Modeling Procurement Problems of Fresh Raw Materials Using Blockchain Technology

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**Abstract.**  The procurement of fresh raw materials is critically challenged to balance cost-efficiency with effective management of shelf life. This study addresses these challenges by developing a comprehensive framework that integrates blockchain technology and a modified Mixed Integer Linear Programming (MILP) model to improve procurement processes. The research utilizes a modified MILP model to incorporate shelf-life constraints to optimize procurement decisions. The results demonstrate that extending the shelf life of raw materials leads to higher total procurement costs primarily due to increased holding costs, although it significantly reduces computational effort and improves procurement efficiency. This study highlights the importance of balancing the operational benefits of extended shelf lives with the financial implications of higher holding costs and potential waste. The findings provide valuable insights for organizations aiming to refine their procurement strategies and enhance overall cost-effectiveness.

**Keywords:** Procurement, Fresh raw materials, Blockchain technology.

# INTRODUCTION

The procurement of fresh raw materials is one of the most important components of the food and agricultural supply chains [1]. The quality of fresh raw materials has a direct impact on the quality of final products consumed by consumers [2]. Globally, many manufacturing organizations have adopted more modern business models to meet market demands. These models rely greatly on outsourcing approaches, especially the procurement process playing a significant role [3]. However, the complexity of the procurement process, as well as the uncertainties and obstacles in selecting suitable suppliers provide substantial challenges for manufacturing businesses. Consequently, raw materials, semi-finished items, and components account for about 70% of manufacturing costs [4]. Therefore, selecting suitable suppliers is important, since it has a substantial impact on overall manufacturing costs. Organizational productivity and profitability are dependent on high-quality materials, easy traceability [5], transparency [6], immutable records [7], and secure information flow [8], all of which have an impact on supplier selection and real-time order allocation.

The fresh food supply chain is a complicated network that includes a diverse variety of stakeholders, such as suppliers, distributors, retailers, and producers of fresh and processed agricultural products [1] [9]. This complex system requires competent management to ensure that all parties involved operate efficiently and securely. The integration of innovative technology, such as blockchain, has emerged as an essential strategy for navigating supply chain challenges. Blockchain technology might offer the transparency and security required to traverse these challenges by granting stakeholders access to accurate, reliable, and immutable data [10]. According to Maity, Tolooie [11], blockchain provides a stable digital platform that improves the efficiency of modern business models. Thus, a trustworthy system and secure transactions are essential, and blockchain technology enables these capabilities [12]. Furthermore, blockchain might improve product quality, elimination of human errors, reduced fraud, and faster issue resolution [13] [14]. Despite its potential, blockchain adoption in procurement processes, particularly for fresh raw materials, is still in its infancy, exhibiting substantial gaps in both practical implementation and research.

This research aims to address the gaps through developing a comprehensive framework for integrating blockchain technology into the procurement of fresh raw materials. The study will examine at how blockchain may be applied to improve procurement efficiency. The research will use a modified Mixed Integer Linear Programming (MILP) method based on the mathematical model published by Yadav and Prakash Singh [10]. Furthermore, the research will evaluate the practical implications of blockchain adoption on procurement practices, including its impact on cost reduction, supplier relationship management, and overall supply chain performance. The outcomes are expected to provide valuable insights into the practical application of blockchain technology in the procurement of fresh raw materials, offering a robust framework that can be adopted by industry practitioners to achieve more efficient and secure procurement processes.

# METHODS

## Mixed Integer Linear Programing

Several key assumptions are used to governed the procurement problem: (1) Procurement costs, demand, and supplier capacity are known and fixed. (2) Shortages, late deliveries, discounts, and overstocks are not permitted. (3) Rejected items are immediately disposed of, with no associated cost considered in the model. (4) Inventory holding cost applies only if materials are stocked for the next planning period. (5) Only unimodal trucks with constant volume are used; multiple products can be transported together to optimize space. (6) Transportation cost is fixed, regardless of distance or fuel. (7) Plant capacity is fixed for all items but varies by period. The notation used in MILP is as follows:

|  |  |  |  |
| --- | --- | --- | --- |
|  | : index for product/raw material |  | :Demand |
|  | : index for supplier |  | :Truck capacity |
|  | : index for period |  | :The purchasing authenticity factor for lot i from supplier j in period t. |
|  | : Procurement lot size of the ith at time t from the jth supplier. |  | :The ordering process authenticity factor for lot i from supplier j in period t. |
|  | : The jth supplier uses the trucks for the ith product  at t period. |  | :The transportation authenticity factor for lot i from supplier j in period t. |
|  | : Inventory of the ith product in the t period. |  | :The holding process authenticity factor for lot i from supplier j in period t. |
|  | :Number of blocks generated throughout the purchasing process for lot i from supplier j in period t. |  | :Cost of unit block generated throughout the purchasing process for lot i from supplier j in period t. |
|  | :Number of blocks generated throughout the ordering process for lot i from supplier j in period t. |  | :Cost of unit block generated throughout the ordering process for lot i from supplier j in period t. |
|  | :Number of blocks generated throughout the transportation for lot i from supplier j in period t. |  | :Cost of unit block generated throughout the transportation for lot i from supplier j in period t. |
|  | :Number of blocks generated throughout the Holding process for lot i from supplier j in period t. |  | :Cost of unit block generated throughout the holding process for lot i from supplier j in period t. |
|  | :Supplier capacity |  | :IoT devices in purchasing process |
|  | :Plant capacity |  | :IoT devices in ordering process |
|  | :Volume of product i |  | :IoT devices in transportation process |
|  | :Purchasing cost of item i from supplier j at period t. |  | :IoT devices in holding process |
|  | :Ordering cost of item i from supplier j at period t. |  | :Average data transfer rate across IoT devices during the purchasing process. |
|  | :Transportation cost of item i from supplier j at period t. |  | :Average data transfer rate across IoT devices during the ordering process. |
|  | :Holding cost of item i from supplier j at period t. |  | :Average data transfer rate across IoT devices during the transportation process. |
|  | :Block size |  | :Average data transfer rate across IoT devices during the holding process. |
|  | :Total time for receiving and transferring data in the purchasing process. |  | :Total time for receiving and transferring data in the transportation process. |
|  | : Total time for receiving and transferring data in the ordering process. |  | :Total time for receiving and transferring data in the holding process. |
|  | |  | |

The MILP problem for fresh raw material procurement is formulated as follows [9]:

Objective Function:

|  |  |
| --- | --- |
|  | (1) |
|  | (1a) |
|  | (1b) |
|  | (1c) |
|  | (1d) |
|  | (1e) |
|  | (1f) |
|  | (1g) |
|  | (1h) |
| Subject to: |  |
|  | (2) |
|  | (3) |
|  | (4) |
|  | (5) |
|  | (6) |
|  | (7) |
|  | (8) |
|  | (9) |
|  | (10) |
|  | (11) |
|  | (12) |
|  | (13) |
|  | (14) |
|  | (15) |
|  | (16) |

The MILP model aims to minimize the total cost of procurement as denoted in equation (1), which includes numerous components such as purchasing (1b), ordering (1d), transportation (1f), and holding costs (1h), as well as costs associated with blockchain device data transfer (1a, 1c, 1e, 1g). Equation (2) is ensuring inventory balance. Equation (3) guarantee that the purchasing lot size does not exceed the supplier's capacities. Equation (4) restricts the total inventory and procurement lot size to the plant's capacity. Equation (5) ensures product demand is satisfied through purchasing from selected suppliers. Equation (6) calculates the required truck capacity based on the procurement lot size. Equations (7-10) ensure that the total number of blocks generated during the transportation, holding, and purchase processes is consistent with IoT device capabilities, while also accommodating specific vehicle and inventory capacities. Equations (11-12) ensure that inventory is only considered if the product is available.

## Modified Mixed Integer Linear Programing

The MILP model proposed by *Yadav and Prakash Singh [10]* is then modified to incorporate shelf life variables related to the procurement of fresh raw materials. The modification establishes additional constraints on inventory levels, ensuring that products or raw materials are purchased, stored, and utilized within their permissible shelf life. The modified model aims to optimize procurement decisions through ensuring that fresh raw materials are utilized within their effective shelf life. The specifics of the modified model are as follows:

|  |  |
| --- | --- |
|  | (17) |
|  | (18) |

The constraint (17) ensures that the inventory in period 𝑡 is not greater than the number of raw materials processed during the shelf life. Additionally, self-life of fresh raw material i denoted as period, meaning that the product i must not be stored for more than . The index 𝑘 defines the time after the product is received. In this case, if the product is received in period 𝑡, then 𝑘=0 is period 𝑡; 𝑘=1 is period 𝑡+1; 𝑘=2 is period 𝑡+2, and so on.

## Lingo code for the proposed MILP model

The MILP model in this study was generated and solved using Lingo 18.0 software, which executed on an AMD Ryzen 57520U processor. This configuration provides the processing capability required to perform the complicated computations involved in optimizing the procurement process for fresh raw materials. The exact code used in Lingo for the MILP model is described as follows:

MODEL:

TITLE Optimization of fresh raw material procurement considering Blockchain;

SETS:

PERIODS /1..2/:;

TIME /1..2/:;

PRODUCTS /1..2/ : PVol, SL;

SUPPLIERS /1..2/;

IJT(PRODUCTS, SUPPLIERS, PERIODS) : X, OC, PC, TBC, NOB, PBC, SC, NPB, TC, NOT, NTB, OBC, Y;

IT(PRODUCTS, PERIODS) : INV, D, W, PLC, HC, NHB, HBC;

IK(PRODUCTS, TIME) : DEM;

ENDSETS

MIN =

@SUM(IJT(I, J, T) : F1 \* PBC(I, J, T) \* NPB(I, J, T)) +

@SUM(IJT(I, J, T) : PC(I, J, T) \* X(I, J, T)) +

@SUM(IJT(I, J, T) : F2 \* OBC(I, J, T) \* NOB(I, J, T)) +

@SUM(IJT(I, J, T) : OC(I, J, T) \* Y(I, J, T)) +

@SUM(IJT(I, J, T) : F3 \* TBC(I, J, T) \* NTB(I, J, T)) +

@SUM(IJT(I, J, T) : TC(I, J, T) \* D(I, T) \* NOT(I, J, T)) +

@SUM(IT(I, T) : F4 \* HBC(I, T) \* NHB(I, T)) +

@SUM(IT(I, T) : HC(I, T) \* INV(I, T));

@FOR(IT(I, T) | T #EQ #0: INV(I, T) = 0);

@FOR(IT(I, T) | T #EQ #1 : @SUM(SUPPLIERS(J) : X(I, J, T)) = D(I, T) + INV(I, T));

@FOR(IT(I, T) | T #GT #1 : INV(I, T-1) + @SUM(SUPPLIERS(J) : X(I, J, T)) = D(I, T) + INV(I, T));

@FOR(IJT(I, J, T) : X(I, J, T) <= SC(I, J, T));

@FOR(IT(I, T) : INV(I, T) + @SUM(SUPPLIERS(J) : X(I, J, T)) <= PLC(I, T));

@FOR(IJT(I, J, T) : @SUM(TIME(K) | K #GE #T : DEM(I, K)) \* Y(I, J, T) - X(I, J, T) >= 0);

@FOR(IJT(I, J, T) : NOT(I, J, T) >= PVol(I) / TVol \* X(I, J, T));

@FOR(IJT(I, J, T) : NPB(I, J, T) >= N1 \* R1 / BS \* TD1 \* X(I, J, T) / D(I, T));

@FOR(IJT(I, J, T) : NOB(I, J, T) >= N2 \* R2 / BS \* TD2 \* Y(I, J, T));

@FOR(IJT(I, J, T) : NTB(I, J, T) >= N3 \* R3 / BS \* TD3 \* NOT(I, J, T));

@FOR(IJT(I, J, T) : NHB(I, T) >= N4 \* R4 / BS \* TD4 \* W(I, T));

@FOR(IT(I, T) :

@IF(T #GT# SL(I), INV(I, T) = 0));

@FOR(IJT(I, J, T) :

@SUM(TIME(K) | K #GE #T : X(I, J, K)) <= SL(I) \* @SUM(TIME(K) | K #LE #T : X(I, J, K)));

@FOR(IT(I, T) | T #GT SL(I) : INV(I, T) = 0);

@FOR(IJT(I, J, T) : @GIN(X));

@FOR(IJT(I, J, T) : @GIN(NOT));

@FOR(IJT(I, J, T) : @GIN(NPB));

@FOR(IJT(I, J, T) : @GIN(NOB));

@FOR(IJT(I, J, T) : @GIN(NTB));

@FOR(IJT(I, J, T) : @GIN(NHB));

@FOR(IJT(I, J, T) : @BIN(Y));

@FOR(IT(I, T) : @BIN(W));

END

## Data Collection

The data utilized in this study comprises numerical data obtained from previous research studies, as summarized in **TABLE 1**. This data serves as the foundation for our analysis and is critical in developing the procurement model for fresh raw materials. The numerical data was sourced from reliable and peer-reviewed studies, ensuring its accuracy and relevance to the research context. **TABLE 2** shows the procurement lot size and blockchain data for two products, two suppliers, and two periods. Product first lot size is 265 units in period 1 and 175 units in period 2, while product second sizes are 425 and 312 units. Transportation generates the most blockchain blocks, with 13 blocks per period for product 1. **TABLE 3** outlines procurement costs, where product first costs range from 5000 to 6000 units, and product second from 5500 to 7000 units. Transportation and blockchain-related costs are particularly high, with supplier second total blockchain costs reaching up to 80000 units in period 2. Thus, **TABLE 4** provides IoT device data, with all processes having an authenticity factor of 1. Delay times are longest in the purchasing process (600 ms), while holding uses the most IoT devices (4), reflecting its complexity.

**TABLE 1**. Data of IoT

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Details |  |  |  |  |
| Authenticity Factor | 1 | 1 | 1 | 1 |
| Data Flow rate | 16 | 12 | 12 | 14 |
| Delay Time | 600 | 480 | 360 | 240 |
| No. of IoT Devices | 1 | 2 | 3 | 4 |
| Volume of the truck =2500 | |  |  |  |
| BS =10240 | |  |  |  |

**TABLE 2**. Dataset

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| 2 Products, 2 Suppliers, 2 Periods | | | | | | |
| t | I |  | j=1 | j=2 | D |  |
| 1 | 1 |  | 265 |  | 265 | 0 |
|  |  |  | 4 |  |  |  |
|  |  |  | 3 |  |  |  |
|  |  |  | 13 |  |  |  |
|  | 2 |  | 175 |  | 175 | 0 |
|  |  |  | 4 |  |  |  |
|  |  |  | 3 |  |  |  |
|  |  |  | 13 |  |  |  |
| 2 | 1 |  |  | 425 | 425 | 0 |
|  |  |  |  | 4 |  |  |
|  |  |  |  | 3 |  |  |
|  |  |  |  | 13 |  |  |
|  | 2 |  | 166 | 146 | 312 | 0 |
|  |  |  | 2 | 2 |  |  |
|  |  |  | 3 | 3 |  |  |
|  |  |  | 1 | 7 |  |  |

**Table 3**. Procurement cost and blockchain cost

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Cost | I | j=1 | | j=2 | | Details | I | t=1 | t=2 |
| t=1 | t=2 | t=1 | t=2 |
| PC | 1 | 5000 | 6000 | 5200 | 5500 | Demand | 1 | 265 | 425 |
|  | 2 | 5500 | 7000 | 6000 | 6500 |  | 2 | 175 | 312 |
| OC | 1 | 500 | 500 | 700 | 700 | PLC | 1 | 280 | 450 |
|  | 2 | 700 | 700 | 1000 | 1000 |  | 2 | 200 | 320 |
| TC | 1 | 7500 | 7500 | 5000 | 5000 | HC | 1 | 200 | 250 |
|  | 2 | 10000 | 10000 | 7000 | 7000 |  | 2 | 300 | 350 |
| SC | 1 | 1000 | 1000 | 1500 | 1500 | HBC | 1 | 170 | 108 |
|  | 2 | 1100 | 1100 | 1500 | 1500 |  | 2 | 120 | 113 |
| PBC | 1 | 50000 | 50000 | 75000 | 75000 | Product | 1 | 25 | 25 |
|  | 2 | 55000 | 55000 | 80000 | 80000 | Volume | 2 | 45 | 45 |
| OBC | 1 | 50000 | 50000 | 75000 | 75000 |  |  |  |  |
|  | 2 | 55000 | 55000 | 80000 | 80000 |  |  |  |  |
| TBC | 1 | 50000 | 50000 | 75000 | 75000 |  |  |  |  |
|  | 2 | 55000 | 55000 | 80000 | 80000 |  |  |  |  |

# RESULTS AND DISCUSSION

The results from the procurement simulation involving 2 products, 2 suppliers, and 2 periods with varying shelf lives highlight a significant relationship between shelf life, procurement costs, and computational efficiency. The analysis shows that as the shelf life of fresh raw materials increases, the objective value, representing the total cost, also rises (**FIGURE 1**), primarily due to the growing holding costs associated with longer storage periods. Meanwhile, the computational effort required to solve the problem, indicated by CPU time, decreases as shelf life extends (**FIGURE 2**).

**TABLE 4**. Result details

|  |  |  |
| --- | --- | --- |
| 2 Products, 2 Suppliers, 2 Periods | | |
| Self life (day) | Objective Value (Rp) | CPU time (sec) |
| 3 | 7707189 | 9556 |
| 5 | 8003448 | 8862 |
| 7 | 8223250 | 8780 |
| 10 | 8421277 | 8013 |

|  |  |
| --- | --- |
|  |  |
| **FIGURE** **1**. Objective value versus self-life | **FIGURE 2**. Objective value versus CPU time |

As shown in Table 2, the objective value of 3 days self-life is Rp 7,707,189, with a CPU time of 9556 seconds. In this case, the shorter shelf life requires more frequent procurement cycles, which leads to lower holding costs but increased administrative and logistical efforts to manage continuous orders. As the shelf life increases to 5 days, the objective value rises to Rp 8,003,448, while the CPU time decreases to 8862 seconds. This indicates that extending the shelf life slightly allows for reduced frequency in procurement, but the longer storage time results in higher holding costs. When the shelf life is extended further to 7 days, the objective value increases to Rp 8,223,250, and CPU time is reduced to 8780 seconds. At this stage, the holding costs become more substantial as fresh raw materials remain in inventory longer, but the reduced frequency of orders improves the efficiency of the procurement process, as reflected by the decreasing CPU time. Finally, for a shelf life of 10 days, the objective value reaches Rp 8,421,277, the highest observed cost, while CPU time decreases further to 8013 seconds. The extended shelf life allows for infrequent procurement, but the associated holding costs significantly contribute to the higher overall procurement cost.

The observed pattern indicates that while extending the shelf life of products offers operational flexibility by reducing the frequency of procurement activities, it simultaneously leads to increased holding costs. Holding costs, which include various expenses such as storage, handling, and potential spoilage of fresh raw materials, become increasingly significant as the shelf life extends [15]. With longer shelf lives, materials remain in inventory for extended periods, leading to higher costs associated with maintaining stock and managing the quality of perishable goods. This presents particular challenges in the procurement of fresh raw materials, where maintaining optimal stock levels and minimizing spoilage are crucial for cost efficiency. Moreover, the rise in holding costs with longer shelf lives directly impacts the overall procurement cost, making it a critical factor in the decision-making process [16]. Organizations must balance the benefits of operational flexibility, such as fewer procurement cycles and reduced logistical complexity, against the financial implications of increased holding costs.

Interestingly, the decline in CPU time with longer shelf lives reflects an improvement in computational efficiency. As the shelf life extends, the procurement process becomes less dynamic due to fewer required order cycles, thereby simplifying the optimization problem. This reduction in computational complexity leads to shorter CPU times, indicating that extended shelf lives facilitate more straightforward problem-solving and optimization processes. Consequently, while longer shelf lives offer advantages in terms of procurement frequency and operational stability, they necessitate careful management of holding costs to ensure that the overall procurement strategy remains both cost-effective and efficient.

# CONCLUSIONS

This study examines the influence of shelf life on the procurement of fresh raw materials using a modified Mixed Integer Linear Programming (MILP) model. The findings reveal a significant increase in total procurement costs with longer shelf lives due to rising holding costs, which encompass storage, handling, and potential spoilage expenses. While extending shelf life offers operational benefits such as fewer procurement cycles and reduced logistical complexity, it also leads to higher overall costs. Additionally, longer shelf lives reduce computational effort, as indicated by shorter CPU times, due to a less dynamic procurement process. However, a limitation of this study is that the model does not account for the waste generated when products are stored beyond their shelf life, which could further influence the overall cost and effectiveness of the procurement strategy. Thus, the study underscores the need for a balanced approach in procurement strategies, weighing the advantages of operational stability against the financial impact of holding costs, while also considering potential waste to optimize both cost-efficiency and process effectiveness.

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