MODELING ASSOCIATION PATTERNS OF IT NETWORK DISRUPTIONS IN PT PLN (PERSERO) CORPORATE USING ASSOCIATION RULE MINING

Fadly Muhammad - 23522302
Master of Informatics Study Program
School of Electrical and Informatics Engineering
Bandung Institute of Technology, Jalan Ganesha 10 Bandung
fadly.padomuhammad@gmail.com

***Abstract* — This study aims to model the association pattern of a corporate's IT network interference using Association Rule Mining (ARM) techniques with the Apriori and FP-Growth algorithms. In this case, the corporate being studied is PT PLN (Persero). The goal is to identify and analyze frequent fault patterns and to provide recommendations to improve network reliability and performance. The data used consists of 7141 rows and 7 attributes.**

The research method includes literature study, data collection, preprocessing, data processing using Apriori and FP-Growth algorithms, then followed with analysis and evaluation of the results. The results with parameterized support value and confidence level of 0.02 and 0.8 respectively, showed significant correlation between various disorders. The Apriori algorithm identified that in 4% of the total events, the combination of BW REDUCE and VEHICLE ATTACHMENT/STRIKE always leads to the event of CABLE: FO CABLE break type F8 with 100% confidence. The FP-Growth algorithm showed that in 4% of the events, BW REDUCE always leads to the event CABLE: F8 type FO CABLE BREAK with 99% confidence.

The analysis shows that FP-Growth is more efficient in finding frequent itemsets. Suggested recommendations include integrating analysis results with automated monitoring systems, strengthening collaboration with ICON+ Subholding to understand and address the causes of disruptions, and implementing data analysis-based solutions. This research will significantly aid PT PLN (Persero) in optimizing IT network performance, enhancing service reliability, and reducing the effects of disruptions on company operations.

Keywords— Association Rule Mining, Apriori, FP-Growth, IT Network Disruptions, PT PLN (Persero)

I. INTRODUCTION

As the main provider of electric energy services in Indonesia, it is essential for PT PLN (Persero) to have a reliable IT network infrastructure. This IT network supports various business operations, including data management, customer information systems, financial analysis, and internal-external communications. Disruptions in the IT network can cause significant impacts such as decreasing employee-productivity, poor system performance, decision-making delays, and financial losses.

The complexity of corporate's IT networks, which encompass a wide range of devices, apps, and services, is recently increasing. Thus, making it harder to detect, assess, and manage interruptions. To overcome these obstacles, competent data analysis techniques are therefore needed. Since it can offer insightful information about the relationships between different variables in data pertaining to IT network disruptions, Association Rule Mining (ARM) is a pertinent method to use.

ARM is used to identify relationships or patterns between items in a dataset and discover association rules between combinations of itemsets. This technique helps uncover patterns hidden in the data and make inferences about the relationships between the items, ultimately supporting better business decision-making. In the context of PT PLN (Persero), ARM can be applied to analyze IT network operational data, including network usage logs and event records, to identify patterns related to disruptions.

With ARM, PT PLN (Persero) can uncover patterns that may not be apparent through manual analysis; such as the relationship between certain times of the day and the frequency of disruptions; or the correlation between the type of device used and the type of disruption that often occurs. This information can help to improve network monitoring, identify factors that cause disruptions, and take proactive steps for prevention. ARM can be a powerful instrument for maximizing corporate's IT network performance, enhancing service reliability, reducing the negative effects of disruptions on company operations, and giving decision-makers insightful information.

II. LITERATURE REVIEW

.

A. Data Mining

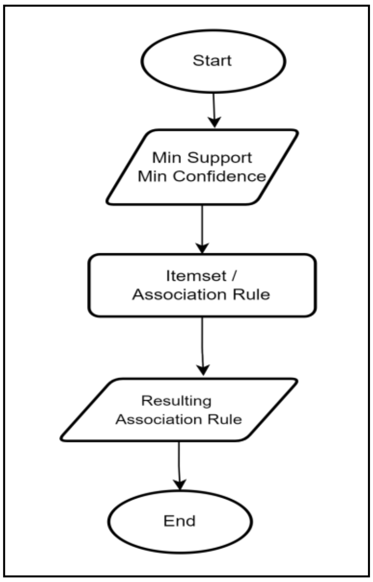
Data mining is a scientific discipline that integrates methods from machine learning, statistics, pattern recognition, databases, and visualization which can be used to identify information retrieval problems from huge databases. In another view, data mining is a process of finding patterns from a very large amount of data stored in a storage area using pattern recognition technology, statistical techniques, and mathematics.

Data mining, often called knowledge discovery in databases (KDD), is an activity that involves collecting and using historical data to find regularities, patterns or relationships in large data sets. The terms of data mining and knowledge discovery in databases are often used interchangeably to describe the process of finding information hidden in large databases.

B. Association Rules

Association Rules Mining (ARM) is a data mining technique to find associative rules between a combination of items. It is also a procedure used to find the relationships between items in a specified dataset. Finding the most common combination of an itemset and establishing both the condition and the outcome are the two stages of association rules.

Fig. 1. *Association Rule Mining* Process

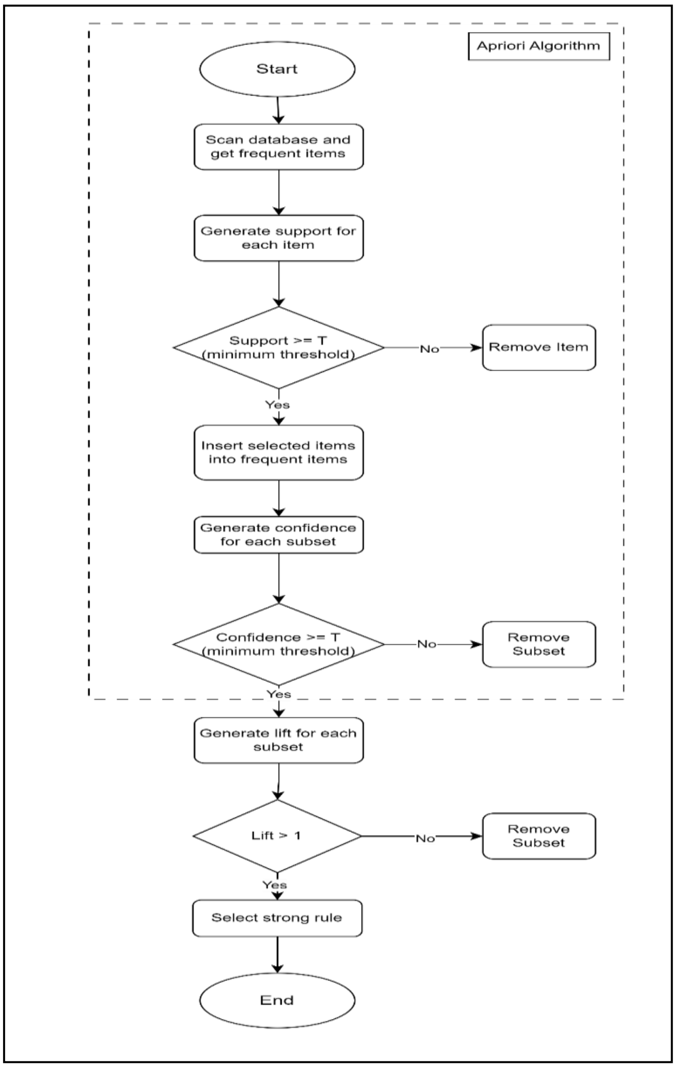


This overall flowchart illustrates the main steps in the association rule formation process. The final result can be used to gain valuable insights from the analyzed data.

C. Apriori

Apriori algorithm was coined by Agrawal. The main concept is to calculate the pattern of occurrence of items that appear in data transaction with several iterations. Every iteration starts with the generation of candidate itemsets, after which each candidate's support value is determined. To generate candidates, it can basically be done by compiling a combination of items that have been found before. This algorithm is based on the a priori law: if an itemset turns out to be infrequent, its superset should likewise be infrequent, negating the need for additional checks. A feature of the a priori algorithm is that if an itemset is included in a large itemset, then all subsets of the itemset are also included in the large itemset.

Fig. 2. *Apriori* Algorithm Steps



Some terms that are often used in the a priori algorithm are as follows:

a) Support, indicates how often an itemset appears in a transaction, the probability of a customer buying multiple products together out of all transactions. Support for an "X=>Y" rule is the probability.

The formula for finding the support value is:

$$Support\ A = \frac{Transaction\ amount\ contains\ A\ and\ B}{Total\ Transactions} \times 100\% \quad (1)$$

b) Confidence, to measures how often the consequent itemset appears if the antecedent itemset also appears, the probability of multiple products being purchased together where one of the products is definitely purchased. Example: if there are n transactions where X is purchased, and there are m transactions where X and Y are purchased together, then the confidence of the rule if X then Y is m/n.

The formula for finding confidence is:

$$Confidence\ A = \frac{Transaction\ amount\ contains\ A\ and\ B}{Total\ Transactions\ A} \times 100\% \quad (2)$$

c. Minimum support, a parameter that sets the maximum occurance frequency or support count that must be met by a group of data in order to be utilized as a rule.
d. Minimum confidence, which is a parameter that defines the minimum level of confidence that must be met by a qualified rule.
e. Itemset, a group of products.
f. Support count, the occurrence frequency of a product group or itemset from all transactions.
g. Candidate itemsets, the itemsets for which their support count will be calculated.
h. Large itemsets, the itemsets that occur frequently, or itemsets that have exceeded the minimum support limit that has been given.
i. Lift, the measures of how it is more often the consequent itemset appears in a transaction if the antecedent itemset also appears, compared to if they appear independently. It shows how strong the relationship between the antecedent and consequent itemsets. Lift greater than 1 indicates a positive dependency between the two.
j. Antecedent, i.e. the thing/event that initiates
k. Consequent, i.e. the effect or result

D. FP-Growth

Frequent Pattern Growth (FP-Growth) is an alternative algorithm that can be used to determine the most frequent itemset in a data set. Instead of using the resulting candidates, as done in the Apriori method, the FP-Growth algorithm searches for frequent itemsets using the tree construction idea, which known as FP-Tree. By using FP-tree, the FP-Growth algorithm can directly obtain frequent itemsets, so the FP-Growth algorithm is faster than the Apriori algorithm.

The FP-Growth algorithm uses the FP-Tree data structure to represent the transactions. It shows how to build the FP-Tree from the original transaction representation, sorting by retaining only frequent 1 itemsets, and storing them in the FP-Tree. After the FP-Tree is formed, the next step is to obtain frequent itemsets without performing candidate generation.

E. Relevant Research

1. Research entitled "Data Mining Analysis of Purchases with Association Rule Market Basket Analysis using the FP-Growth Algorithm" by Rafi Dio et al in August 2023. His research analyzed 450 shopping transactions using the FP-Growth algorithm.
The results of his research are the formation of 8 association rules with a lift ratio value> 1 and a confidence value of at least 30%. It generated 4 reliable association rules that show product combinations which are frequently purchased together.
2. Research entitled "Food Menu Sales Recommendation System in Culinary MSMEs Using Association Rule" by Ade Kania Ningsih in December 2020.
His research uses the apriori algorithm by analyzing 100 transaction data. It produced 12 rules with 5% support and 80% confidence; finding patterns of purchases that often occur together in culinary MSME data transaction. This aims to find products that are often purchased together and to improve marketing strategies.

III. SYSTEM DESIGN

A. System Requirements Analysis

The system requirements analysis in this research involves understanding the identification and analyzing disruption patterns in the PT PLN (Persero) corporate IT network using Association Rule Mining techniques. In order for this research to be successful and produce valuable insights, system requirements analysis must be carried out carefully. The followings are important components in system requirements analysis:
a) Data Requirements,
b) Algorithm and Technology Requirements,
c) Analysis and Evaluation System Requirements,
d) System Functional Requirements,
e) User Requirements
With an indepth analysis to the system requirements, this research can be designed and implemented effectively, so that the goal of optimizing the performance of the PT PLN (Persero) corporate IT network can be achieved.

B. System Scope

PLN ICON+ is a Sub Holding of PT PLN (Persero) that specializes in information and communication technology. PLN ICON+ has a crucial role in ensuring the connectivity and communication throughout the organization, making sure that it runs smoothly and without a hitch. Dataset was taken from the 2023 PT PLN IT Network Disruption data. The dataset consists of 7141 rows and 7 attributes.

There are some challenges in this research which includes several aspects to be addressed in order to achieve an informative and high-quality analysis results. These challanges are:

- Data limitations in terms of quantity, quality, and existence
- Complex data preprocessing, mainly due to different data formats and variations

- Choosing the right parameters for the association pattern algorithm, such as support and confidence levels
- The ability to correctly interpret these rules is key to generate useful insights for management and decision-makers.

C. System Design

In order to guarantee the successful and efficient application of Association Rule Mining (ARM) approaches for the investigation of association patterns of PT PLN (Persero) IT network interruptions, this research system was created in multiple stages. The stages are as follows:

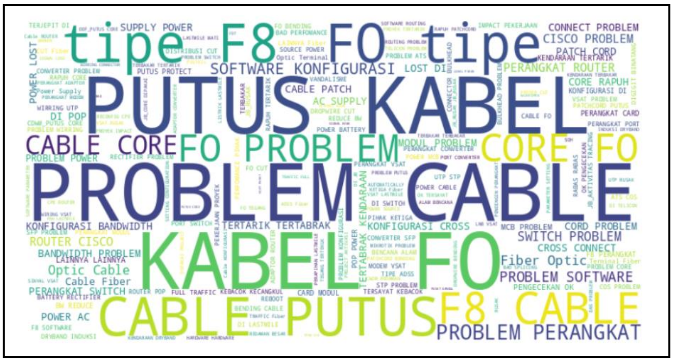
1) Tools, several tools are needed such as a laptop, python, jupyter notebook, mlxtend library
2) Preprocessing and Data Processing, at this stage the dataset will be entered for preprocessing where the goal is to produce clean data to be processed and allow for development. Then the dataset is ready for further analysis using the apriori and fp-growth algorithms.
3) Visualization, uses the matplotlib. Further, seaborn libraries are used to help in understanding and interpretating the data. Visualization makes it possible to visually convey the information contained in the data and understand the characteristics/patterns of the data to be further analyzed to facilitate decision making.
4) Algorithm Implementation. It is the process of using the mlxtend library in order to apply the Apriori and FP-Growth algorithms to the previously transformed dataset. Furthermore, determining important parameters, such as support and confidence levels according to the needs of the analysis being carried out.
5) Association Pattern Analysis, which analyzes the results of the association pattern algorithm to identify the relationship patterns between the types of disorders that occur in the dataset. Examine the association rules generated to determine the relationship between the types of disorders that appear simultaneously or sequentially.
6) Deployment model, which moves the machine learning model from the development environment to the production environment so that it can be practically used to handle new data. In the context of using Association Rule Mining for the analysis of PT PLN (Persero) corporate IT network disruption data, the deployment model involves applying the association rules that have been formed into an environment that can be accessed by users for decision making.

IV. MODEL SYSTEM ANALYSIS AND TESTING

In the analysis and testing stage of the model system, the steps taken aim to evaluate the performance and validity of the model that has been built. This stage ensures that the model is able to generate accurate and reliable insights to support decision making.

A. WordCloud Visualization

Fig. 3. *WordCloud* Visualization



According to the visualization, the terms "CABLE PROBLEM" and "CABLE DISCONNECTION" stand out as being highly prevalent. This suggests that these terms (refer to cable or connectivity disconnections) are the key issues and are the crucial elements in the data being analyzed. It shows that these terms are frequently included in issues that are discussed or reported.

B. Test Scenario

Test scenario is done to evaluate the accuracy of the implementation of the Association Rule Mining method. The data used is PT PLN IT Network Disruption in 2023 and the test is carried out with variations in threshold values (minimum support and minimum confidence). The testing process will be repeated in n times, adjusted to the data used, to determine the optimal and effective threshold value to be used in the system. The results of Apriori and FP-Growth calculations produces a series of association rules from various iterations of the support value. Evaluation is done on the association rules using the lift ratio to assess the validity of the calculations performed.

1) Apriori and FP-Growth Requirements

The dataset must be formatted appropriately such that each row represents a single transaction or event before the apriori algorithm can be used in association analysis. The attribute that has to be examined is "Interference (Incident)". The term "itemset format" describes a data representation in which, each row represents one transaction or event, and each column represents the presence or absence of an item in that transaction.

a) Creating transaction data, which converts the dataset into a format suitable for association analysis. Make sure that each row represents one transaction or event, and the attribute or variable to be analyzed is Interference (Incident).

b) Transforming the dataset into a transaction/itemset format. Each transaction or event should contain a collection of items that occur together or sequentially. In this case, we will see if there is a pattern of association between the types of disturbances that occur.

c) DataFrame format. We will have a DataFrame where each row represents one transaction, and each column represents the presence or absence of an "Incident".

2) Parameter Value

TABLE I. PARAMETER THRESHOLD VALUE

Parameter	Value
Minimum Support	0.02
Minimum Confidence	0.8

Minimum support of 0.02 means that the itemset considered for the association rule must appear in at least 2% of all occurrences in the dataset. Minimum confidence of 0.8 means the association rule considered must be true in at least 80% of the cases where the antecedent occurs.

3) Itemset Combination. Algorithm testing is done to explore and identify association patterns between itemsets in the dataset. In this testing scenario, we will assess the combinations of itemsets that consist of 1 itemset, 2 itemsets, 3 itemsets, and 4 itemsets. This test is conducted to understand how various combinations of items relate to each other. It is also used to identify patterns that are valuable for the analysis of PT PLN (Persero)' IT network disruptions.

C. Testing results

1) Combination of 1 Itemset Apriori

Resulting in 28 frequent itemsets for this test. The following below presents the 5 largest itemsets based on support.

TABLE II. COMBINATION RESULTS OF 1 APRIORI ITEMSET

Combination of 1 Itemset Apriori		
No	***Itemset***	***Support***
1	CABLE: FO CABLE break type F8	0.35
2	CABLE : CORE FO PROBLEM	0.23
3	DEVICE: CISCO ROUTER PROBLEM	0.17
4	Fiber Optic Cable	0.15
5	SOFTWARE: CONFIGURATION CROSS CONNECT PROBLEM	0.12

The largest support value of 0.35 indicates that the disturbance in the form of a break in the type F8 fiber optic cable occurred in 35% of all events recorded in the dataset. This means that more than one-third of all incidents recorded on the PT PLN (Persero) IT network involved a break in the F8 type fiber optic cable. This implies that F8 fiber optic cable rupture is a somewhat frequent and serious issue that requires extra care to fix or avoid.

2) Combination of 2 Itemset Apriori

Resulting in 33 frequent itemsets for this test. The following table presents the 5 largest itemsets based on support.

TABLE III. COMBINATION RESULTS OF 2 APRORI ITEMSETS

Combination of 2 Itemset Apriori		
No	***Itemset***	***Support***
1	(CABLE: FO CABLE break type F8, CABLE: CORE FO PROBLEM)	0.12
2	(CABLE: Broken FO CABLE type F8, pulled by vehicle)	0.08
3	(CABLE: F8 type FO CABLE, Fiber Optic Cable)	0.07
4	(CABLE: CORE FO PROBLEM, Fiber Optic Cable)	0.06
5	(DEVICE: CISCO PROBLEM ROUTER, Fiber Optic Cable)	0.04

This association indicates that there is a correlation between the F8 type fiber optic cable breakage fault and the CORE FO PROBLEM. The support value of 0.12 means that 12% of all recorded incidents in the dataset contain both types of faults. That is, in 12% of the recorded incidents, the cable break of F8 type fiber optic cable always occurs together with the fiber optic cable core problem.

3) Combination of 3 Itemset Apriori

Produced 10 frequent itemsets for this test. The 5 largest itemsets can be seen in the table below IV below.

TABLE IV. COMBINATION RESULTS OF 3 APRORI ITEMSETS

Combination of 3 Apriori Itemsets		
No	***Itemset***	***Support***
1	(Fiber Optic Cable, CABLE: CORE FO PROBLEM, CABLE: CABLE BREAK FO type F8)	0.04
2	(TRACTED/BUILT BY VEHICLE, BW REDUCE, CABLE: BREAKED FO type F8 CABLE)	0.04
3	(Fiber Optic Cable, SOFTWARE: BANDWIDTH CONFIGURATION PROBLEM, DEVICE: CISCO ROUTER PROBLEM)	0.03
4	(CABLE: CORE FO PROBLEM, ATTRACTED/BUILT BY VEHICLE, CABLE: BREAKED CABLE FO type F8)	0.03
5	(PROBLEM MODULE, SOFTWARE: PROBLEM BANDWIDTH CONFIGURATION, DEVICE: PROBLEM CISCO ROUTER)	0.03

The support value of 0.04 indicates that the combination of problems with fiber optic cables in general. ‘Fiber optic cable cores’ and ‘F8 type fiber optic cable breaks’ occur together in 4% of all events recorded in the dataset. This means that it is relatively rare for these problems to occur together, but there is still a relationship between these three types of problems. This could indicate that when a problem occurs with a fiber optic cable there is often also a F8-type cable break, indicating a potential systemic breakdown or weakness in the fiber optic cable infrastructure.

4) Combination of 4 Itemset Apriori

Produce only 1 frequent itemset for this test.

TABLE V. COMBINATION RESULTS OF 4 APRORI ITEMSETS

Combination of 4 Apriori Itemsets		
No	***Itemset***	***Support***
1	(PROBLEM MODULE, Fiber Optic Cable, SOFTWARE: CONFIGURATION BANDWIDTH PROBLEM, DEVICE: CISCO ROUTER PROBLEM)	0.03

The support value of 0.03 means that 3% of all fault incidents recorded in the dataset involve these four factors together. This indicates that problems with network device modules, fiber optic cables, bandwidth configuration in software, and Cisco routers are frequently existed together. When a problem occurs in the device module, it is also often found in the fiber optic cable, which could be due to physical or cable quality issues. At the same time, problems in the software bandwidth configuration often arise, which can be caused by interference with network hardware such as Cisco routers. Problems with Cisco routers, which are the center of network traffic management, can impact bandwidth performance and overall network stability.

5) Apriori Association Rule Result

Produced 20 association rules for this test. Below list presented 1 of the strongest associations based on support and confidence.

- Antecedents: BW REDUCE, PULLED / HIT BY VEHICLE
- Consequents: CABLE: BREAKED FO type F8 CABLE
- Antecedents Support: 0.04
- Consequences Support: 0.35
- Support: 0.04
- Confidence: 1
- Lift: 2.85
- Leverage: 0.02
- Zhangs_Metric: 0.67

The results of this association show that within 4% of the total events in the dataset, there is a combination of BW REDUCE and VEHICLE ATTACHED/STRIKED events that always leads to the CABLE event: FO CABLE break type F8. A confidence of 100% indicates that this relationship is very strong. A lift of 2.85 indicates that the occurrence of the antecedents increases the likelihood of the consequents more than twice as much as if there was no relationship between them. Zhang's Metric and Leverage both bolster the significance of this rule.

Management can use this information to better understand and handle network interruptions by concentrating preventive efforts on combinations of antecedents that are consistently known to result in certain issues with FO cables.

6) FP-Growth Itemset Combination

Resulting in 72 frequent itemsets for this test. The following below presents the 5 largest itemsets based on support.

TABLE VI. FP-GROWTH ITEMSET COMBINATION RESULTS

FP-Growth Itemset Combination		
No	***Support***	***Itemset***
1	0.35	(CABLE: FO cable break type F8)
2	0.23	(CABLE: CORE FO PROBLEM)
3	0.17	(DEVICE: CISCO ROUTER PROBLEM)
4	0.15	(Fiber Optic Cable)
5	0.12	(CABLE: FO CABLE break type F8, CABLE : CORE FO PROBLEM)

Support of 0.35 means that the itemset "CABLE: FO CABLE break type F8" appears in 35% of the total transactions in the dataset. This suggests that the type F8 FO cable break incident is a fairly common problem, occurring in more than a third of all recorded events.

7) FP-Growth Association Rule Result

Produced 20 association rules for this test. Here below is presented 1 of the strongest associations based on support and confidence.

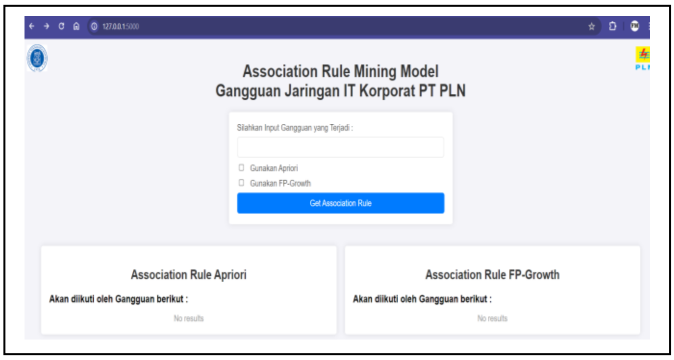
- Antecedents: BW REDUCE
- Consequents: CABLE: FO CABLE break type F8
- Antecedents Support: 0.04
- Consequences Support: 0.35
- Support: 0.04
- Confidence: 0.99
- Lift: 2.81
- Leverage: 0.03
- Zhangs_Metric: 0.67

This association result shows that in 4% of the total events in the dataset, there is a combination of BW REDUCE events always leading to CABLE events: FO CABLE break type F8. A confidence level of 99% indicates that this association is very strong. PT PLN (Persero) should pay special attention to bandwidth reduction as an early indication of FO cable problems. When a bandwidth reduction occurs, the technical team should immediately check the condition of the F8 type FO cable to prevent or mitigate larger problems.

D. Deployment Model

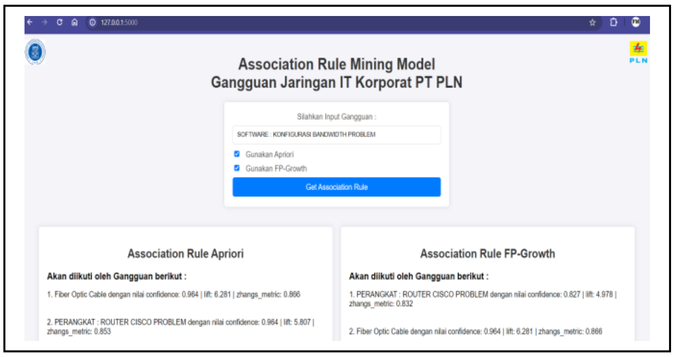
In order to integrate the developed model into the production environment for practical and efficient use, model deployment is a crucial stage in the data analysis process. In this study, The PT PLN (Persero) IT network fault association model utilizing the Apriori and FP-Growth algorithms has been effectively integrated into a web application.

Fig. 4. *Deployment Model* 1 Results



The application provides two algorithm options: the Apriori algorithm and the FP-Growth algorithm. These options can be selected as needed. Once the input items are entered and the algorithm is selected, the application will process the data and display the recommendation results in two separate sections, each one is the result from the Apriori algorithm and FP-Growth algorithm respectively.

Fig. 5. *Deployment Model* 2 Results



This results section will display the association rules found, allowing users to understand the patterns of disturbances that occur and take appropriate actions to improve the reliability of the IT network.

V. CONCLUSIONS AND RECOMMENDATIONS

By using the association rule mining method with the Apriori algorithm and the FP-Growth algorithm with a support value of 0.02% and a confidence value of 0.8%, it results in 20 association rules from each algorithm among various variables in the PT PLN (Persero) IT network disruption data. The test results obtained are:

1. Utilizing the Apriori algorithm, it shows that in 4% of the total events in the dataset, there is a combination of BW REDUCE and VEHICLE ATTACHED/STRIKED events that always leads to the CABLE event: FO CABLE BREAK type F8 with 100% confidence level, which indicates that this relationship is powerful.

2. Utilizing the FP-Growth algorithm, it shows that in 4% of the total events in the dataset, there is a combination of BW REDUCE events that always leading to CABLE events: FO CABLE DISCONNECT type F8 with 99% confidence level, which indicates that this relationship is very strong.

The implementation of Association Rule Mining algorithms, both Apriori and FP-Growth algorithm allows an effective and efficient patterns identification of IT network disruptions that often occur. It provides the most preventive measures. Thus, the management are more informed and secure for the decisions-making regarding the network maintenance.

Based on the conclusions that have been described, there are several suggestions that can be conveyed:
1. Integrate this association analysis's findings with an automated monitoring system to get early alerts when patterns of recognized disturbances emerge.
2. Strengthen collaboration with ICON+ Subholding to better understand and address the causes of network disruptions, and further to implement more effective solutions based on data analysis.
3. PT PLN (Persero) can optimize the components that are often the source of interference. This could include replacing hardware that is often problematic, updating software, or increasing network capacity in certain areas.
4. To make sure that the analysis model is always current and reliable in identifying disturbance patterns, conduct regular evaluations of the analysis results and update the minimal support and minimum confidence parameters in accordance with the most recent developments in disturbance data.

REFERENCES

[1] Dio, R., Hidayati, J., Putera, D. A., & Dermawan, A. A. (2023). Analisis Data Mining Pembelian dengan Association Rule Market Basket Analysis menggunakan Algoritma FP-Growth. *Penelitian dan Aplikasi Sistem dan Teknik Industri* .

[2] Idris, A. I., Sampetoding, E. A., Ardhana, V. Y., Maritsa, I., Sakri, A., Ruslan, H., & Manapa, E. S. (2022). Comparison of Apriori, Apriori-TID and FP-Growth Algorithms in Market Basket Analysis at Grocery Stores. *International Journal of Informatics and Computer Science*.

[3] Maulidah, A., & Bachtiar, F. A. (2021). Penerapan Metode Association Rule Mining untuk Asosiasi Ulasan terhadap Aspek Tempat Wisata Jawa Timur Park 3. *Teknologi Informasi dan Ilmu Komputer (JTIIK)*.

[4] Musdalifah, I., & Jananto, A. (2023). Analisis Perbandingan Algoritma Apriori Dan. *Jurnal Ilmiah Komputer*.

[5] Ningsih, A. K., & Witanti, W. (2020). Sistem Rekomendasi Penjualan Menu Makanan di UMKM Kuliner Menggunakan Association Rule. *Information Communication & Technology*.

[6] Rerung, R. R. (2018). Penerapan Data Mining dengan Memanfaatkan Metode Association Rule untuk Promosi Produk. *Jurnal Teknologi Rekayasa - JTERA*.

[7] Saputra, R., & Sibarani, A. J. (2020). Implementasi Data Mining Menggunakan Algoritma Apriori Untuk Meningkatkan Pola Penjualan Obat. *Jurnal Teknik Informatika dan Sistem Informasi*.

[8] Setianingsih, D., & Hakim, R. F. (2015). PENERAPAN DATA MINING DALAM ANALISIS KEJADIAN TANAH LONGSOR DI INDONESIA DENGAN MENGGUNAKAN ASSOCIATION RULE ALGORITMA APRIORI. *Prosiding Seminar Nasional Matematika dan Pendidikan Matematika UMS*.

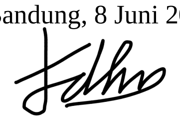
[9] Siahaan, A. (2023). ANALISIS ALGORITMA APRIORI DALAM PENGENDALIAN PERSEDIAAN BARANG. Universitas Medan Area.

[10] Zhao, Z., Jian, Z., Gaba, G. S., Alroobaea, R., Masud, M., & Rubaiee, S. (2021). An improved association rule mining algorithm for large data. *Journal of Intelligent Systems*.

PERNYATAAN

Dengan ini saya menyatakan bahwa makalah yang saya tulis ini adalah tulisan saya sendiri, bukan saduran, atau terjemahan dari makalah orang lain, dan bukan plagiasi.

Bandung, 8 Juni 2024



Fadly Muhammad (23522302)