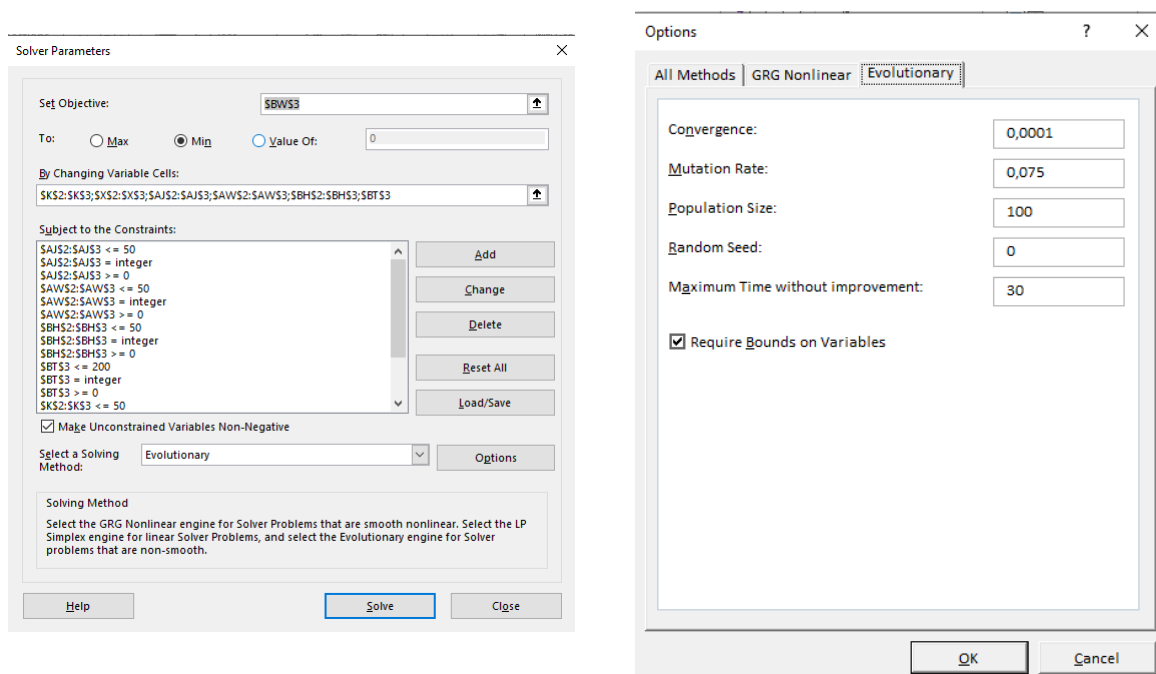


Figure A.1.1 Excel Solver Configuration

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