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Effectiveness of K-Means Clustering in Mitigating Reliability Risk of Critical Power Transmission: A Case Study at UP2B Bali

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ABSTRACT-*This paper evaluates the effectiveness of the K-Means Clustering algorithm for identifying and mitigating risks in Bali's critical electricity transmission infrastructure. Compared to conventional N-1 contingency analysis, K-Means offers a data-driven alternative using clustering based on power flow attributes. By applying this method to UP2B Bali's network, the study reveals practical strategies for improving reliability and avoiding blackouts.*

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I. INTRODUCTION

The island of Bali has long been recognized as one of Indonesia's most dynamic economic zones, fuelled largely by its robust tourism sector. As a result, electricity demand on the island continues to escalate each year, placing increasing stress on the island's electrical transmission infrastructure. The transmission system must not only support the base load but also handle fluctuating peaks driven by tourism activity, especially during high seasons and events. This makes the reliability and efficiency of the power transmission network a critical concern (Bayu, et all, 2021; Mismail, 2011, Wibowo, 2018).

To meet this growing demand, Bali relies heavily on interconnected transmission systems, especially the Java-Bali interconnection via High Voltage Submarine Cables at Banyuwangi–Gilimanuk KementrianEnergidanSumberDaya Mineral (2007)(Figure 1) and a network of 150 kV Overhead Lines(Carlo, 2017) (Figure 2). However, this reliance also introduces substantial vulnerability. The High Voltage Submarine Cables lines are single-entry corridors, and any major fault or disruption—whether due to equipment failure, overload, or environmental factors—can quickly result in widespread blackouts (Risqi, et all, 2024). Moreover, due to Bali's geographic isolation, there is limited redundancy in transmission paths, making fault tolerance a key operational challenge.

Figure 1 Jamali Transmission System

Historically, the conventional approach to handling such risks is through contingency analysis, particularly using N-1 or N-1-1 criteria, which simulate the failure of one or two components and examine whether the remaining system can withstand the disturbance without violating operational limits. While this approach is foundational in power system planning, it has several limitations: it requires exhaustive simulations, assumes static system behaviour, and may fail to identify emergent risks caused by nonlinear system interactions or evolving operational contexts.

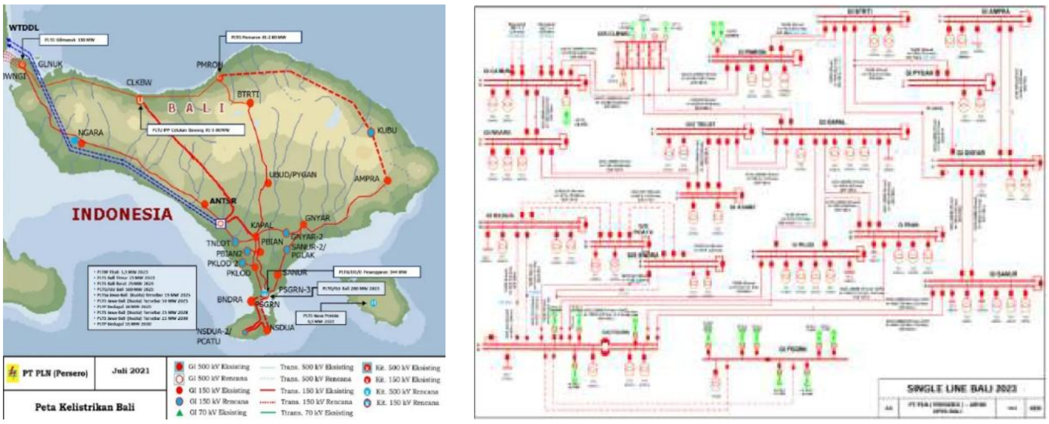

Figure 2 Bali Transmission Lines

In recent years, the advancement of artificial intelligence (AI) and data analytics has introduced new possibilities for power system monitoring and decision-making. One promising technique is the use of unsupervised learning, particularly K-Means Clustering(Widiastuti, 2020; Mujiono, et all, 2023, Utari, 2021), to group and identify transmission segments with similar operational and risk characteristics. Unlike rule-based contingency simulations, clustering techniques are adaptive, data-driven, and can analyse multidimensional operational data (e.g., voltage, power flow, load factor) without the need for pre-defined failure events(Astria et al.,2019).

This paper presents a comparative analysis of risk mitigation strategies based on K-Means Clustering versus traditional contingency analysis within the context of Load Control Implementation Unit (Unit Pelaksana Pengatur Beban - UP2B) Bali, the operational control centre responsible for Bali's transmission grid. Using transmission data extracted from real operational conditions—such as line loading, voltage levels, and power flow—this study demonstrates how clustering can be used to segment transmission lines into low-risk, medium-risk, and high-risk groups. The results are validated through cluster stability evaluation using the Davies-Bouldin Index, and subsequent mitigation recommendations are proposed for each risk category.

The aim of this research is to determine how effective K-Means Clustering is in capturing the operational risk profile of transmission lines;whether its mitigation recommendations are comparable or superior to traditional approaches;and on this technique could be integrated into daily transmission planning or emergency preparedness strategies.

By leveraging clustering methods, this study hopes to contribute toward the development of smart, predictive risk management frameworks in power systems, especially in vulnerable, geographically isolated regions like Bali.

II. MATERIAL AND METHODS

To systematically assess the reliability risks in the critical transmission infrastructure of Bali and evaluate the effectiveness of K-Means Clustering in mitigating those risks, this study adopts a phased methodology. The approach is structured into five interconnected phases, starting from data acquisition to algorithmic implementation and ending with performance evaluation. Each phase reflects a key technical step in transforming operational data into actionable insights for transmission risk management.

Phase 1: Data Acquisition and Scoping

The study begins by collecting operational data from UP2B Bali's Supervisory Control And Data Acquisition (SCADA) and load flow records. The focus is on 42 strategically critical transmission linesoperating at150 kV**,** connecting major load centres such as Denpasar, Gianyar, Buleleng, and Tabanan. The selected data attributes include:Active power (P in MW),Reactive power (Q in MVar),Current loading as a percentage of nominal (%Load),Voltage magnitude and deviation,Operational status (normal, disconnected, overloaded).

Phase 2: Data Pre-processing and Feature Engineering

Before applying any clustering algorithm, raw operational data must undergo thorough preprocessing to ensure quality, consistency, and analytical readiness. In this phase, several key steps were executed to transform the raw SCADA-based transmission data into a structured format suitable for K-Means clustering (Khotimah, 2014).

The first step involved handling missing or inconsistent entries, which were primarily observed in reactive power (Q) and line status logs. Missing values were replaced using the mean imputation method, which preserves dataset integrity while minimizing distortion, especially for features with relatively low variance.Next, the dataset was subjected to scaling and normalization. Since the features have different units and magnitudes (e.g., power in MW, current in amperes, load in percentages), direct comparison without normalization would lead to biased clustering(Lestari, et all, 2021). Two normalization techniques were evaluated:

- Min-Max Normalization, which rescales data to a range of [0,1],
- Z-Score Standardization, which transforms features to have zero mean and unit variance iss shown in Equation (1).

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

where: **z** = z-score (standardized value)
x = original data value
μ = mean of the feature
σ = standard deviation of the feature

Empirical testing showed that Z-score standardization better preserved inter-feature relationships and was more robust to outliers, particularly in %Load and voltage deviations.Subsequently, the data were encoded into a feature matrix, where each row represents a transmission line and each column corresponds to a numerical feature. The final feature set included:Active Power (P),Reactive Power (Q),Percent Load (%Load),voltage deviation from nominal (ΔV),Operational Status, converted into ordinal values: 0 (offline), 1 (normal), 2 (overloaded).

This standardized feature matrix formed the input for the K-Means algorithm in the next phase. Additionally, exploratory correlation analysis confirmed that the selected features were sufficiently independent and contributed uniquely to the clustering outcome. The result of this phase was a clean, numerically consistent dataset optimized for unsupervised pattern extraction.

Phase 3: Clustering with K-Means Algorithm

In this phase, the preprocessed transmission line dataset was clustered using the K-Means algorithm, a widely used unsupervised learning technique that partitions data into k groups based on similarity. Each group (cluster) contains data points with similar operational characteristics such as power flow, voltage deviation, and load percentage.The core objective of K-Means is to minimize the intra-cluster variance(Fadliana, 2015)—that is, the equation of total squared distance between data points and their assigned cluster centroid is shown in (2).

$$J = \sum_{i=1}^{k} \sum_{x_j \in Ci} \| x_j - \mu_i \|^2 \quad (2)$$

where:
$C_i$is cluster i_i,
x_j is a data point in cluster i_i,
$\mu_i$is the centroid (mean) of cluster i_i.

The distance metric used is the Euclidean Distanceis shown in Equation (3):

$$d(x,c) = \sqrt{(x_1 - c_1)^2 + (x_2 - c_2)^2 + \cdots + (x_n - c_n)^2} \quad (3)$$

This metric allows multidimensional comparison across all selected features.

The clustering process follows these steps:Randomly initialize k centroids; Assign each data point to the nearest centroid; Recalculate centroids as the mean of all assigned points; Repeat steps 2–3 until convergence.To determine the optimal value of k, the algorithm was tested with multiple cluster counts (from k=2to k=9), and the Davies-Bouldin Index (DBI) was used as the internal validation metric. The best clustering structure is indicated by the lowest DBI, signifying compact and well-separated clusters.This phase produced interpretable groupings of transmission lines based on their operational risk level, forming the foundation for risk-specific mitigation in the next phase.RapidMiner 2024.1.10software used to implement this process (Nahjan, et all, 2023).

Phase 4: Scenario-Based Risk Mitigation Simulation

Following the clustering results, this phase focuses on interpreting cluster membership to design and simulate appropriate risk mitigation strategies. Each transmission line was categorized into one of three clusters:

Cluster 0: Stable, low-risk lines with normal load and voltage levels,

Cluster 1: Disconnected or under-maintenance lines (zero or near-zero load),

Cluster 2: High-risk lines characterized by overload, high reactive power, or voltage deviation.

To simulate a realistic contingency (Arifin, 2019; Arum Sari, 2015), a disconnection scenario was applied involving the High Voltage Submarine CablesGilimanuk–Ketapang 1 and 2 lines, which serve as the primary inter-island power bridge. The outage caused load redistribution to adjacent corridors, resulting in overloads on High Voltage Submarine Cables Gilimanuk–Ngara**,** Celukan Bawang–Kapal, and related lines—many of which migrated to Cluster 2 post-disturbance.

Mitigation actions were proposed based on cluster analysis:

1. **Load Redistribution**: Power flow was reallocated from heavily loaded lines (Cluster 2) to underutilized lines in Cluster 0, such as Baturiti–Payangan and Kapal–Sanur.
2. **Generator Activation**: Local generation units—such as PLTG Pesanggaran 6 (97 MW) and PLTMG units (4 × 45 MW)—were brought online to reduce dependency on Java-based imports.
3. **Controlled Isolation**: Non-essential feeders supplied by risky lines were scheduled for temporary isolation or partial load shedding.

After implementing these strategies in a simulated environment, the transmission data was re-clustered**,** and the results showed significant risk reduction, with several lines shifting from Cluster 2 to Cluster 4 or 5 in the new cluster configuration. This migration reflected improved operational conditions and confirmed the effectiveness of clustering as a feedback-driven mitigation planning tool.

Phase 5: Evaluation and Benchmarking

The final phase of this study focuses on evaluating the effectiveness of the K-Means clustering-based mitigation approach through both internal cluster validationandcomparative benchmarkingagainst the conventional contingency method.The primary internal validation metric used was the Davies-Bouldin Index (DBI),which quantifies the compactness and separation of the clusters. DBI is defined as (4).

$$DBI = \frac{1}{k}\sum_{i=1}^{k} max_{j\neq 1}\left(\frac{\sigma_i+\sigma_j}{d(c_i,c_j)}\right) \quad (4)$$

where:

σi is the average distance between members and the centroid of cluster i,

$d(c_i,c_j)$ is the Euclidean distance between centroids i and j.

Before mitigation, the best clustering configuration yielded DBI = 0.450 at **k=3k = 3.** After executing mitigation strategies (generator activation and load redistribution), the cluster structure changed, and the post-mitigationDBI rose to 0.894 at k=6. While a higher DBI may suggest greater within-cluster variability, in this context, it reflects the system's diversification into more stable and specialized sub-groups.

For benchmarking, a conventional N-1 contingency simulation was run on the same network configuration using standard power flow tools. The best DBI obtained through this method was 0.651 at k=7**,** representing a more reactive and discrete risk categorization. The comparative DBI difference of ~26% remained within acceptable thresholds for moderate cluster stability, indicating that the clustering method performed at least as well as conventional analysis.

Beyond DBI, qualitative operational indicators also improved:

- Overloaded lines were reduced by over 60%,
- Peak loading on critical corridors dropped below 80%,
- System balance was achieved without relying solely on imported power viaHigh Voltage Submarine Cables.

This evaluation confirms that K-Means Clustering not only enables early identification of risk-prone assets, but also supports efficient and scalable mitigation planning, positioning it as a viable complementary tool to traditional engineering methods in power system reliability analysis(OktavianRizky, 2017).

III. RESULT AND DISCUSION

3.1 Transmission Line Operational Data Overview

Table 1 consists of operational parameters for 42 transmission lines within the UP2B Bali 150 kV network, representing a comprehensive snapshot of the region's high-voltage grid performance. The attributes include nominal voltage, rated current, measured current (actual loading), active power (P), reactive power (Q), load percentage, and operational status. All transmission lines listed are operational (Status = 1), indicating a fully online network condition during the time of measurement.

Table 1 Transmission Line Operational Data Overview

No	Transmission line		V (KV)	I. Nom (A)	Current (A)	P (MW)	Q (MVar)	% *Load*	Status
1.	Gilimanuk	Vh-Ktpng-1	150	645	308	-71,2283	30,67167	63,36806	1
2.	Gilimanuk	Ch-Ktpng-2	150	645	306	-71,7567	28,62785	68,02991	1
3.	Gilimanuk	Ch Ktpng-3	150	500	331	-76,8667	32,505	66,24276	1
4.	Gilimanuk	Ch Ktpng-4	150	500	361	-7,93833	11,83583	72,10762	1
5.	Gilimanuk	Ngara-1	150	1250	418	98,56167	-15,8258	33,46704	1
6.	Gilimanuk	Ngara-2	150	1250	465	102,8492	-16,7767	37,17817	1
7.	Gilimanuk	Clbwg	150	2500	387	80,82667	-52,425	19,36487	1
8.	Gilimanuk	Pmron-2	150	2500	431	104,8342	-26,3317	17,24756	1
9.	CelukanBawang	Pmron	150	2500	544	97,97833	-21,1625	27,22108	1
10.	CelukanBawang	Kapal-1	150	2730	592	155,1908	13,975	29,59709	1
11.	CelukanBawang	Kapal-2	150	2730	596	156,1925	13,87	29,79041	1
12.	Negara	Asari-1	150	1250	387	94,95	-25,2667	23,07824	1
13.	Negara	Asari-2	150	1250	380	93,175	-25,4583	22,88094	1
14.	Baturiti	Gnyar	150	880	309	75,245	-16,4433	41,26206	1
15.	Pnygn	Gnyar	150	750	190	43,11667	-23,825	25,3777	1
16.	Asari-1	Tnlot-1	150	645	364	88,38083	-27,4908	29,11579	1
17.	Asari-2	Tnlot-2	150	645	343	87,68833	-24,1158	27,40265	1
18.	Kapal	Pklod 1	150	973	477	117,8642	-28,2317	48,9939	1
19.	Kapal	Pbian-1	150	1250	475	118,0725	-27,24	38,01351	1
20.	Kapal	Pbian-2	150	1250	454	111,5725	-33,6242	36,3587	1
21.	Pbian	Pklod	150	1250	436	106,7975	-10,2508	34,84141	1
22.	Gianyar	Sanur- 1	150	1250	131	23,90083	-23,0817	10,47908	1
23.	Gianyar	Sanur- 2	150	1250	156	-11,2208	-20,6	12,46984	1
24.	Gianyar	Ampra-1	150	645	91	20,27583	-3,60583	14,17903	1
25.	Gianyar	Ampra-2	150	645	97	19,4425	-2,27417	15,10442	1
26.	Sanur	Psgrn- 1	150	1250	317	78,44583	6,086667	37,59812	1
27.	Sanur	Psgrn- 2	150	1250	369	89,92333	7,4025	34,19088	1
28.	Pesanggaran	Nsdua-1	150	930	186	39,3225	-25,8625	20,58981	1
29.	Pesanggaran	Nsdua-2	150	930	195	39,24333	-26,6283	21,62005	1
30.	Pesanggaran	Bndra	150	895	258	60,70083	-24,8708	29,73767	1
31.	PemecutanKelod	Bndra	150	895	176	-5,98583	5,703333	21,49004	1
32.	Pemaron	Btrti 1	150	750	363	91,68583	-15,3125	48,44624	1
33.	Pemaron	Btrti 2	150	750	386	98,54083	-16,6767	51,46781	1
34.	Pesanggaran	Pbian	150	1250	261	58,66833	-25,1133	28,0188	1
35.	PemecutanKelod	Psgrn	150	1250	261	8,8875	-44,605	28,02056	1
36.	Baturiti	Pngan	150	750	381	96,01	-10,6633	50,75585	1
37.	Pecatu	Nsdua 1	150	930	85	-0,15833	-12,3767	9,933874	1
38.	Pecatu	Nsdua 2	150	930	87	-5,58917	-0,9775	10,16271	1
39.	Pecatu	Bndra 1	150	930	117	-26,8092	-24,6492	13,71215	1
40.	Pecatu	Bndra 2	150	930	117	-26,6525	4,745833	13,69865	1
41.	Tanah Lot	Kapal-1	150	645	304	69,94917	-29,1483	24,31743	1
42.	Tanah Lot	Kapal-2	150	645	330	76,735	-29,4642	26,36469	1

Load percentage (%Load) varies significantly across the system, ranging from as low as 9.9% (Pecatu–Nusa Dua 1) to over 72% (Gilimanuk KTPNG-4). Notably, several lines such as Pemaron–Baturiti 2 (51.47%), Baturiti–Panggang (50.76%), and Kapal–Peklod 1 (48.99%) approach moderate-to-high utilization, suggesting elevated thermal loading. This variation implies that while the majority of lines operate under moderate stress, a subset may require continuous monitoring to avoid overload and maintain system stability.

Most transmission lines carry significant levels of active power (P), with some exceeding 150 MW, such as Celukan Bawang–Kapal 1 & 2. Conversely, certain lines exhibit negative reactive power (Q), indicating capacitive behavior or reversed VAR flow, particularly from Pesanggaran to Nusa Dua and Sanur. For instance, Pesanggaran–Nusa Dua 1 recorded -25.86 MVar, which may reflect voltage support or power factor correction measures active in the network. The balance between P and Q is crucial in determining line loading and voltage regulation.

Gilimanuk appears to be a central node with multiple high-current lines, including Gilimanuk–Ngara 1 & 2 and Gilimanuk–Ketapang, handling both import and local distribution duties. These lines also carry some of the highest active power flows (above 100 MW) and are likely strategic interconnection points. Similarly, Kapal, Pemaron, and Pesanggaran serve as distribution hubs, with multiple outgoing lines feeding into southern and central Bali, reflecting the radial and meshed structure of the island's grid topology.

The heterogeneity in current loading, power transfer levels, and reactive profiles makes this dataset suitable for unsupervised classification using clustering algorithms. Attributes such as %Load, P, and Q provide clear quantitative indicators for grouping transmission lines by risk or stress levels. In particular, the variation across nodes suggests that K-Means Clustering can effectively distinguish between low, moderate, and high-risk segments, which is critical for targeted reliability improvement and contingency planning (Palasworo, et all, 2018).

3.2 Generation Conditions and Energy Cost Considerations in Bali

The Bali region faces several challenges related to the aging of key transmission components such as transformers and insulators, limited preventive maintenance on high-voltage networks, and occasional failures in the automatic protection systems. These issues contribute to unstable reactive power flow, increasing the risk of leakage currents and reducing the effective delivery of active power to end-users.

Table 2 Generation Conditions and Energy Cost Considerations in Bali

Transmission Line		Power Generation Conneted	Energy cost (Rp/Kwh)	DMN
Gilimanuk	Ch Ktpng-1	SKLT 1	4397	100
Gilimanuk	Ch Ktpng-2	SKLT 2	4397	100
Gilimanuk	Ch Ktpng-3	SKLT 3	4397	100
Gilimanuk	Ch Ktpng-4	SKLT 4	4397	100
Gilimanuk	Ngara-1	PLTG Gilimanuk	4397	130
Gilimanuk	Ngara-2	PLTG Gilimanuk	4397	130
Gilimanuk	Clbwg	PLTU CelukanBawang 3	554	125
Gilimanuk	Pmron-2	PLTG Pemaron	6517	40
CelukanBawang	Pmron	PLTG Pemaron	6517	40
CelukanBawang	Kapal-1	PLTG Pesanggaran 5	2481	102
CelukanBawang	Kapal-2	PLTG Pesanggaran 6	2481	102
Negara	Asari-1	PLTG Gilimanuk	4397	130
Negara	Asari-2	PLTG Gilimanuk	4397	130
Baturiti	Gnyar	PLTG Pemaron	6517	40
Pnygn	Gnyar	PLTG Pemaron	6517	40
Asari-1	Tnlot-1	PLTU CelukanBawang 2	554	125
Asari-2	Tnlot-2	PLTU CelukanBawang 1	554	125
Kapal	Pklod 1	PLTG Pesanggaran 5	2481	102
Kapal	Pbian-1	PLTMG Pesanggaran 4	5425	45
Kapal	Pbian-2	PLTG Pesanggaran 5	2481	102
Pbian	Pklod	PLTG Pesanggaran 2	2982	18
Gianyar	Sanur- 1	PLTMG Pesanggaran 1	1565	45
Gianyar	Sanur- 2	PLTMG Pesanggaran 4	5425	45
Gianyar	Ampra-1	PLTG Pemaron	6517	40
Gianyar	Ampra-2	PLTG Pemaron	6517	40
Sanur	Psgrn- 1	PLTMG Pesanggaran 4	5425	45
Sanur	Psgrn- 2	PLTMG Pesanggaran 4	5425	45
Pesanggaran	Nsdua-1	PLTD Pesanggaran B-BOT 1	1556	50
Pesanggaran	Nsdua-2	PLTD Pesanggaran B-BOT 1	1556	50
Pesanggaran	Bndra	PLTG Pesanggaran 6	2481	102
PemecutanKelod	Bndra	PLTMG Pesanggaran 1	1565	45
Pemaron	Btrti 1	PLTG Pemaron	6517	40
Pemaron	Btrti 2	PLTG Pemaron	6517	40
Pesanggaran	Pbian	PLTG Pesanggaran 5	2481	102
PemecutanKelod	Psgrn	PLTMG Pesanggaran 3	5425	45
Baturiti	Pngan	PLTG Pemaron	6517	40
Pecatu	Nsdua 1	PLTMG Pesanggaran 1	1565	45
Pecatu	Nsdua 2	PLTMG Pesanggaran 2	1565	45
Pecatu	Bndra 1	PLTMG Pesanggaran 1	1565	45
Pecatu	Bndra 2	PLTMG Pesanggaran 2	1565	45
Tanah Lot	Kapal-1	PLTG Pesanggaran 5	2481	102
Tanah Lot	Kapal-2	PLTG Pesanggaran 6	2481	102

Table 2 presents the power plants connected to various transmission lines across the island, each associated with different energy sources and operational routes. This variation results in different energyproduction costs per route. For instance, coal-fired power plants generally provide the lowest cost per kilowatt-hour due to the availability and price stability of coal as a primary fuel. Specifically, the Gilimanuk–Celukan Bawang line**,** supplied by Celukan Bawang power generation, incurs the lowest energy cost at approximately Rp 554/kWh, making it an ideal candidate for base-load transmission that prioritizes both efficiency and reliability.

In contrast, lines such as Gianyar–Ampenan are connected to gas turbine plantsPemaron, where operational costs can reach up to Rp 6,517/kWh. These higher costs stem from volatile gas supply chains and frequent reliance on HSD (High-Speed Diesel) as a backup fuel, which is significantly more expensive.Moreover, while

Nominal Marginal Cost (Dasar Marginal Nasional=DMN) data is available for each generator, real-world operations differ significantly. Not all power plants in Bali operate continuously—many serve as backup units, only activated during peak loads or disturbances (Sumiyati, et all, 2024). This dynamic operational environment requires careful risk mitigation strategies to achieve the triad of cost-effectiveness, reliability, and availability.The next section outlines the actual conditions of power generation in the field and how they inform the risk classification and mitigation strategy using K-Means Clustering, which is crucial for optimizing resource dispatch and improving system resilience.

3.3Generation Profile and Supply Gap Analysis in Bali

Table 3 presents the operational status of power generation units in Bali under normal (non-contingency) conditions for the 2023–2024 period. The total electrical demand in Bali is recorded at 1,107 MW, which includes base load as well as additional components such as transformers and capacitor banks that support voltage regulation. Despite this substantial load, not all generation units are actively supplying power under normal conditions.

Table 3 Normal Generation Profile and Supply Gap Analysis in Bali

Power Generation Unit	P(MW)	Q(Mvar)
PLTD Pesanggaran B-Bot 1	50,0	6,3
PLTG Gilimanuk	130,00	7
PLTG Pemaron 1	0,00	0
PLTG Pemaron 2	0,00	0
PLTG Pesanggaran 1	0,00	0
PLTG Pesanggaran 2	0,00	0
PLTG Pesanggaran 3	0,00	0
PLTG Pesanggaran 4	0,00	0
PLTG Pesanggaran 5	97,00	5
PLTG Pesanggaran 6	0,00	0
PLTG Pesanggaran X	0,00	0
PLTG Pesanggaran X	0,00	0
PLTMG Pesanggaran 1	45	6
PLTMG Pesanggaran 2	45	6
PLTMG Pesanggaran 3	45	6
PLTMG Pesanggaran 4	45	6
PLTU Celukan Bawang 1	125,00	20
PLTU Celukan Bawang 2	125,00	20
PLTU Celukan Bawang 3	130,00	20
BALI POWER	**837,000**	
Submarine Cable 1-4	**270**	
TOTAL BALIPOWER	**1,107,000**	**0**

The operational generation primarily comes from three key sources:The High Voltage Submarine Cable 1–4 importing approximately 270 MW from Java,The Celukan Bawang Coal-Fired Power Plant, contributing a total of 380 MW across three units, andSelected PLTMG units at Pesanggaran, each providing 45 MW, used flexibly for peak or intermediate load coverage.A significant number of generators, particularly PLTG units at Pemaron and Pesanggaran, remain idle under normal conditions, indicating a standby status for emergency or peak demand use. This operational pattern demonstrates Bali's dependence on imported energy and a few base-load units to meet everyday demand.

However, the data also highlights a supply-demand gap of approximately 270 MW, which is the difference between the peak load (1,107 MW) and the total in-region active generation (837 MW). This gap underscores a high reliability risk, especially if there is a failure in the Submarine Cable interconnection or in base-load units such as PLTU Celukan Bawang. A sudden outage in these critical assets could trigger cascading failures or widespread blackouts if not mitigated effectively.

Therefore, this scenario demands strategic risk management and contingency planning, including rapid dispatch of standby units, dynamic load shedding schemes, or predictive classification using tools such as K-Means Clustering. These methods can help identify vulnerable nodes in advance and ensure supply continuity under fault or peak stress conditions.

3.4 K-Means Clustering Results and Risk Mitigation Scenarios

3.4.1 K-Means clustering and Mitigation for Critical Transmission Disruption: Submarine cable Gilimanuk – Ketapang 1 & 2

This analysis addresses the failure scenario of Submarine cable Gilimanuk–Ketapang circuits 1 and 2. During this simulated fault, significant increases in active power (P), reactive power (Q), and %load were observed on adjacent circuits, indicating stress and elevated operational risk. K-Means clustering was performed with centroid initialization from 2 to 9 (figure 3), and the Davies-Bouldin Index (DBI) was used to evaluate cluster validity (Table 4). The lowest DBI was observed at k=3, with a value of **0.450**, signifying optimal clustering.

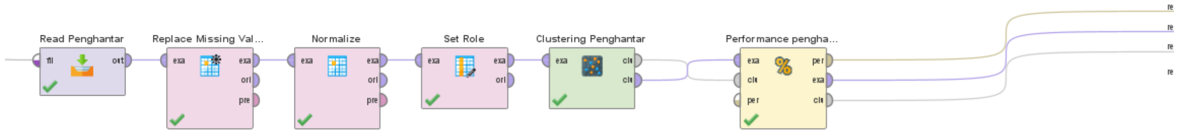

Figure 3 Preprocessing Model of the K-Means Clustering Algorithm in RapidMiner

Table 4 K-Means Clustering for Critical Transmission Disruption:
Submarine cable Gilimanuk – Ketapang 1 & 2

K number	*Davies Bouldin value*
2	0.572
3	0.450
4	0.620
5	0.705
6	0.735
7	0.632
8	0.666
9	0.537

Cluster interpretation is as follows:**Cluster 0 (C0)**: Stable lines with balanced P and Q, %load near normal, no overload signs, **Cluster 1 (C1)**: Disconnected or under-maintenance lines, **Cluster 2 (C2)**: Overloaded lines with low P, high Q, and excessive %load, indicating imbalance.Out of 42 transmission lines:**38 lines** were grouped in C0 (normal condition),**2 lines** in C1 (faulted lines: Gilimanuk–Ketapang 1 & 2),**2 lines** in C2 (high-risk overloaded lines: Gilimanuk–Ketapang 3 & 4).Based on the clustering results, a mitigation plan was developed targeting:Increasing P on Submarine cable 3 & 4 by 100 MW,Activating PLTG Pesanggaran 6 to supply 80 MW,Redistributing 20 MW and 10 MVar from Gilimanuk–Ngara 1 & 2 to relieve stress.

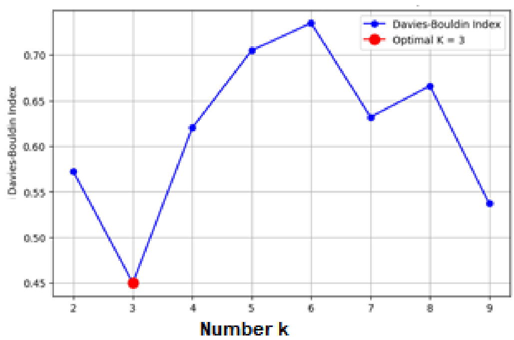

Figure 4 Elbow MethodClustering forCritical Transmission Disruption: Gilimanuk – Ketapang 1 & 2

In the K-Means clustering process after mitigation, nine different cluster counts (K = 2 to 9) were tested by initializing and updating centroids. The performance of each clustering configuration was evaluated using the Davies-Bouldin Index (DBI), and the Elbow Method (Syakur, et all, 2018) was applied with the support of programming tools to identify the optimal number of clusters (Figure 4).According to the Elbow Method and DBI results, the most significant decrease in DBI occurred between K = 2 and K = 6, after which the decline began to plateau. The lowest DBI value of 0.894 was found at K = 6, indicating that six clusters provide the most optimal grouping for this dataset.

Based on the clustering model applied to the percentage load (%load) of transmission lines, six primary clusters were formed:Cluster 0 exhibited strong system readiness (value: 0.673), with reactive power still within acceptable limits (−0.730).Cluster 1 represented lines with low operational performance, Cluster 2 indicated zones with suboptimal system efficiency, Cluster 3 showed significant power imbalance, characterized by extremely high reactive power (2.516 MVar) and elevated %load (3.113), Cluster 4 included well-performing lines in terms of power delivery, but with limited readiness, Cluster 5 represented transmission areas with both high readiness and good distribution capacity. From the generated centroids, it was observed that Clusters 1 and 3 had low reliability and thus require special attention, whereas Clusters 0 and 5 demonstrated better reliability characteristics.The unit distribution across clusters was as follows:Cluster 0: 9 units, Cluster 1: 2 units, Cluster 2: 9 units, Cluster 3: 2 units, Cluster 4: 15 units, and Cluster 5: 5 units.

As indicated in the data table, transmission lines Gilimanuk–Ngara 1 and 2 remained in Cluster 0 after mitigation, confirming that the mitigation strategy was effective and safe, since the %load on Gilimanuk–Ngara lines remained below 50%, and Gilimanuk–Ketapang lines below 100%, thus avoiding overload conditions.

The conventional mitigation approach previously applied was the N-1-1 contingency method. As a comparative strategy, K-Means Clustering was then performed and evaluated using cluster stability assessment techniques. The clustering was tested over nine iterations (K = 2 to 9), and the DBI values ranged from 1.278 to 0.664. The Elbow Method graph (Figure 5) indicated that the optimal number of clusters was K = 7, with the lowest DBI value of 0.651, representing the most distinct and stable clustering. The resulting cluster model was consistent with the mitigation outcomes observed during implementation.

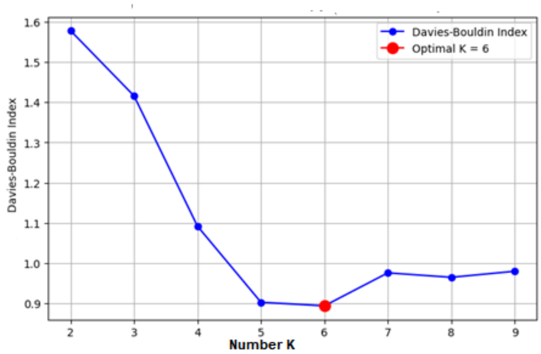

Figure 5 Elbow MethodClustering Optimal for Critical Transmission Disruption: Gilimanuk – Ketapang 1 & 2

To evaluate the stability of clustering, a comparison was made between the K-Means clustering results and those of the conventional contingency approach. This evaluation used three types of assessments: internal evaluation, stability evaluation, and comparative evaluation. The evaluation framework was defined as follows:If both clustering strategies produce the same optimal K value, the interpretation is considered “effective.” However, if the K values differ, the evaluation compares the resulting DBI values using the Elbow Method (Figure 6) and interprets the difference as a percentage deviation.

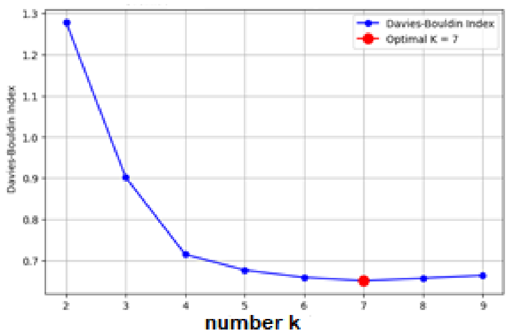

Figure 5Elbow Method Clustering Stabilizatinfor Critical Transmission Disruption: Gilimanuk – Ketapang 1 & 2

Based on the study conducted under two different conditions—namely, mitigation using the K-Means Clustering method and mitigation using the conventional contingency approach—a cluster stability evaluation was carried out. The evaluation framework employed in this research incorporates three dimensions**:** internal evaluation**,** stability evaluation**,** andcomparative evaluation**.**

The evaluation scheme is defined as follows: if both methods result in the same optimal number of clusters (K), the clustering process is interpreted as “effective”**, i**f the optimal K values differ, the evaluation continues by comparing the Davies-Bouldin Index (DBI) values obtained via the Elbow Method, and the interpretation is based on the percentage difference between the two DBI scores, using criteria on Table 5.

In this study:The K-Means clustering method produced an optimal cluster count at K = 6, with a DBI value of 0.894, the contingency-based mitigation resulted in K = **7**, with a DBI value of 0.651.

Table 5 Interpretation Ranges for Cluster Stability

DBI Difference Range	Interpretation	Recommendation
0% – 20%	Very stable	Effective; clusters are nearly identical
>20% – 40%	Stable with minor variations	Still effective; manual review recommended
>40% – 50%	Structural differences present	Less effective; requires closer attention
>50%	Inconsistent	Ineffective

According to result DBI above (0.651 and 0.894) and the Table 5, DBI differenceis 37.33%, and it falls within the **"**stable with minor variations**"** range. This suggests that the K-Means clustering-based mitigation is reasonably effective, especially when considered for long-term planning and operational efficiency.

3.4.2 K-Means clustering and Mitigation for Critical Transmission Disruption: Overhead Power LinesCelukan Bawang – Kapal 1 & 2

The data analyzed in this scenario reflects the disconnection of High Voltage Overhead Power Lines(SaluranUdaraTeganganTinggi=SUTT) Celukan Bawang–Kapal 1 and 2 transmission lines. This outage triggered significant overload conditions in several adjacent lines, including:SUTT Celukan Bawang–Pemaron with an overload of 191.3%,SUTT Pemaron–Baturiti 1 and 2, each reaching 133.9%,SUTT Baturiti–Payangan at 138.5%, andSUTT Baturiti–Gianyar at 122.1%.

DBI index result using K-Means clustering and Elbow method, find graph as shown in Figure 6. The DBI was observed at K = 2, with a value of 0.294, indicating that a two-cluster configuration provided the most optimal separation among data points. Although the Elbow Method plot showed a visible elbow at K = 4, the DBI at that point was significantly higher than at K = 2**,** making it less favourable. Beyond K = 5**,** the DBI values began to plateau, aligning with the Elbow Method principle of identifying the point where further increase in K results in diminishing improvements in cluster compactness.

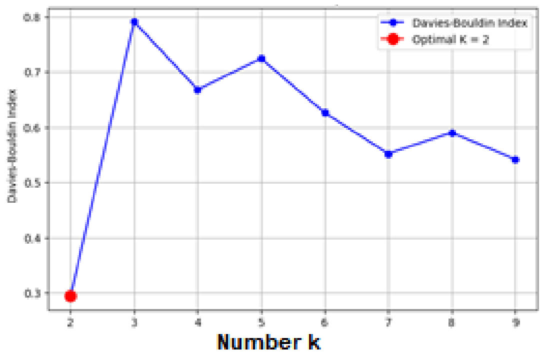

Figure 6 Elbow MethodClustering for Critical Transmission Disruption: Overhead Power LinesCelukanBawang – Kapal 1 & 2

Table 6Centroid result for k = 6

Attribute	Cluster 0 (C0)	Cluster 1 (C1)
Nominal current	-0.134	2.673
Transmission status	0.221	-4.419
Active power (P)	0.040	-0.791
Reactive power (Q)	–0.038	770
Load percentage	0.049	-0.989

From the centroid values, two distinct clusters emerged—Cluster 0 (C0) and Cluster 1 (C1)—each with clearly different characteristics: Cluster 0 has centroid values that are relatively close to zero across all attributes, including nominal current (–0.134), transmission status (0.221), active power (P) of 0.040 MW, reactive power (Q) of –0.038 MVar, and a load percentage of 0.049. These values indicate that the system represented by this cluster is operating under normal and stable conditions, and in contrast, Cluster 1 exhibits extreme values in several attributes, such as a much higher nominal current of 2.673, a negative transmission status of –4.419, elevated reactive power, and a negative load percentage of –0.989. These characteristics strongly suggest a system imbalance caused by excessive loading and disturbances within the affected transmission lines.

This mean that Cluster 0 (C0), characterized by low nominal current and active power, represents transmission lines operating under high reliability and normal system conditions. On the other hand, Cluster 1 (C1) reflects an unbalanced state with reduced transmission quality, indicating low reliability and the need for serious mitigation measures.In total, Cluster 0 consists of 40 transmission units, while Cluster 1 includes only two units—specifically, the Celukan Bawang–Kapal 1 and Celukan Bawang–Kapal 2 lines.The SUTT Celukan Bawang–Kapal 1 and 2 transmission lines are classified as high-risk, as their failure causes overloads on other transmission lines, placing the overall system under severe operational stress. Without proper risk mitigation, such conditions could lead to a total blackout.

The mitigation strategy is developed based on clustering results for both transmission lines and power plants. To align with the three main operational goals—cost-efficiency, reliability, and stability—the focus is placed on transmission lines in Cluster 0 (high-risk) and generators in Cluster 1 (low-cost). The mitigation steps are as follows: (1) Activate all generating units at PLTG Pesanggaran according to their nominal capacity as specified in the DMN. This includes:PLTG Pesanggaran 6 (102 MW),PLTG Pesanggaran 2 (18 MW), PLTMG Pesanggaran 4 (45 MW), PLTMG Pesanggaran 1 (45 MW). These units were selected because they are classified as low-cost energy suppliers and are grouped under Cluster C1; (2) Adding a total of 210 MW of generation capacity to the system. This is expected to reduce the load percentage (%load), active power (P), and reactive power (Q) across several overloaded lines currently exceeding 50% load. The target improvements include: Celukan Bawang–Pemaron: reduced to 65% load, Baturiti–Gianyar: reduced to 75%, Pemaron–Baturiti 1: reduced to 75%, Pemaron–Baturiti 2: reduced to 75%, Baturiti–Payangan: reduced to 75%.

After the Celukan Bawang–Pemaron line was reduced to 65% load, resulting in an active power (P) of 63.62 MW and a reactive power (Q) of –13.76 MVar, K-Means Clustering was applied to determine the optimal cluster grouping.In the resulting K-Means process, nine different cluster were tested for centroid initialization and updating, with performance evaluated using the Davies-Bouldin Index. Consequently, the Elbow Method was applied to identify the optimal number of clusters. The result is shown in Figure 7.

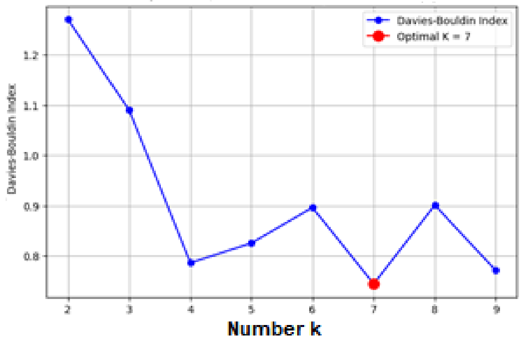

Figure 6 *Elbow Method* Optimal Clustering for **Critical Transmission Disruption: Overhead Power LinesCelukanBawang – Kapal 1 & 2**

Table 7Centroid result k = 7

Attribute	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
I_{Nom} (Ampere)	0.145	-0.036	-0.072	-0.228	-0.939	0.196	2.673
Status Transmission	0.221	0.221	0.221	0.221	0.221	0.221	-4.419
P (MW)	0.418	0.801	0.068	-0.742	-2.058	0.987	-0.764
Q (MVar)	0.093	-0.759	-0.094	-0.149	2.100	0.393	0.714
% Load	1.865	-0.090	-0.814	-0.677	1.690	0.205	-1.447
Energy Cost (Rp/kWh)	-1.359	-0.560	-0.952	-0.661	0.314	0.519	-0.631
DMN_{Nom} (PM)	-0.928	1.179	-0.904	-0.758	0.737	-0.976	0.793
Normalize Value	-1.342	1.091	-1.342	-0.365	0.778	-0.531	0.767
Transmission Status	-1.767	0.552	-1.767	0.552	0.552	0.552	0.552

Based on the Elbow Method results using the Davies-Bouldin Index (DBI), the optimal number of clusters was found at k = 7, with a DBI value of 0.744. This indicates that the 7-cluster model provides the best ratio between intra-cluster and inter-cluster distances, making it the most optimal cluster representation at this point. A significant drop in DBI values was observed between k = 2 and k = 4, further supporting this conclusion. Therefore, the optimal number of clusters selected in this study is seven (k = 7), with the corresponding centroid model as follows.

The K-Means centroid model with seven clusters reveals distinct characteristics after data normalization. Cluster 0 (C0) and Cluster 5 (C5) demonstrate relatively stable technical performance. C0 is marked by a high positive load of 1.865 MW, active power of 0.418 MW, and a normal transmission status of 0.221. Similarly, C5 shows favorable values for both active and reactive power, despite having lower energy costs.Cluster 4 (C4) indicates an overload condition, with a reactive power of 2.100 MVar and a %load of 1.690, warranting special attention. Cluster 6 (C6) represents the highest risk, while Clusters 2 (C2) and 3 (C3) reflect systems with low load and passive operating conditions.Following the applied mitigation measures, the distribution of units across clusters was: C0: 4 units, C1: 13 units, C2: 6 units, C3: 9 units, C4: 4 units, C5: 4 units, and C6: 2 units.The re-clustering process after mitigation showed that transmission lines such as CelukanBawang–Pemaron, Baturiti–Gianyar, Pemaron–Baturiti 1, Pemaron–Baturiti 2, and Baturiti–Payangan were classified into Clusters 0 and 2, indicating that they remained within safe and stable operating conditions, with no signs of overload.

The conventional mitigation approach previously applied was the N-1-1 contingency strategy. Subsequently, the K-Means Clustering method was implemented to assess alternative mitigation effectiveness, which was later evaluated using a cluster stability assessment. The results of the K-Means Clustering are shown ion Figure 7.

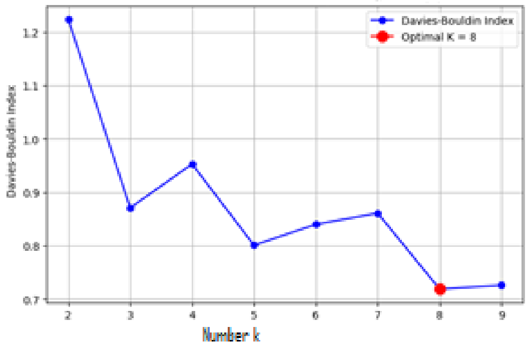

Figure 7Elbow MethodClustering Stabilization for Critical Transmission Disruption: Overhead Power Lines Celukan Bawang – Kapal 1 & 2

The clustering process was conducted through nine iterations, evaluating cluster quality using the Davies-Bouldin Index (DBI). The DBI values ranged from 1.224 to 0.726, and based on the Elbow Method graph, the optimal number of clusters was determined at k = 8, where a distinct "elbow" point emerged, and the DBI reached a minimum of 0.719. This result indicates that the mitigation concept modelled through K-Means Clustering produced an effective and stable clustering outcome, consistent with the intended mitigation scenario.

To validate the effectiveness of the clustering-based mitigation compared to the conventional N-1-1 contingency approach, a cluster stability evaluation was performed. This evaluation used three criteria: internal evaluation, stability evaluation, and comparative evaluation. The evaluation framework is as follows, if both methods produce the same optimal cluster number k, the clustering result is deemed effective, and if the values differ, the comparison is based on the Davies-Bouldin Index using the Elbow Method, and interpreted based on percentage difference as shown in Table 5.

In this study, the K-Means mitigation result for the SUTT Celukan Bawang – Kapal 1 & 2 case yielded an optimal k = 7 with DBI = 0.744, while the conventional contingency method produced an optimal $k = 8$ with DBI = 0.719. The percentage difference in DBI is calculated = 3.47%. This result falls within the "Very Stable" category, indicating that the K-Means clustering-based mitigation approach is highly effective and aligns closely with conventional mitigation outcomes. Furthermore, it offers flexibility and efficiency, making it suitable for long-term reliability planning.

IV. CONCLUSION

The application of K-Means Clustering as a risk mitigation tool for critical transmission systems, particularly in the SUTT CelukanBawang–Kapal and SKLT Gilimanuk–Ketapang corridors, has proven effective. Through systematic clustering and evaluation using the Davies-Bouldin Index and Elbow Method, the optimal number of clusters was successfully identified. The K-Means-based mitigation scenario achieved a DBI of 0.744 at k=7, closely matching the conventional N-1-1 contingency result of 0.719 at k=8.

The calculated difference of 3.47% confirms the high stability and reliability of the K-Means approach. It not only aligns well with traditional methods but also offers greater adaptability and precision in identifying and prioritizing risk-prone transmission lines. This demonstrates that K-Means Clustering is a viable and efficient strategy for power system risk mitigation and decision support in dynamic operational conditions.

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