

Inventory Optimization through FP-Growth-Based Association Rule Mining of Material Stock Usage Patterns

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Abstract—This research focuses on analyzing the usage patterns of material stock at PT Baruna Energi Solusindo Teknik using Association Rule Mining (ARM) with the FP-Growth algorithm. The company often experiences material shortages or excess inventory due to manual and inaccurate stock planning. To address this issue, the study aims to discover frequent itemsets and association rules among materials used in water purification installations, enabling more data-driven procurement decisions. The research employs secondary data on material usage transactions from April 2024 to March 2025, which is processed using RapidMiner software. The FP-Growth algorithm identifies material combinations with high support and confidence values. For instance, Membrane RO has a support value of 75.9%, indicating that it is used in over three-quarters of all projects. Additionally, the combination {Membrane RO, PVC Pipe 1"} → SDL PVC 1" shows a confidence value of 83.3%, signifying a strong association among these items. The results suggest that stock optimization can be achieved by prioritizing frequently used items and associated combinations in procurement planning. This method not only improves inventory efficiency but also helps prevent stockouts and overstocking. The FP-Growth algorithm proves to be suitable and effective in identifying meaningful patterns in stock usage data.

Keywords: Association Rule Mining; FP-Growth; Material Stock; Inventory Optimization; Data Mining

1. INTRODUCTION

Inventory plays a vital role in ensuring the continuity of a company’s operations, both in the production and distribution of goods. It consists of raw materials and finished goods stored intentionally for future use in manufacturing or sales [1]. Poor inventory control can result in two critical issues: *stockout* and *overstock*. A *stockout* can delay the production and installation process, decreasing customer satisfaction and possibly causing customers to switch to competitors. Meanwhile, *overstock* leads to excessive storage costs and capital tied up in unused materials [2]. These challenges are particularly complex in companies that manufacture custom products using a wide variety of raw materials. Therefore, a data-based analytical approach is needed to help companies better understand stock usage patterns and make more accurate stock planning decisions.

PT Baruna Energi Solusindo Teknik is a company that manufactures, installs, and maintains water purification machines. The company customizes products based on client requests and water source types, resulting in a wide variety of materials used during production such as pumps, UV lights, pipes, ball valves, and various sensors. The highly dynamic and project-based nature of orders from various clients such as PDAMs and local governments leads to fluctuations in material demand. Currently, the company’s stock planning still relies on manual estimations that are often inaccurate, leading to frequent *overstock* and *stockout* problems. This study proposes a solution by analyzing material usage patterns using *Association Rule Mining* with the FP-Growth algorithm to support more precise inventory planning.

The utilization of material stock data is crucial for resolving operational issues in manufacturing. One effective analytical technique for this purpose is data mining, which involves identifying significant patterns in large datasets that cannot be processed manually [3]. This study applies association rule mining using the FP-Growth algorithm, a method designed to uncover relationships between frequently co-occurring itemsets in complex, high-volume databases [4]. FP-Growth, an enhancement of the Apriori algorithm, offers greater efficiency in identifying frequent itemsets and is well-suited for analyzing transactional material stock data [5].

Several recent studies have explored the use of *Association Rule Mining* in the context of inventory and transaction analysis. Fitriah, Riadi, and Herman (2023) used the Apriori algorithm to analyze 140 sales transactions at a clothing store in Bengkulu. Their results helped optimize the placement of items that were frequently purchased together, although their research primarily focused on item arrangement rather than broader inventory control strategies [6]. Hartono and Fitriah (2020) implemented the FP-Growth algorithm to discover hidden purchase patterns for improving product promotion and inventory solutions. They found that higher *support* values generated fewer but stronger associations, with confidence levels reaching up to 99.37%. However, their focus was more on promotional placement rather than predictive stock planning [7].

In a different domain, Pranata and Utomo (2020) applied FP-Growth to enhance spare part inventory efficiency in a motorcycle repair shop. Their study showed that the algorithm could help reduce the risk of *stockout* by identifying frequently co-purchased items with confidence values up to 80%. However, the complexity of spare part management in that context is relatively limited compared to an industrial manufacturer [5]. Habibah, Solehudin, and Primajaya (2022) applied the FP-Growth algorithm to analyze transaction data at a local convenience store. The results helped

improve stock management by identifying frequently bought item combinations, although the study’s scope was limited to retail and not applicable to custom-built production [8].

The most recent related study by Gultom (2024) implemented FP-Growth to manage electrical goods inventory in a company with poorly structured storage systems. The algorithm effectively identified purchase patterns and helped improve item placement and stock levels. Nevertheless, the study emphasized product arrangement rather than dynamic material demand based on project customization [9].

From these previous studies, a research gap can be identified in the limited application of *Association Rule Mining* in environments with highly variable, project-based material usage. While the use of Apriori or FP-Growth has proven beneficial for retail, warehouse, or spare part settings, there is still limited implementation in manufacturing scenarios where material demand depends heavily on client-specific projects and fluctuates month to month.

Therefore, this research aims to analyze material usage patterns at PT Baruna Energi Solusindo Teknik using *Association Rule Mining* with the FP-Growth algorithm. The goal is to optimize inventory management by identifying frequent itemsets of materials used in combination, thus enabling the company to better predict future stock needs. The expected outcome is a more accurate, data-driven stock planning system that reduces the risks associated with both *stockout* and *overstock* conditions, improving operational efficiency and customer satisfaction. The main contribution of this study lies in applying Association Rule Mining in a project-based manufacturing context, which remains underexplored in prior research. This study provides a practical framework for integrating transactional material data with pattern recognition, offering valuable insights for companies dealing with dynamic, customized production. The results contribute not only to improved inventory control at PT Baruna Energi Solusindo Teknik but also to the broader application of data mining techniques in flexible manufacturing environments.

2. RESEARCH METHODOLOGY

2.1 Research Stages

This study follows a structured methodology to analyze material stock usage patterns at PT Baruna Energi Solusindo Teknik using the Association Rule Mining method with the FP-Growth algorithm. The research stages were systematically designed to ensure effective data analysis, pattern discovery, and the formulation of actionable insights to improve inventory efficiency. The research process is divided into several key phases as depicted in Figure 1. Each stage represents a critical component in achieving the research objectives.

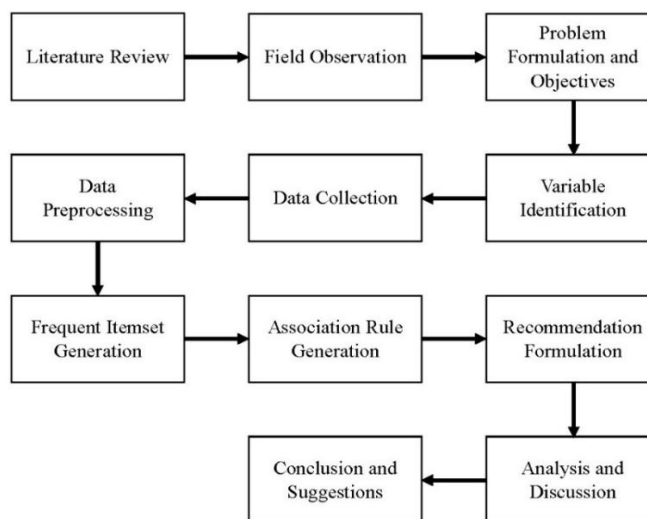


Figure 1. Research Flowchart of the Association Rule Mining Process Using FP-Growth

The research process was systematically divided into sequential stages to ensure that each objective of the study was addressed thoroughly and methodically. Each stage is outlined below, detailing the steps taken from data collection to the formulation of actionable insights.

a. Literature Review

A comprehensive review was conducted to identify theoretical foundations, previous studies on inventory optimization, and the application of Association Rule Mining (ARM) techniques, particularly the FP-Growth algorithm. The review also highlighted the research gap in project-based inventory environments.

b. Field Observation

Observations were carried out at PT Baruna Energi Solusindo Teknik to understand the operational flow of material usage, procurement practices, and stock management challenges. This stage provided contextual grounding and helped align the research with real-world problems.

c. Problem Formulation and Objectives

The main research question was formulated: *"How can material usage patterns be analyzed to optimize stock management in a project-based manufacturing company?"* The objective was to identify frequent item combinations that can be used to improve inventory planning and reduce stock inefficiencies.

d. Variable Identification

The dependent variable in this study is *material usage pattern*, while the independent variables include *material types, categories, and transaction periods*. These variables directly influence the co-occurrence and correlation among material combinations.

e. Data Collection

The dataset was collected from company records spanning a 12-month period (April 2024 to March 2025). The data includes transactional records detailing the types and quantities of materials used in various projects. A total of 228 transaction entries were recorded, covering 83 different material types.

f. Data Preprocessing

Data preprocessing involved cleaning the dataset by removing duplicates and null values. Data was then transformed into a binary transaction format suitable for ARM, where each transaction represented a set of co-used material items. This transformation was conducted using RapidMiner, ensuring compatibility with the FP-Growth operator.

g. Frequent Itemset Generation

The FP-Growth algorithm was applied to the cleaned dataset with a minimum support threshold of 0.5 (50%), meaning only itemsets appearing in at least 50% of transactions were considered. This threshold was chosen to prioritize frequently used items and reduce noise from rare combinations. A higher support value ensures fewer but more significant itemsets, suitable for strategic inventory decisions.

h. Association Rule Generation

Association rules were generated based on a minimum confidence threshold of 0.8 (80%), indicating a strong likelihood that the consequent item appears when the antecedent does. This value was selected to ensure only strong and reliable relationships were included in the rule set, enhancing their relevance for decision-making.

i. Recommendation Formulation

The generated rules were interpreted to provide inventory stocking recommendations. For example, if Membrane RO and Pipa PVC 1" frequently appear with SDL PVC 1", then stocking these items together is advised. The goal is to minimize overstock and stockout risks by aligning procurement with actual usage patterns.

j. Analysis and Discussion

This stage involved analyzing the frequent itemsets and association rules generated by the FP-Growth algorithm based on predefined support and confidence thresholds. Rules were evaluated using support, confidence, and lift to identify the strongest material usage patterns. To validate the results, a manual prediction testing was conducted by applying the generated rules to unseen transaction data. The predicted material combinations were then compared manually with actual usage, and a high degree of similarity was found. This confirmed that the rules not only captured meaningful patterns statistically but also aligned with real-world material usage, making them suitable for guiding inventory planning decisions.

k. Conclusion and Suggestions

The final stage involved summarizing the research findings, reflecting on the effectiveness of FP-Growth in identifying usage patterns, and offering practical suggestions for stock optimization. The study also outlines directions for future research, including the integration of forecasting techniques and cross-departmental validation.

2.2 Inventory

Inventory, encompassing raw materials, work-in-process (WIP), finished goods, and operational supplies, plays a vital role in ensuring production continuity, cost efficiency, and responsiveness to market demand. Effective inventory management helps balance procurement, manufacturing, and distribution activities to avoid production delays and minimize storage costs. Poor control may lead to excess inventory and capital lock-up or stockouts that disrupt operations and customer satisfaction. Raw materials are particularly critical in manufacturing, as shortages can halt production, while overstocking inflates operational costs through waste or obsolescence. Inventory types include raw materials, WIP, supplies, merchandise, and finished goods, each contributing uniquely to operational efficiency depending on the stage of the production process [10]–[12].

2.3 Data Mining

Data mining is the process of analyzing large datasets to uncover hidden patterns, correlations, and trends that support strategic decision-making, comprising stages such as data selection, preprocessing, transformation, pattern discovery, and interpretation [13], [14]. The process begins with data selection, where relevant information is extracted from large datasets for further analysis. This is followed by preprocessing, which involves cleaning the data to remove incomplete or inconsistent entries, ensuring accuracy and reliability. Next, the transformation stage formats the data to match the analytical requirements, discarding data that does not meet structural standards. The core phase, data

mining, applies specific techniques or algorithms to the prepared data to identify useful patterns and insights aligned with the goals of knowledge discovery [15].

2.4 Association Rule Mining

Association Rule Mining is a technique in data mining used to discover relationships among items in large datasets. It identifies rules such as “if item A is present, item B is likely to be present,” based on parameters like support, confidence, and lift. These rules are especially valuable for decision-making in inventory, marketing, and recommendation systems. The technique relies heavily on frequent itemset mining as its foundation [15], [16].

Association utilizes sequential if-then statements to indicate potential relationships between data items or variables within large datasets across various types of databases. This technique is widely used to uncover sales correlations in transactional data, supporting more informed decision-making in market analysis and inventory management [17].

In the process of association rule mining, three primary measures are used to evaluate the strength and relevance of patterns: support, confidence, and lift ratio. These metrics help determine the interestingness of discovered associations within transaction datasets.

Support indicates the proportion of transactions in the dataset that contain a particular item or itemset. It provides the fundamental basis for further evaluation of association rules.

$$\text{Support}(A, B) = \frac{\text{Number of Transactions Containing Both A and B}}{\text{Total Number of Transactions}} \quad (1)$$

Confidence measures the likelihood of occurrence of item B in transactions where item A is present. It evaluates the conditional probability of the co-occurrence of two items.

$$\text{Confidence}(A, B) = \frac{\text{Number of Transactions Containing Both A and B}}{\text{Number of Transactions Containing A}} \quad (2)$$

Lift ratio quantifies the strength of an association rule by comparing the observed confidence with the expected confidence under the assumption of independence between the items.

$$\text{Lift Ratio}(A, B) = \frac{\text{Confidence}(A, B)}{\text{Support}(B)} \quad (3)$$

These formulas serve as the foundation for extracting meaningful patterns and evaluating the significance of association rules within transactional data [18].

2.5 FP-Growth

The FP-Growth (Frequent Pattern Growth) algorithm is an efficient method for mining frequent itemsets without generating candidate sets explicitly, as done in the Apriori algorithm. It uses a tree-based structure (FP-tree) to compress the database, thus significantly reducing computation time and improving scalability for large datasets. FP-Growth is preferred in business applications that demand fast and accurate association rule extraction [19].

FP-Growth (Frequent Pattern Growth) is a data mining algorithm that utilizes a divide-and-conquer strategy to efficiently identify frequent itemsets within a dataset. Unlike traditional methods that rely on candidate generation, FP-Growth compresses the dataset by constructing a compact data structure known as an FP-Tree (Frequent Pattern Tree). This tree represents frequent items in a hierarchical prefix format, enabling faster pattern extraction [20], [21].

The Frequent Pattern Tree (FP-Tree) is a data structure used to compress transaction data by organizing frequently occurring items in a tree-based format. The construction of the FP-Tree begins with a root node assigned a null value. Each transaction in the dataset is then mapped onto the tree based on the ordered sequence of its itemset. If an item in a transaction matches an existing node in the FP-Tree, the node’s frequency count is incremented rather than creating a new node. This approach enables more compact data representation, which significantly reduces memory usage and enhances processing speed. The FP-Growth algorithm operates through three main stages: the generation of the conditional pattern base, the construction of the conditional FP-Tree, and the extraction of frequent itemsets [22].

2.6 RapidMiner

RapidMiner is a leading open-source data science platform that enables predictive analytics through a visual, drag-and-drop interface, making it accessible to both technical and non-technical users [23]. It supports various data mining techniques, including FP-Growth, and provides comprehensive tools for data preprocessing, modeling, evaluation, and visualization. In association rule mining, RapidMiner offers significant advantages such as faster processing speeds with FP-Growth compared to Apriori, scalability for large datasets, and informative visual outputs that aid interpretation and decision-making [24]. Its operator-based workflow simplifies complex analytical tasks without requiring coding, supporting a wide range of business applications such as inventory management, product promotion, and store layout optimization. These features make RapidMiner an effective and appropriate tool for identifying material usage patterns in this study [25].

3. RESULT AND DISCUSSION

3.1 Data Collection and Preparation

The dataset used in this study comprises transaction records of raw material usage over a 12-month period (April 2024 to March 2025). The collected data includes dates and the quantities of each material used. Prior to analysis, a data preprocessing stage was conducted, consisting of:

- a. Data Cleaning: Duplicate and empty data entries were removed using the Remove Duplicates and Filter Examples operators in RapidMiner.
- b. Data Transformation: Numeric data were converted into binary format using the Numerical to Binomial operator, and date entries were assigned an "id" role to prevent them from being included in the analysis.

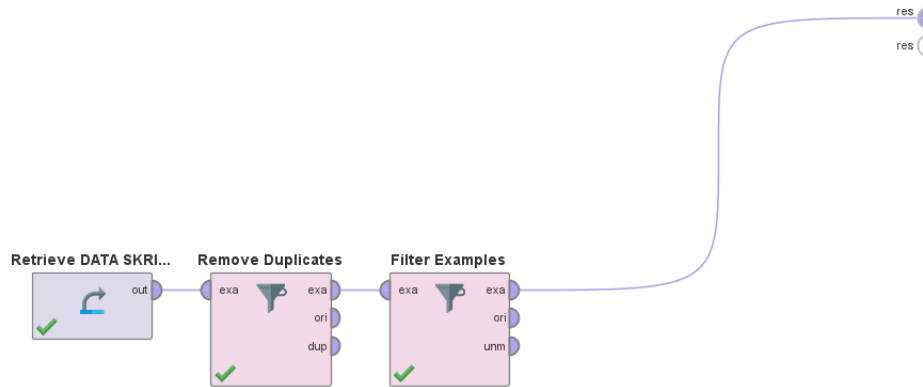


Figure 2. Data Cleaning Process on RapidMiner

In Figure 2, the data cleaning process is performed in RapidMiner using the *Remove Duplicates* and *Filter Examples* operators to eliminate duplicate and missing data. These operators automatically remove such records, resulting in a clean and refined dataset suitable for further analysis.

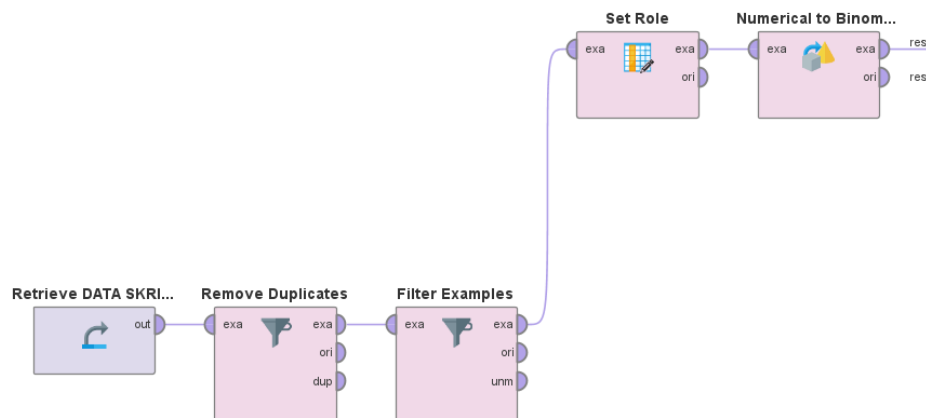


Figure 3. Data Transformation Process on RapidMiner

Figure 3 illustrates the data transformation process in RapidMiner. During this stage, data is modified using the *Set Role* operator, where the date attribute initially treated as a value is reassigned as an "id" to exclude it from further analysis. Subsequently, the data format is converted into a binomial (binary) type, where values equal to 0 are transformed into "False" and values ≥ 1 are converted into "True."

Table 1. Preprocessing Result

Row No.	Tanggal	Ball Valve 1"	Ball Valve 1/2"	Ball Valve 3/4"	...	Water Mur 1"	Water Mur 1/2"	Water Mur 3/4"
1	Mon Apr 01	false	false	false	...	true	true	true
2	Tue Apr 02	true	false	false	...	true	true	true
3	Wed Apr 03	false	false	false	...	false	true	true
4	Fri Apr 05	true	false	false	...	false	true	false
5	Sat Apr 06	false	false	false	...	true	true	true
6	Sun Apr 07	false	true	true	...	true	true	true

Row No.	Tanggal	Ball Valve 1"	Ball Valve 1/2"	Ball Valve 3/4"	...	Water Mur 1"	Water Mur 1/2"	Water Mur 3/4"
7	Tue Apr 09	false	false	false	...	true	true	true
8	Wed Apr 10	false	false	false	...	true	true	true
9	Thu Apr 11	false	false	false	...	true	false	false
10	Fri Apr 12	false	false	true	...	true	false	true
...
220	Thu Mar 20	false	false	false	...	false	false	false
221	Fri Mar 21	false	false	false	...	false	false	false
222	Sat Mar 22	false	false	false	...	false	false	false
223	Mon Mar 24	true	true	true	...	true	true	true
224	Tue Mar 25	false	false	false	...	false	false	false
225	Thu Mar 27	false	false	false	...	false	false	false
226	Sat Mar 29	false	false	false	...	false	false	false
227	Sun Mar 30	false	false	false	...	false	false	false
228	Mon Mar 31	false	false	false	...	false	false	false

Based on the results of the data transformation using RapidMiner, the date attribute initially assigned the role of a value was changed to the “id” role to prevent it from interfering with the formation of association rules. Furthermore, the material usage data, originally in numeric form, was converted into a binomial format, where values equal to 0 were transformed into “False” and values ≥ 1 were converted into “True.” This transformation process is illustrated in Table 1, which presents the data structure after binarization, making it suitable for association rule mining.

3.2 Frequent Itemset Generation

Once the data was cleaned and formatted, the FP-Growth algorithm was employed to generate frequent itemsets, i.e., groups of materials that appear together in transactions with high frequency. A minimum support threshold of 0.5 (50%) was applied. This means that only item combinations appearing in at least 50% of the total transactions were considered significant. This threshold was chosen to balance between including meaningful patterns and avoiding rare or coincidental associations.

The Frequent Itemset Generation phase was carried out using the FP-Growth operator in RapidMiner. This operator is specifically designed to identify combinations of items (in this case, materials) that frequently occur together within a given dataset. The purpose of this step is to uncover patterns of material usage that are consistently repeated across transactions.

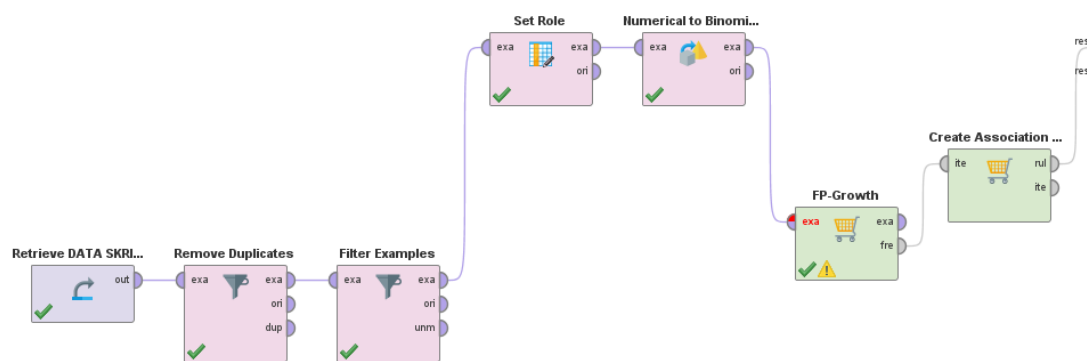


Figure 4. Association Rule Mining Process on RapidMiner

Figure 4 illustrates the stages of the Association Rule process in RapidMiner. This phase is conducted to generate frequent itemsets, where the data having undergone preprocessing is sorted based on the frequency of item occurrence. Subsequently, only the itemsets with a frequency greater than 50% are selected for the construction of association rules. The results of the frequent itemset generation are presented in Table 2 below.

Table 2. Frequent Itemset Generation Result

Size	Support	Item 1	Item 2
1	0.759	Membran RO	
1	0.697	Pipa PVC 1"	
1	0.627	SDL PVC 1"	



2	0.579	Membran RO	Pipa PVC 1"
2	0.526	Membran RO	SDL PVC 1"
2	0.522	Pipa PVC 1"	SDL PVC 1"

Table 2 presents the results of the frequent itemset generation. The findings indicate that three items have a support value greater than 0.5, namely: Membran RO with a support of 0.759, Pipa PVC 1” with 0.697, and SDL PVC 1” with 0.627.

3.3 Association Rule Generation

The next stage is the construction of association rules, in which potential item combinations are derived from the frequent itemsets with a support value of ≥ 0.5 . This process is performed using RapidMiner, specifically employing the Create Association Rule operator. In this step, a minimum confidence threshold of 0.8 is applied. The confidence value represents the probability that a particular item combination will occur. Thus, a minimum confidence of 0.8 implies that only combinations with a likelihood of occurrence greater than 80% are included. This threshold helps reduce the number of irrelevant rules and ensures that the analysis focuses on highly significant and meaningful associations [26].

Table 3. Association Rule Generation Result

No.	Premises	Conclusion	Support	Confidence	Lift
1	Pipa PVC 1"	Membran RO	0.57894737	0.83018868	1.0941215
2	SDL PVC 1"	Pipa PVC 1"	0.52192982	0.83216783	1.19329727
3	SDL PVC 1"	Membran RO	0.52631579	0.83916084	1.10594608

Table 3 displays the results of the association rule generation performed in RapidMiner. The output includes several item combinations along with their corresponding support, confidence, and lift ratio values. Based on the results, three association rules were identified:

- a. Rule 1: Pipa PVC 1” has a support value of 0.579. If Pipa PVC 1” is used, then Membran RO is also used, with a confidence of 0.830 and a lift ratio of 1.094.
- b. Rule 2: SDL PVC 1” has a support value of 0.522. If SDL PVC 1” is used, then Pipa PVC 1” is also used, with a confidence of 0.889 and a lift ratio of 1.193.
- c. Rule 3: SDL PVC 1” has a support value of 0.526. If SDL PVC 1” is used, then Membran RO is also used, with a confidence of 0.839 and a lift ratio of 1.106.

These results highlight strong associations between commonly used materials, which can serve as the basis for more efficient inventory planning and procurement strategies.

3.4 Recommendation Formulation

Based on the analysis of material stock usage patterns utilizing the Association Rule Mining approach with the FP-Growth algorithm, a number of materials were identified as having high levels of support, indicating frequent occurrence within the transactional dataset. Notably, Membran RO exhibited a support value of 0.759, followed by Pipa PVC 1” with a support value of 0.697, and SDL PVC 1” with a support value of 0.627. These figures demonstrate that these materials appeared in more than 50% of all recorded transactions, thus highlighting a usage frequency that is significantly above the average for other materials within the same inventory system. This suggests that such materials play a critical role in the company’s operational and production activities. Furthermore, the analysis uncovered several strong associative patterns among certain materials, as evidenced by the combination of Pipa PVC 1” with Membran RO, SDL PVC 1” with Pipa PVC 1”, and SDL PVC 1” with Membran RO. These associations are supported by high confidence and lift values, indicating that these items are not only frequently used together but also exhibit strong co-occurrence patterns within the same transaction context, implying they are likely components of the same installation or operational process.

Table 4. Comparison Between Company Stock and Association Rule Results

Material Name	Routinely Stocked by Company	Identified in Association Rule
Elbow 90 1"	✓	✗
Elbow 90 1/2"	✓	✗
SDL PVC 1"	✓	✓
Elbow 90 3/4"	✓	✗
SDD 1"	✓	✗
Pipa 4"	✓	✗
Pipa PVC 1"	✓	✓
Membran RO	✗	✓

Table 4 presents a comparison between the materials routinely stocked by PT Baruna Energi Solusindo Teknik and those identified through the FP-Growth algorithm as frequent itemsets. The results highlight both alignment and disparity between actual procurement practices and data-driven findings. Items such as SDL PVC 1" and Pipa PVC 1" appear in both categories, suggesting consistency between frequent usage and stock availability. However, Membran RO, despite showing the highest support value (0.759) in the association rule analysis, is not routinely stocked, indicating a potential risk of stockout for a high-demand item. On the other hand, several materials such as Elbow 90 (all sizes), SDD 1", and Pipa 4" are regularly stocked but were not identified as frequent itemsets, suggesting these items may contribute to overstock. This discrepancy underlines the importance of integrating association rule mining into inventory planning, as it helps prioritize materials based on actual usage trends rather than manual estimation alone. By aligning stock decisions with historical usage patterns, the company can improve forecasting accuracy, reduce inventory costs, and ensure greater responsiveness to project-based material demands.

3.5 Discussion

The dataset used in this study consists of 345 records of material usage transactions collected over a 12-month period from April 2024 to March 2025. After a thorough data cleaning and transformation process in RapidMiner, the FP-Growth algorithm was applied with a minimum support threshold of 50% and minimum confidence threshold of 80%. The results identified Membran RO (75.9%), Pipa PVC 1" (69.7%), and SDL PVC 1" (62.7%) as the most frequently used materials. These materials appeared together in numerous transactions, especially in projects related to water purification systems that require pressure-based filtration and piping.

The association rules generated reveal strong co-occurrence patterns. For instance, the rule {SDL PVC 1"} → {Pipa PVC 1"} with a confidence of 83.2% and lift of 1.193, and the rule {Pipa PVC 1"} → {Membran RO} with a confidence of 83.0% and lift of 1.094, suggest that these items are commonly used in the same type of installation. This is likely because membrane filtration systems often require integrated support components such as high-pressure pipes (Pipa PVC) and housing elements (SDL PVC), which form a functional package in water purification installations. These patterns indicate that the usage of certain items is not random but project-driven, particularly in government or PDAM installations where design templates are standardized.

To validate the strength of the rules, a manual prediction testing was conducted using a subset of recent transactions not included in the model training. Predictions were made based on the generated rules and compared with actual material combinations in the test data. The results showed a strong alignment, affirming that the rules reflect realistic usage behavior.

When compared to previous studies, the findings support and extend prior research. For example, Hartono and Fitriana (2020) found strong confidence values in FP-Growth applications for inventory planning, although their focus was more on retail promotions. Similarly, Pranata and Utomo (2020) applied FP-Growth to spare part inventory and identified confidence values up to 80%, but in a domain with more static demand. This study differs by applying FP-Growth in a dynamic, project-based manufacturing context—where demand varies across projects—which remains underexplored in the literature. Therefore, the results not only confirm previous findings but also fill a methodological gap by demonstrating the algorithm's utility in flexible production settings.

In conclusion, the use of FP-Growth successfully uncovered material usage patterns that are meaningful and operationally relevant. These insights can guide better procurement strategies, reduce the likelihood of overstock or stockout, and support more precise, data-driven inventory management.

4. CONCLUSION

Based on the findings and discussions conducted throughout this study, it can be concluded that the Association Rule Mining method, implemented through the FP-Growth algorithm, has proven effective in identifying meaningful patterns in the usage of material stock at PT Baruna Energi Solusindo Teknik. This analytical approach succeeded in extracting frequent itemsets and generating association rules that reveal strong interrelationships among materials commonly used together in production and installation activities. Notably, materials such as Membran RO, Pipa PVC 1", and SDL PVC 1" demonstrated support values exceeding 0.5, indicating that these items appeared in more than 50% of all transactions within the dataset. In addition, the association rules involving these items recorded confidence levels above 0.8, signifying that when one item is used, there is a high probability that the associated item is used simultaneously. These findings suggest a high degree of co-occurrence and compatibility among these materials. The implications of this analysis are practical and actionable. The company can leverage these insights by prioritizing the procurement of high-support materials and planning bundled purchases of strongly associated items. This strategy will help reduce the risks of overstocking and stockouts, which can disrupt operational efficiency and increase costs. Overall, the research has achieved its objective of optimizing inventory management by utilizing data-driven insights derived from actual material usage patterns. However, this study has certain limitations. The analysis is based solely on transactional data without integrating forecasting methods or real-time demand factors. Additionally, the evaluation of rule effectiveness was limited to internal validation and manual testing, without broader operational deployment. Future research is recommended to combine association rule mining with time-series forecasting or clustering methods to enhance prediction accuracy. It is also suggested to expand the validation process by involving multiple

stakeholders, including field technicians and procurement divisions, to refine the interpretability and implementation of the rules.

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