Quality Analysis of Telemetry Tracking and Command at Ground Stations using the Association Rule Mining Approach

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Abstract. LAPAN built several remote ground stations to support the telemetry tracking and command (TTC) system for the LAPAN-A2 and LAPAN-A3 satellites. These remote ground stations are located in Kototabang/KT (West Sumatra), Biak/BK (Papua), Parepare/PR (South Sulawesi), Rumpin/RP, Rancabungur/RB (Bogor, West Java), and Svalbard/SV (Norway). Problems that often arise in the TTC process are telecommands not being sent (commands sent from the ground station to the satellite) or telemetry packages not being received (feedback on telecommands sent by the satellite to the ground station). This research attempted to calculate and analyze the quality of TTC using a data-mining approach, i.e., rule mining. The calculations were performed using five main parameters: satellite name, ground station, azimuth, altitude, and communication status. The research output consisted of a combination of remote ground station parameters that may result in a successful or failed TTC. For the LAPAN-A3 satellite at the Svalbard ground station, 19 failed communication combinations were generated with a dataset of 57,029. Communication failures occur in azimuth and elevation, i.e., areas blocked by obstacles.

Keywords: *associate rule mining; azimuth; elevation; ground station; satellite; telemetry tracking and command.*

1 Introduction

LAPAN-A2 and LAPAN-A3 are experimental microsatellites with ground observations and remote sensing missions [1]. The LAPAN-A2 satellite has a low-altitude orbit with an inclination near the equator [2], and is used for ground

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observation, maritime monitoring, and amateur radio communications [3]. The LAPAN-A3 satellite has a polar orbit with an inclination of 98° and performs remote-sensing missions. Both satellites use ultra-high frequency (UHF) for telemetry tracking and command (TTC) functions, with LAPAN-A2 using a frequency of 437.425 MHz, and LAPAN-A3/IPB using a frequency of 437.325 MHz.

Telemetry is a collection of information that contains real-time satellite health and status data, namely satellite attitude data, operating mode, voltage, current, temperature, and power, on each satellite payload. Telemetry data are obtained in real-time or delayed via long-term telemetry. Tracking accurately monitors the satellite orbits. The satellite orbit tracking process uses two-line element (TLE) calculations based on satellite speed and acceleration calculations resulting from a simplified perturbation model (SGP4) [4],[5]. Telecommand is the activity of sending commands to a satellite, such as turning the satellite payload on or off, or changing the satellite payload parameter values. Commands can be in the form of real-time commands, or a series of commands executed at a certain time via a scheduler.

The ground station plays a crucial role in maintaining the performance of the satellite and its payload. It is responsible for controlling the satellite, monitoring its status through telemetry data, and accurately tracking its orbit [6]. The TTC ground station includes a UHF antenna, transmitter-receiver radio, modem, and transmitter-receiver computer. The computer operates two programs, SatPC32, to control the antenna direction and generate protocol commands and another for interpreting the satellite telemetry [7]. An X-quad-type UHF antenna with a Yaesu G-5500 rotator system is used. Figure 1 illustrates LAPAN-A2 and LAPAN-A3 TTC satellite systems. The alternating lines in Figure 1 indicate two-way communication between the devices (request and response).

To support the TTC system of the two satellites, the National Institute of Aeronautics and Space (LAPAN) built several ground stations in Kototabang/KT (West Sumatra), Biak/BK (Papua), Parepare/PR (South Sulawesi), Rumpin/RP, Rancabungur/RB (Bogor, West Java), and Svalbard/SV (Norway). The remote ground stations are controlled by an operator from the main ground station located in Rancabungur. Table I displays the ratio of ground station utilization in support of the LAPAN-A2 and LAPAN-A3 TTC satellites from 1 October to 31 December 2019, measured in percentage. As shown in Table I, the Kototabang ground station is most commonly used to access the LAPAN-A2 satellite, while the Svalbard ground station is used for the LAPAN-A3 satellite.

A problem that often arises in the TTC process is the difference between the actual position of the ground station antenna (azimuth and elevation) and the satellite position because the TLE is not updated or the transmitter-receiver antenna (transceiver) is not calibrated towards the north pole under parked conditions (both azimuth and elevation must be in a 0-degree position).

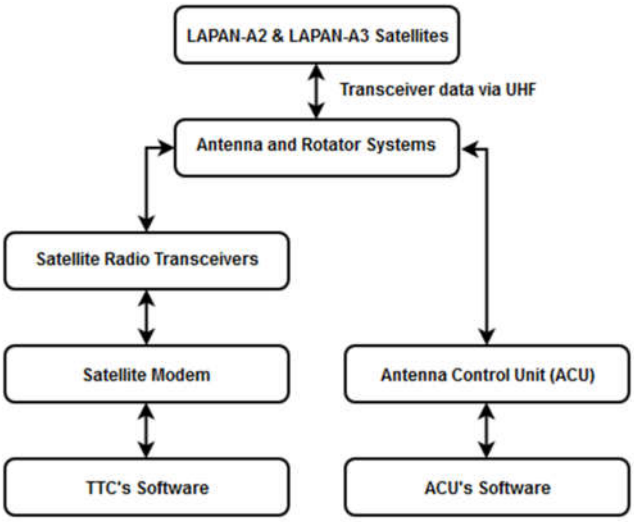

Figure 1 Satellite TTC System LAPAN-A2 and LAPAN-A3.

Table 1 Ground station utilization ratio [8].

Ground Station	LAPAN-A2						LAPAN-A3					
	October		November		December		October		November		December	
	Σ Pass	%	Σ Pass	%	Σ Pass	%	Σ Pass	%	Σ Pass	%	Σ Pass	%
BK	147	21.21	123	17.80	141	19.48	56	9.79	47	8.32	58	10.30
KT	184	26.55	227	32.85	265	36.60	62	10.84	66	11.68	67	11.90
PR	181	26.12	172	25.18	174	24.03	79	13.81	64	11.33	60	10.66
RB	181	26.12	165	24.17	144	19.89	17	2.97	22	3.89	10	1.78
RP	-	-	-	-	-	-	51	9.09	48	8.67	53	9.41
SV	-	-	-	-	-	-	306	53.50	317	56.11	315	55.95
Total	693	100	691	100	724	100	572	100	565	100	563	100

To communicate with a satellite, precise azimuth and elevation antenna positions are required facing the satellite [9]. In addition, obstacles such as mountains, hills, buildings, and telecommunications towers in the environment around the ground station can also hinder the transmission and reception of signals from the ground station to the satellite (obstructing the line of sight). Some of these problems can cause telecommands not being able to send or receive telemetry packets. The remote condition of the ground station means that the calibration process cannot be carried out quickly, apart from the time and money required.

Azimuth and elevation are important parameters for antenna calibration because they determine the direction and angle of the antenna's radiation pattern. Proper calibration of these parameters ensures that the antenna is pointing in the correct direction and at the correct angle, which is essential for accurate and reliable measurements. Calibration also helps ensure that the antenna operates within its specified parameters and that the measurement results are repeatable and traceable. In addition, calibration helps to identify any changes in the antenna's performance over time, which can be caused by factors such as wear and tear, environmental conditions, or damage [10][11]. The concepts of azimuth, elevation, ground station, and satellite are illustrated in Figure 2.

The simulation results from [12] and [13] showed that a TLE that was not updated affected the error in the azimuth position and elevation of the ground station antenna in tracking satellite positions. The research conducted in [12] only compared the use of the old TLE with the new TLE to obtain the difference between the azimuth and elevation of the ground station antenna relative to the satellite. This research aimed to develop previous research by combining TLE calculations, TTC log data, and association rule mining (ARM). The aim of this study was to measure the health of ground stations by combining TTC log data with the ARM approach. An unhealthy ground station is characterized by a high number of cases of failure in carrying out two-way communication with satellites so that calibration must be performed. The ARM results combined with the blockage profile can be used to assist in making decisions about whether the ground station needs to be calibrated to reduce maintenance costs. Table 2 presents a comparison of several studies using the rule mining approach for several scopes.

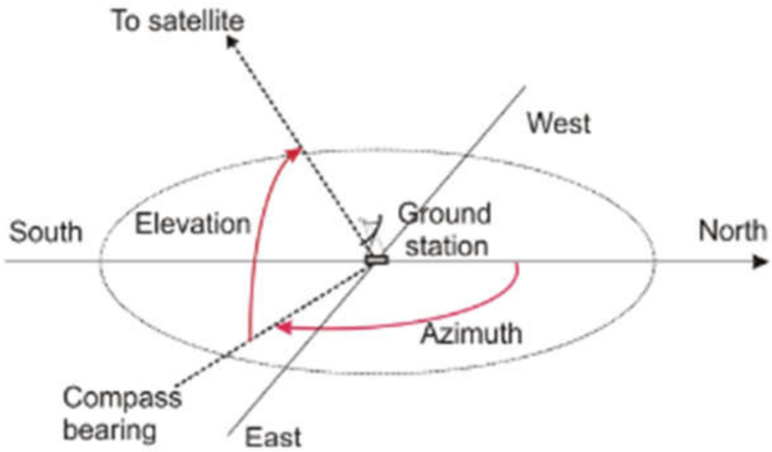

Figure 2 Azimuth, elevation, ground station, and satellite [14].

Table 2 Studies of the rule mining for several scopes.

Ref.	Methods Used	Limitation	Strength	Dataset
[15]	Modified FP-Growth algorithm and Mean Product of Probabilities (MPP) to rank rules and compute the proportion of items for one rule.	Large number of candidate rules generated and subjective choices required by domain experts.	Proposed new method called FP-GCID.	Transactional dataset generated in the first phase. Clusters generated by the DBSCAN algorithm.
[16]	Animal dynamic migration optimization (ADMO) method – ARM-PSO, ARM-AMO, ARM-MOPSO, ARM-WOA, and ARM-DE methods.	ADMO may not be effective for extracting key rules when the number of key rules is extremely small. ADMO currently only handles discrete variables and not continuous variables.	ADMO has faster mining speed and obtains more key rules	Eleven open-source datasets were used for validation (a real-world elevator case).
[17]	Modified Apriori-based algorithm for representation of alarm data in binary form.	Spurious rules are found with small minimum support and traditional ARM techniques require high computational effort.	Method allows identifying groups of components affecting reliability and availability of CTIs, and also reduces computational effort and does not find spurious rules.	Synthetic alarm database generated by a simulated CTI model.
[18]	Analysis of spatial distribution characteristics of traditional villages with application of the Apriori association rule algorithm in spatial analysis.	-	The strength of an association rule can be measured by its support and confidence. The weighted average distance analysis method is used to calculate the correlation between elements.	Spatial distribution of traditional villages in Anhui Province.
[19]	Apriori algorithm used for Association Rule Mining with bottom-up approach to identify frequent items in the database.	Lack of recommendations for mental health comorbidities and logistic regression prone to overfitting.	ARM has shown potential for knowledge discovery in healthcare data. Identified high-risk factors for suicide attempts in individuals with diabetes.	Dataset included 3,266,856 subjects with diabetes (0.2% of patients had a documented diagnosis of suicide attempts).
[20]	Predicting quantitative variables in ARM and use of Kullback-Leibler divergence to consider complete data distributions.	Classical ARM algorithms cannot handle quantitative variables. Comparing distributions with classical regression algorithms is valuable.	New approach for predicting quantitative variables in ARM which uses Kullback-Leibler divergence to consider complete data distributions.	Bank and Telco customer dataset.
[21]	Improved Apriori algorithm for equipment quality information mining and matrix-based strong association rule extraction algorithm proposed.	Single approach and incomplete consideration of contradictions and defects in the classical Apriori algorithm.	Improved Apriori algorithm for association rule mining. This aims to provide information support for equipment quality analysis.	Five experimental data sets were used in the study
[22]	Association rule mining used to analyze crossroad accidents. Factors like head-to-the-side collisions and spring season associated with accidents.	Heterogeneous nature of accident data and unequal distribution of features in each group.	The strength of the inter-dependency of factors is represented by the total lift. The relative frequency of occurrence of factor combinations is represented by the size of the balloon.	The study analyzes a crossroad accident dataset (576 transactions related to two different types of accidents).

The contribution of this research lies in the problem statement because there has been no similar research regarding how to calculate the performance of ground stations for calibration decision-making using a rule mining approach. Most of the research that used a rule-mining approach was done outside the ground station scope.

2 Research Methods

The research process included four stages: data collection, preprocessing, identification of communication status, and ARM implementation, as shown in Figure 3.

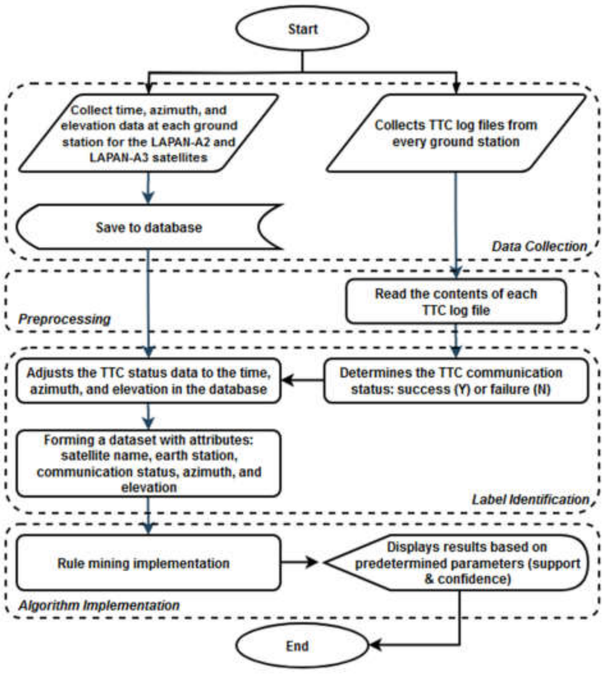

Figure 3 Research methods.

However, there were some limitations. (1) Not considering the satellite's attitude towards the ground station, which can affect the TTC quality, and the APRS payload condition on the LAPAN-A2 satellite, which can interfere with the TTC quality [23]. (2) Radio frequency interference (RFI) in the ground station environment was ignored, and it was assumed that the TLE used for satellite tracking was always up-to-date. Other studies [24]-[26] found that the RFI can significantly affect the performance of ground stations and impede satellite tracking. The presence of permanent uplink signals can cause intermodulation interference, and the intermodulation products from GSM and uplink satellite signals have the potential to interfere, particularly in urban areas [27]. (3) In addition, this study ignored the Doppler effect in the low earth orbit (LEO) satellite communication systems. The Doppler effect can significantly impact the efficiency of communication links owing to rapid changes in the Doppler frequency shift caused by the relative motion between the satellite and the user terminal [28][29]. (4) The research data were collected from 1 October 2019 to 31 December 2019 (92 days) using logfile data and tracking/pass data.

2.1 Data Collection

The data collection process involved the retrieval of LAPAN-A2 and LAPAN-A3 satellite data from the Kototabang, Parepare, and Svalbard ground stations. The data collected included the time, azimuth, and elevation of the satellite to the ground station during its passage. To automate the data collection process, Java-based software was used with the SGP4 mathematical model. The collected data were stored in the MariaDB database, with the TLE updated automatically every six hours and downloaded from the Celestrak webpage [30]. The database stores the collected data with attributes, such as satellite name, ground station, time, azimuth, and elevation. The collected data in the form of log file data contain information such as time, telecommands, telemetry, and communication status during TTC operations. Prior to the analysis, the data must be preprocessed to eliminate any data that is irrelevant to the research objectives.

2.2 Preprocess

In this study, data pre-processing involved two main steps: data selection and data cleaning. First, the selection process was conducted by choosing only log file data with a capacity of greater than 1 KB. Redundancy or duplication in the database was eliminated by cleaning both the logfile and tracking data. Finally, noisy data were removed because they do not provide useful information [31][32].

2.3 Identify Communication Status

The communication status was determined by identifying the entire content of the log file. Every two lines after the timeline containing a no-response string ‘server busy’, ‘no beep’, ‘no RF ack’, ‘time out’, and/or ‘no echo’ indicates a failed communication status. A failed communication status is marked with an N (No) label, while a successful communication status is marked with a Y (Yes) label. Figure 4 shows an example of the LAPAN-A3 satellite log file from the Svalbard ground station with failed and successful communications.

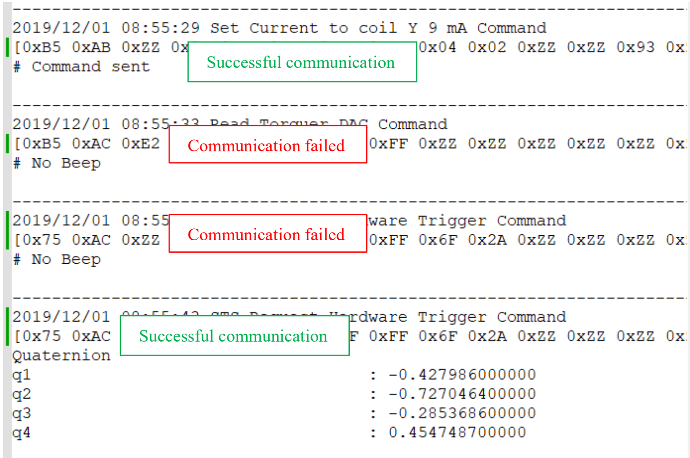

Figure 4 Example of a LAPAN-A3 satellite log file.

The log file in Figure 4 is then converted into Table 3 using four attributes: satellite name, ground station, time, and communication status. Next, the names of the satellites, ground stations, and times in Table 3 are used to determine the equivalent azimuth and elevation from the tracking database, as shown in Figure 5. The equivalent results shown in Figures 4 and 5 are presented in Table 4. The data listed in Table 4 are candidate datasets for use as the ARM inputs. The time attribute was removed from the ARM dataset, leaving only satellite name, ground station, communication status, azimuth, and elevation.

Satellite ▲ 1	GS	Datetime	Azimuth	Elevation
A3	SV	2019-12-01 08:55:29	36.405	14.067
A3	SV	2019-12-01 08:55:30	36.540	14.184
A3	SV	2019-12-01 08:55:30	36.675	14.303
A3	SV	2019-12-01 08:55:31	36.675	14.303
A3	SV	2019-12-01 08:55:31	36.813	14.422
A3	SV	2019-12-01 08:55:32	36.813	14.422
A3	SV	2019-12-01 08:55:32	36.951	14.542
A3	SV	2019-12-01 08:55:33	36.951	14.542
A3	SV	2019-12-01 08:55:33	37.091	14.663

Figure 5 Example of LAPAN-A3 satellite log file.

Table 3 Communication status logs.

Satellite Name	Ground Station	Time	Communication Status
A3	SV	2019/12/01 08:55:29	Y
A3	SV	2019/12/01 08:55:33	N
A3	SV	2019/12/01 08:55:39	N
A3	SV	2019/12/01 08:55:43	Y

Table 4 Sample candidate dataset

Satellite Name	Ground Station	Time	Communication Status	Azimuth	Elevation
A3	SV	2019/12/01 08:55:29	Y	36	14
A3	SV	2019/12/01 08:55:33	N	37	14
A3	SV	2019/12/01 08:55:39	N	37	15
A3	SV	2019/12/01 08:55:43	Y	38	16

2.4 Association Rule Mining (ARM)

ARM is a data mining method that aims to find a set of items that often appear together. The ARM operates on datasets/transactions. The support formula is given in Eq. (1) [33]:

$$Support = \frac{number\ of\ transactions\ containing\ A\ and\ B}{total\ transaksitotal\ transaction} \tag{1}$$

The support value indicates the degree to which the domination level of an item/itemset is from the entire transaction. The support value determines whether an item/itemset is feasible for finding its confidence from all existing transactions, whereas the degree of dominance indicates that items A and B are purchased together and can also be used to find the dominance level of a single item. The confidence value indicates a conditional relationship between two items (how often item B is purchased if people buy item A). The confidence formula is given as follows [33]:

$$Confidence = \frac{number\ of\ transactions\ containing\ A\ and\ B}{number\ of\ transactions\ containing\ A} \tag{2}$$

2.5 Apriori Algorithm

The association rule search algorithm is an a priori algorithm. The pseudocode for the Apriori algorithm is as follows [34]:

Algorithm 1. Apriori Algorithm

```
L1 = large 1-itemsets;
for (k = 2, Lk-1 ≠ 0; k++) start
Ck = apriori-gen(Lk-1); //new candidate
for all transactions t ∈ D start
    Ct = subset (Ck , t); // the candidates contained within t
    for all candidates c ∈ Ct do
        c.count++;
```

End
$L_k = \{ c \in C_k \mid c.\text{count} \geq minSup \}$ // all candidates
End
answer = $\cup_k L_k$;

The following is a description of the variables in the Apriori algorithm: k-itemset (an item set that has k items), Lk (a large set of k-item sets), k (represents the number of iterations), Ck (set of k-item set candidates), Ct (candidates contained in t), t ∈ D (t is in the set D), c ∈ Ct (c is in the set Ct), and c ∈ Ck (c is in the set Ck.).

2.6 FP-Growth Algorithm

The FP-Growth algorithm is an advancement of the Apriori algorithm that utilizes a prefix tree, also known as the FP-tree, to detect frequent-item sets. As referenced in [35], the FP-Growth algorithm can extract frequent-item sets directly from the FP-Tree. The FP-Tree is created in the frequent-item set search process, which involves using the FP-growth algorithm. Subsequently, association rules were generated from the obtained frequent-item sets, while satisfying the minimum support (minSupp) and minimum confidence (minConf) thresholds. The FP-Growth calculation begins by determining the minimum support and confidence values for the sales data obtained from the database. After the support and confidence values are inputted and processed, the system determines the k-item set that can be formed. The result of the k-item set, which has been processed by the system, is stored as a set of association rules [36].

3 Results And Discussion

3.1.1 Collection and Selection of Data

The selected dataset contained information on satellite name, ground station, communication status, azimuth, and elevation. It is composed of five datasets from three ground stations: Kototabang (LAPAN-A2 and LAPAN-A3), Parepare (LAPAN-A2 and LAPAN-A3), and Svalbard (LAPAN-A3). The trajectory of the LAPAN-A2 satellite is repeated every 26 to 27 days, with a 92-day logfile period covering 3.4 orbits, while the LAPAN-A3 satellite has a 16-day orbit period and a 92-day logfile representing 5.75 orbits. During the three-month period, a maximum of 14 passes per day for the LAPAN-A2 satellite when crossing the Kototabang and Parepare ground stations resulted in 1260 passes. Calculations were performed on 53.65% of the total passes (676 passes) at Kototabang, resulting in 34,442 datasets, whereas 41.67% (525 passes) were used at Parepare, resulting in 15,533 datasets. For the LAPAN-A3 satellite, a maximum of four passes per day over three months when crossing the Kototabang and Parepare ground stations results in 360 passes. At Kototabang, 54.17% of the total passes

(195 passes) were used for calculations, resulting in 9,235 datasets, whereas 54.72% (197 passes) were used at Parepare, resulting in 9,813 datasets.

Table 5 Recapitulation of communication status based on logfile data and tracking data.

Ground Station	Satellite	Start	End	Number of Files	Amount of TTC	Successful Comm.	Comm. Failed	Ratio (%)
KT	LAPAN-A2	2019-10-10 06:27:30	2019-10-31 12:49:01	184	11392	4308	7084	37,82
		2019-11-01 00:50:44	2019-11-30 13:35:48	227	11263	3770	7493	33,47
		2019-12-01 05:14:13	2019-12-31 14:58:35	265	11787	7127	4660	60,46
	LAPAN-A3	2019-10-03 02:20:35	2019-10-31 14:38:47	62	2910	849	2061	29,18
		2019-11-01 02:22:21	2019-11-30 15:11:42	66	3004	569	2435	18,94
		2019-12-01 14:45:11	2019-12-31 03:36:54	67	3321	1244	2077	37,46
PR	LAPAN-A2	2019-10-01 01:26:19	2019-10-31 07:37:34	179	5621	2683	2938	47,73
		2019-11-01 01:01:56	2019-11-30 12:04:12	172	5727	3450	2277	60,24
		2019-12-01 00:07:49	2019-12-31 15:02:52	174	4185	2691	1494	64,30
	LAPAN-A3	2019-10-01 02:03:57	2019-10-31 13:04:01	73	3138	1295	1843	41,27
		2019-11-01 00:48:53	2019-11-30 13:36:59	64	3290	1150	2140	34,95
		2019-12-01 01:21:34	2019-12-31 13:53:41	60	3385	1444	1941	42,66
SV	LAPAN-A3	2019-10-01 01:47:37	2019-10-31 15:03:05	306	18486	5572	12914	30,14
		2019-11-01 00:21:26	2019-11-30 15:33:44	317	19107	5825	13282	30,49
		2019-12-01 00:58:10	2019-12-31 14:19:25	315	19443	6659	12784	34,25

A maximum of 14 passes per day can be obtained over three months at the Svalbard ground station when the LAPAN-A3 satellite crosses, resulting in 1,260 passes. A total of 74.44% of the total passes (938 passes) were used for the calculations, resulting in 57,036 datasets. Table 5 summarizes the communication status dataset for October, November, and December 2019 (92 days) based on the log files and tracking data, with 2,531 log files and 126,059 TTC communications.

Table 6 shows an example of the resulting dataset used as the input for the ARM.

Table 6 Example of a ground station dataset.

Satellite Name	Ground Station	Elevation	Azimuth	Communication status
A3	SV	EL21	AZ45	Y
A3	SV	EL21	AZ46	N
A3	SV	EL22	AZ47	N
A3	SV	EL23	AZ48	Y
A3	SV	EL23	AZ49	Y
A3	KT	EL75	AZ44	Y
A3	KT	EL77	AZ48	Y
A3	KT	EL80	AZ63	Y
A3	KT	EL82	AZ105	Y
A3	PR	EL15	AZ241	N
A3	PR	EL15	AZ240	N
A3	PR	EL14	AZ238	Y
A3	PR	EL14	AZ238	N

3.1.2 Application of Association Rule Mining

The aim of ARM implementation is to discover association rules and large item sets based on the given values of minSup and minConf. The minimum length of the resulting rule was set to four, and it must include the communication status attribute. The minConf value of 0.9 was chosen based on previous research [37], which suggests that a confidence value of over 90% is effective for finding classification rules. Based on research conducted by [38], the minSup value of 0.01-0.02 is more accurate than that of the C4.5 algorithm. A value of 0.001 was chosen because no rules were found for the minSup value of 0.01 and minLen five that involved all dataset attributes. A value of 0.001 indicates that the dominance level of the five attributes or combinations involved was only 0.1% of the entire dataset.

A comparison of the association rules generated by the Apriori and FP-Growth algorithms is shown in Table 7. The same association rules were generated by both algorithms except for the A3-SV dataset. Although both algorithms produced the same number of rules, the process of generating association rules and the processing time differed. The association rule results showed that the number of association rules increased with a reduction in the minSup value, which confirms the results of previous studies [39][40]. For minLen 5, minSupp

0.001, and minConf 0.9, nine rule combinations for the LAPAN-A2 satellite and six combinations for the LAPAN-A3 satellite were produced at the Kototabang ground station.

Table 7 Comparison of rules generated by the Apriori and FP-Growth algorithms.

Ground Station	Satellite	*minLen*	*minSupp*	*minConf*	Number of Rules	
					Apriori	FP-Growth
KT	A2	4	1%	90%	1	1
		5	1%	90%	0	0
	A3	4	1%	90%	3	3
		5	1%	90%	0	0
PR	A2	4	1%	90%	0	0
		5	1%	90%	0	0
	A3	4	1%	90%	2	2
		5	1%	90%	0	0
SV	A3	4	1%	90%	4	4
		5	1%	90%	0	0
KT	A2	4	0.10%	90%	19	19
		5	0.10%	90%	9	9
	A3	4	0.10%	90%	46	46
		5	0.10%	90%	6	6
PR	A2	4	0.10%	90%	12	12
		5	0.10%	90%	1	1
	A3	4	0.10%	90%	41	41
		5	0.10%	90%	15	15
SV	A3	4	0.10%	90%	61	62
		5	0.10%	90%	19	20

Table 8 illustrates the three combinations with the highest support values for both the LAPAN-A2 and LAPAN-A3 satellites at Kototabang Ground Station. The first combination had 104 occurrences of communication status N, or 0.3% of the entire dataset, at an elevation of 1° and an azimuth of 256°, with a confidence level of 99%. This means that there is a 99% chance of failing to establish TTC, and only a 1% chance of succeeding with this combination.

Analysis of the data collected at the Kototabang ground station indicated that communication failure status for the LAPAN-A2 and LAPAN-A3 satellites occurred more frequently at elevations of 1°-2° and 5°-6°, respectively, with specific azimuth angles. These angles correspond to the acquisition of signals (AoS) from satellites to the west and north, respectively.

Table 8 The results of the Apriori algorithm and the FP-Growth algorithm of the Kototabang ground station with a failed communication status.

Satellite	Elevation	Azimuth	Support	Confidence	Number of Events	Communication Status
A2	1°	256°	0.00302	0.990	104	N
	2°	255°	0.00299	0.972	103	N
	2°	256°	0.00192	0.971	66	N
A3	5°	17°	0.00173	1.000	16	N
	5°	8°	0.00152	1.000	14	N
	6°	8°	0.00152	0.933	14	N

Figure 6 displays the blockage profile of the Kototabang ground station, which depicts the actual condition of obstacles in the ground station environment based on the elevation and azimuth. Several obstacles in profile blockage can potentially disrupt the TTC process [13][41]. However, the results obtained from the ARM combined with profile blockage indicated that the Kototabang ground station is suitable for calibration purposes.

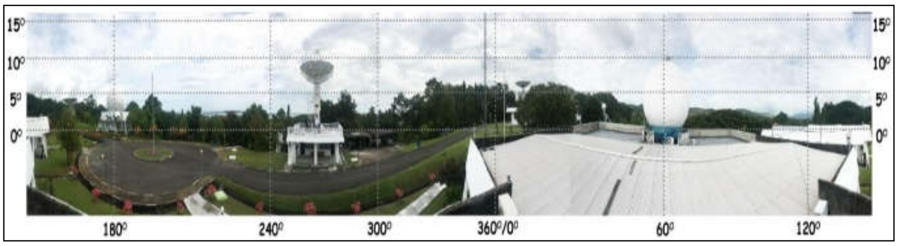

Figure 6 Kototabang ground station blockage profile.

Table 9 lists the two combinations with the highest support values for LAPAN-A2 and LAPAN-A3 at the Parepare ground station. In the first combination, there were 16 instances of successful communication, or 0.1% of the total dataset, with an elevation of 16° and azimuth of 261°. A confidence level of 94% indicated a 94% chance of successful TTC and 6% chance of failure. In the fourth combination, with an elevation of 7° and an azimuth of 5°, there were 12 instances of communication failure (0.12% of the total dataset). This combination is deemed to have a 100% confidence level, meaning that it will definitely fail to achieve the TTC. For elevations below 100, more than 12 combinations of failed communications with a 100% confidence level were experienced by both the LAPAN-A2 and LAPAN-A3 satellites. These failed combinations did not involve azimuths of ±60° and ±270°, which had obstructions, as indicated by the Parepare ground station blockage profile in Figure 7. The blockage profile and ARM results revealed that the Parepare ground station is suitable for calibration.

Table 9 Results of the Apriori and FP-Growth algorithms for the Parepare ground station.

Satellite	Elevation	Azimuth	Support	Confidence	Number of Events	Communication Status
A2	16°	261	0.00103	0.941	16	Y
	4°	209°	0.00132	1.000	13	N
A3	4°	159°	0.00132	1.000	13	N
	7°	5°	0.00122	1.000	12	N

Figure 7 Parepare ground station blockage profile.

Table 10 presents three combinations of failed communications based on the largest support value at the Svalbard ground station. The failed communication status was mostly observed at elevations ranging from 3° to 6°, with varying azimuths. In the first combination, for an elevation of 4° and an azimuth of 14°, there were 133 occurrences of communication status N, or 0.23% of the entire dataset. The first combination has a 100% confidence level, which means that the combination of elevation 4° and azimuth 14° fails to perform TTC. According to the blockage profile at the Svalbard ground station shown in Figure 8, the failed communication was caused by an obstacle in the form of a hill at an elevation of 0-20° at several azimuth points. Obstacles such as hills can obstruct the line of sight between the satellite and the transmitter-receiver antenna. The ARM results, combined with profile blockage, suggest that the Svalbard ground station should consider relocating the antenna or increasing its position by 20° from its original position.

Table 10 Results of the Apriori and FP-Growth algorithms for the Svalbard ground station.

Satellite	Elevation	Azimuth	Support	Confidence	Number of Events	Communication Status
A3	4°	14°	0.00233	1.000	133	N
	4°	15°	0.00224	1.000	128	N
	5°	19°	0.00219	1.000	125	N

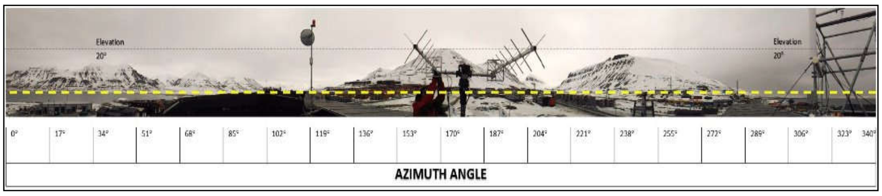

Figure 8 Svalbard ground station blockage profile.

4 Conclusion

This paper proposed a ground station performance evaluation method for making calibration decisions using a rule-mining approach. The calculation method used five main parameters: satellite name, ground station, azimuth, elevation, and communication status. The rule-mining results indicated an unhealthy ground station through a high number of failed communication events with satellites, highlighting the need for calibration. Utilizing rule mining to measure ground station health is feasible, as long as it disregards the satellite's condition towards the ground station and ongoing satellite missions. The rule mining results can aid in determining whether remote ground stations require calibration, leading to cost reduction. Additionally, the rule-mining results combined with profile blockage can determine whether changing the antenna position of the ground station is necessary.

Further research is necessary, including training data with a longer duration or adjusting minSupp and minConf values, to compare the association results with shorter training data. Exploring other data mining methods can also improve the accuracy of ground station health measurements (performance). It is also necessary to consider further research by adding new parameters, namely, radio frequency interference and the Doppler effect, to measure the performance of ground stations.

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