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Development of A Supply Chain Resilience Model For Flood Disasters in PLN Customer Service Unit (ULP)

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ABSTRACT

Flooding can disrupt electricity distribution systems, particularly within the PLN Customer Service Unit (ULP) operational area, affecting both operational performance and customer service delivery. Therefore, it is important to identify potential disruption events and understand the organizational capabilities needed to improve operational resilience during flood conditions. This study develops a Supply Chain Resilience (SCRes) model for flood-related disruptions that may cause widespread outages within PLN ULPs. The research was conducted in the service area of PT PLN (Persero), Distribution Main Unit of South Sumatra, Jambi, and Bengkulu. This study used a Bayesian Network to analyse how flood-related disruption events are interconnected under uncertain conditions. The probability values generated by the model were then converted into expected values to determine disruption priorities. Afterward, the priority disruptions were mapped to SCRes capabilities to examine which capabilities contribute most to mitigating their impacts. The analysis shows that the most significant disruptions involve increasing customer complaints, delays in operation and maintenance activities, impacts on substations and distribution networks, limited mobility of technical personnel, and longer outage durations. Regarding SCRes capabilities, the most contributive elements are Learning and Improvement Capability, coordination among ULP–UP3–UID during disturbances, and Operational Flexibility. The study also identifies capability gaps for several disruptions that are not optimally mitigated by the current capabilities of PLN.

Keywords: Supply Chain Resilience, Bayesian Network, Disruption Events, SCRes Capabilities, Floods.

INTRODUCTION

The electric power distribution system constitutes a critical component in ensuring the continuous delivery of electric energy to customers. Disturbances within the distribution network not only degrade service quality but also bear consequences for corporate operational activities as well as social and economic undertakings of communities. Disruptions such as these can be classified as supply chain disruptions, which are defined as events that hinder the flow of material, information and services within a supply chain system[1],[2]. Flood events can create considerable challenges for electricity distribution operations and service continuity. Within the operational area of PT PLN (Persero) Distribution Main Unit of South Sumatra, Jambi, and Bengkulu, flooding has repeatedly affected field operations, particularly in areas where transportation access becomes limited. Technical teams often face difficulties reaching affected locations, especially when roads are inundated or damaged. As a consequence, repair activities and the delivery of required materials may take longer than under normal operating conditions. Floods can additionally affect substations and distribution networks, resulting in longer service restoration times. Beyond technical network considerations, these conditions also impair customer service by increasing the duration of outages and the volume of customer complaints. Similar conditions have also been reported in disaster-related logistics and humanitarian supply chains, where large-scale disruptions may affect operational coordination and delay recovery processes[3],[4]. Flood-related disruptions in electricity distribution systems rarely occur in isolation. A disruption in one operational activity can trigger a chain of subsequent disturbances, commonly referred to as a cascading disruption[5],[6]. For instance, flooded access roads may prevent technical teams from reaching affected locations on time. As a result, network operation and maintenance activities can be delayed, outage durations may increase, and customer complaints may rise. Therefore, flood-induced disruptions should be analyzed in an integrated manner to better understand the interdependencies among disruptions.

To address these challenges, organizations require resilience capabilities that support their ability to anticipate, respond to, and recover from disruptions under uncertain conditions. In this study, the Supply Chain Resilience (SCRes) approach is used as a relevant framework for understanding and managing operational disruptions in electricity distribution systems[2],[7]. Within this context, SCRes includes not only infrastructure and resource preparedness, but also coordination among units, information sharing, operational flexibility, as well as effective response and recovery capabilities. According to Vanany et al. [6], SCRes capabilities consist of several important dimensions, including readiness, flexibility, integration, as well as response and recovery capabilities. Several previous studies have also highlighted the importance of resilience capabilities and organizational adaptability in responding to supply chain disruptions and uncertain operational conditions[8],[9]. To examine the interrelationships among disruptions under uncertain conditions, this study utilizes a Bayesian Network approach. A Bayesian Network is a probabilistic method capable of representing cause-and-effect relationships among variables through a directed graphical structure[10]. This method is particularly suitable for supply chain disruption analysis because it can model causal relationships, disruption propagation, and system conditions even when historical data are limited[7],[11],[12]. Bayesian Networks have been adopted in many studies involving complex and uncertain systems because they can support the analysis of risk interactions, disruption propagation, and future disruption scenarios[13],[14]. Supply chain resilience has been widely discussed in manufacturing, logistics, healthcare, and humanitarian operations[3],[4],[8],[9]. At the same time, Bayesian Networks have been used in various supply chain studies to examine uncertainty and understand how disruptions affect one another[7],[11],[12],[14]. However, research focusing on flood-related disruptions in electricity distribution systems is still relatively limited, particularly at the operational level of Customer Service Units (ULPs). Studies that combine Bayesian Network analysis with SCRes capability mapping are also rarely found in the electricity distribution sector. This study seeks to address this gap by integrating both approaches to analyse flood-related disruptions and identify resilience capability priorities within PLN ULP operations.

The research was conducted at PLN Customer Service Units (ULPs) within the operational area of PT PLN (Persero) Distribution Main Unit of South Sumatra, Jambi, and Bengkulu. The proposed model combines Bayesian Network analysis and SCRes capability mapping. Bayesian Networks were used to examine the relationships among disruption events and to determine disruption priorities through expected value calculations. The resulting priorities were then assessed against SCRes capabilities to identify the capabilities that contribute most to disruption mitigation and to highlight areas that still require improvement. The overall research process consists of disruption identification and validation, Bayesian Network modelling, expected value analysis, capability mapping, and an evaluation of the relationship between disruption events and resilience capabilities. The research framework is presented in Figure 1. The research process commences with the identification and verification of disruption events, which is then followed by Bayesian Network modelling, expected value calculation, SCRes capability mapping, and culminates with the analysis of the relationship between capabilities and flood-related disruptions.

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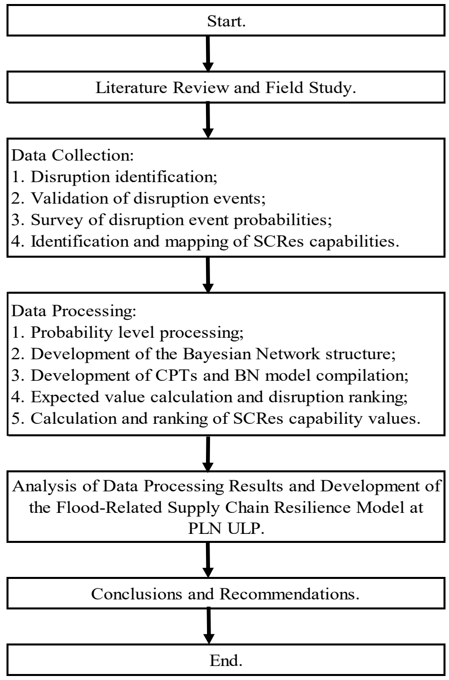

Figure 1. Research Framework

Through this approach, the study is expected to contribute to the development of Supply Chain Resilience research in the electricity sector, particularly in the context of flood-related disruptions. Furthermore, the findings of this study are expected to provide practical insights for PLN in determining organizational capability priorities that need to be strengthened in order to improve the operational resilience of electricity distribution systems against flood-induced disturbances.

METHOD

This study adopts a descriptive-quantitative approach using a case study at PT PLN (Persero) Distribution Main Unit of South Sumatra, Jambi, and Bengkulu. The research investigates flood-related disruption events within the electricity distribution system and the Supply Chain Resilience (SCRes) capabilities of PLN's Customer Service Units (Unit Layanan Pelanggan/ULP) in responding to such disruptions.

The research process began with the identification of disruption events through interviews with selected interviewees and a literature review. Structured approaches for identifying operational failures and evaluating improvement priorities have also been widely applied in industrial engineering studies[15]. Two groups of participants were involved in this study. The first group consisted of three experts who participated in the disruption identification, disruption validation, SCRes capability identification, and capability–disruption mapping processes. These experts were selected using purposive sampling based on their responsibilities and experience in electricity distribution operations, disturbance handling, and flood-related recovery activities within PLN.

Table 1. Interview Profile

No	Position	Organizational Unit	Working Experience
1	Distribution Business Planning Manager	Distribution Main Unit (UID)	24 years
2	Customer Service Unit (ULP) Manager	Customer Service Unit (ULP)	17 years
3	Distribution Operation and Maintenance Manager	Distribution Main Unit (UID)	14 years

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As shown in Table 1, the selected experts represented different managerial perspectives within PLN and possessed extensive experience ranging from 14 to 24 years in electricity distribution planning, operations, maintenance, and disturbance management. Their involvement ensured that the identified disruption events and SCRes capabilities reflected actual operational conditions within PLN Customer Service Units. The use of expert judgement in this study was limited to disruption identification, disruption validation, and capability assessment rather than probabilistic estimation. Expert-based approaches are commonly applied in Bayesian Network studies to define model structure, identify relevant variables, and validate causal relationships, particularly when comprehensive historical data are limited [11],[12],[13]. Accordingly, the expert panel in this study was utilised to support disruption identification, disruption validation, model structuring, and capability assessment activities, whereas the probabilistic assessment used in the Bayesian Network analysis was obtained from a broader group of operational personnel through a questionnaire survey. Initially, 16 potential disruption events related to flooding in electricity distribution systems were identified. The experts assessed these disruption candidates using a 5-point Likert scale to determine their relevance to PLN ULP operational conditions. Disruption events with an average score of at least 3.00 were included in the analysis. In addition, 50 valid respondents from operational units at the ULP, UP3, and UID levels participated in the study. These respondents assessed the probability of occurrence of each validated disruption event. The survey results were then classified into three probability categories: Low, Medium, and High. These probabilities were used as prior probabilities for the first-level nodes in the Bayesian Network model. Therefore, the probability values used in the Bayesian Network analysis were derived from the responses of 50 operational personnel rather than from the expert interviewees.

Table 2. Questionnaire Response Summary

Description	Number
Total questionnaires collected	56
Valid responses used for analysis	50
Invalid responses	6

As shown in Table 2, 56 questionnaires were collected and 50 valid responses were retained for analysis. The responses from these participants were used to estimate the prior probabilities of the first-level nodes in the Bayesian Network model. The probability assessments provided by the respondents were then converted into prior probabilities for the first-level disruption-event nodes. Table 3 presents the resulting prior probability values.

Table 3. Prior Probabilities of Level-1 Disruption Events

Code	Disruption Events	Value				Prior Probability		
		L	M	H	Total	P(L)	P(M)	P(H)
D1	kWh meter maintenance cannot be performed	7	26	17	50	0.140	0.520	0.340
D2	P2TL activities cannot be performed	8	21	21	50	0.160	0.420	0.420
D3	Delays in network operation and maintenance activities	4	22	24	50	0.080	0.440	0.480
D4	Limited mobility of technical teams	4	25	21	50	0.080	0.500	0.420
D5	Affected substations/distribution networks	4	24	22	50	0.080	0.480	0.440
D6	Damaged kWh meters/APP	17	19	14	50	0.340	0.380	0.280
D7	Distribution material logistics disruptions	8	27	15	50	0.160	0.540	0.300
D8	Marketing activities cannot be carried out	11	24	15	50	0.220	0.480	0.300
D9	Billing and disconnection activities are disrupted	11	20	19	50	0.220	0.400	0.380
D10	Meter recording activities are delayed	8	26	16	50	0.160	0.520	0.320
D11	Slow response from field personnel	14	25	11	50	0.280	0.500	0.220
D12	Longer outage durations	6	22	22	50	0.120	0.440	0.440
D13	Increased customer complaints	6	15	29	50	0.120	0.300	0.580

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The prior probabilities shown in Table 3 were used as input probabilities for the first-level nodes in the Bayesian Network model. These probabilities served as the basis for subsequent CPT development and Bayesian Network analysis. The Bayesian Network method was employed to analyze the probabilistic relationships among flood-related disruption events. This approach was selected because it is capable of representing cause-and-effect relationships among variables under uncertain conditions[7],[10] In addition, Bayesian Networks are well suited for systems with limited historical data and complex interdependencies among disruptions[11],[12],[13]. In this study, the Bayesian Network structure was developed in several levels. The first level contains validated disruption events represented as individual nodes. These disruption events were grouped into four Business Process (PB) aggregation nodes, namely PB1, PB2, PB3, and PB4. The aggregation nodes were then connected to the OU (Operational Unit) and PP (Customer Service) nodes, which represent operational and customer service impacts. At the final level, both nodes are linked to DI (Disruption Integration), which represents the overall disruption condition of the electricity distribution system.

The next stage involved the development of the Conditional Probability Tables (CPTs). The CPTs were used to represent the probability of each node based on the states of its parent nodes. Due to the limited availability of comprehensive historical data, the CPTs were developed using a rule-based probabilistic aggregation approach [13]. In this approach, the probability of a child node being in the High state increased as a greater number of parent nodes were in the High state. Conversely, when most parent nodes were in the Low state, the probability of the child node being in the Low state was assigned a higher value. Intermediate combinations of parent-node states were represented by probability distributions dominated by the Medium state[13]. The CPTs were initially developed in Microsoft Excel and subsequently imported into Hugin Lite to generate the probability distribution of each node. This aggregation logic was applied consistently across all intermediate nodes, including PB1–PB4, OU, PP, and DI. The resulting probability distributions for the disruption events were subsequently used to calculate the expected values. In this calculation, a weight of 1 was assigned to the Low category, 2 to the Medium category, and 3 to the High category. The equation used for the expected value calculation is presented in Equation (1).

$$EV = (P_L \times 1) + (P_M \times 2) + (P_H \times 3) \tag{1}$$

The next stage of the study involved identifying SCRes capabilities through interviews with selected interviewees and a review of relevant literature. The SCRes capabilities were categorized into four main dimensions: readiness, flexibility, integration, and response and recovery[16]. The identified capabilities were subsequently compared to the disruption events to assess their potential to mitigate or manage flood-related disruptions. The mapping process was based on "Yes" or "No" responses provided by the interviewees. A "Yes" response indicated that a capability could help mitigate or manage a disruption, while a "No" response indicated a limited contribution to the related disruption event. The final mapping score was determined by counting the number of interviewees who selected "Yes", resulting in a capability–disruption relationship score ranging from 0 to 3. The SCRes capability values were calculated by accumulating the expected value of each disruption event and multiplying it by the corresponding relationship score in the capability–disruption matrix. The equation used for this calculation is given in Equation (2).

$$SCRes\ Score_i = \sum(EV_i \times W_{ii}) \tag{2}$$

where *SCREs Score*$_i$ represents the value of the i-th SCRes capability, EV_j represents the expected value of the j-th disruption event, and W_{ij} represents the relationship value between the i-th capability and the j-th disruption event based on the interviewee assessment results. The resulting SCRes capability values were then used to determine the priority ranking of capabilities and to identify capability gaps within PLN Customer Service Units (ULPs).

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RESULT AND DISCUSSION

Validation Results of Disruption Events

Initial interviews and a literature review identified 16 potential disruption events related to flooding in electricity distribution systems. The interviewees then assessed these disruption events to determine their relevance to PLN Customer Service Unit (ULP) operations. Based on the evaluation results, 13 disruption events achieved an average score of at least 3.00 and were therefore retained for further analysis. Table 4 summarises the detailed validation results.

Table 4. Validation Results of Disruption Events

Code	Disruption Event	Interviewee 1	Interviewee 2	Interviewee 3	Mean	Decision
D1	kWh meter maintenance cannot be performed	5	3	4	4.0	Accepted
D2	P2TL activities cannot be performed	5	4	3	4.0	Accepted
D3	Delays in network operation and maintenance activities	4	4	5	4.3	Accepted
D4	Limited mobility of technical teams	4	4	5	4.3	Accepted
D5	Affected substations/distribution networks	3	5	5	4.3	Accepted
D6	Damaged kWh meters/APP	2	5	3	3.3	Accepted
D7	Distribution material logistics disruptions	4	4	4	4.0	Accepted
D8	Marketing activities cannot be carried out	4	4	4	4.0	Accepted
D9	Billing and disconnection activities are disrupted	5	4	5	4.7	Accepted
D10	Meter recording activities are delayed	4	4	4	4.0	Accepted
D11	Slow response from field personnel	3	4	3	3.3	Accepted
D12	Longer outage durations	4	4	4	4.0	Accepted
D13	Increased customer complaints	4	5	5	4.7	Accepted
D14	Internal communication system disruptions	2	3	3	2.7	Rejected
D15	ULP office services are not optimal	2	4	2	2.7	Rejected
D16	Customers cannot purchase tokens/pay bills	1	2	1	1.3	Rejected

Although internal communication system disruptions (D14) are widely recognised as an important factor in supply chain resilience, this disruption event did not meet the validation threshold in the present study. Based on the expert assessments, communication activities within PLN are generally supported by multiple communication channels and alternative coordination mechanisms, allowing communication processes to continue during flood events. Consequently, the interviewees perceived internal communication disruptions as having a relatively lower impact on operational continuity compared with other flood-related disruption events. Therefore, D14 was excluded from further analysis. The validation results show that flood-related disruptions to the electricity distribution system extend beyond technical network issues to impact operational activities and customer service delivery. The validated disruption events include disruptions to network operation and maintenance activities, the mobility of technical teams, substations and distribution networks, material distribution processes, outage duration, as well as the increase in customer complaints.

Bayesian Network Modeling Results

After the disruption events were validated, a Bayesian Network model was developed to analyze the relationships among flood-related disruptions. The model structure was arranged hierarchically, starting from the disruption events, followed by aggregation nodes, operational and customer service nodes, and finally the end node referred to as Disruption Integration. The final Bayesian Network structure is presented in Figure 2 below.

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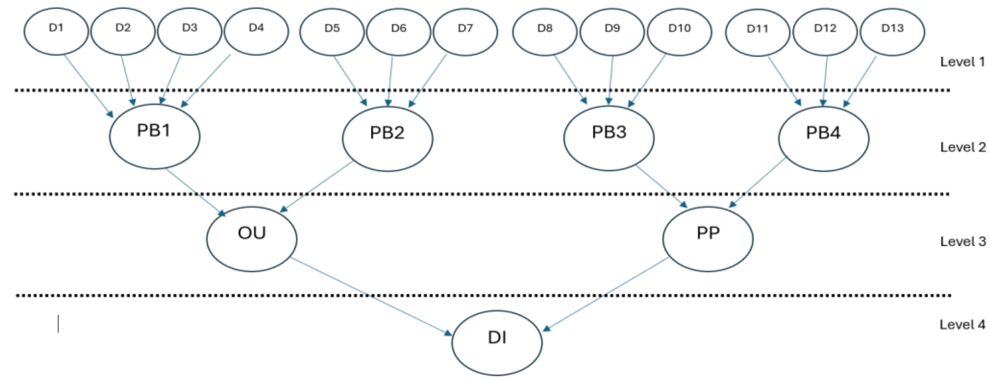

Figure 2. Bayesian Network Structure

The Bayesian Network structure shows that flood-related disruptions are interconnected and may trigger a sequence of subsequent disturbances, commonly known as cascading disruptions. For instance, limited mobility of technical teams may disrupt network operation and maintenance activities, prolong outage durations, and contribute to an increase in customer complaints. These conditions indicate that flood-related disruptions need to be analyzed in an integrated manner rather than as separate events. The Bayesian Network model was implemented using Hugin Lite software to obtain the probability values for each disruption event. The resulting probabilities were subsequently used to calculate expected values and determine the priority level of each disruption. In Tables 2 and 3, "P" represents the probability value, while "S" represents the severity level used in the expected value calculation. The results of the probability and expected value calculations are presented in Table 5 (Level 1) and Table 6 (Level 2, 3, and 4).

Table 5. Probability and Expected Value Disruption Events for Level 1

Level 1														
	D1		**D2**		**D3**		**D4**		**D5**		**D6**		**D7**	
	P	**S**	**P**	**S**	**P**	**S**	**P**	**S**	**P**	**S**	**P**	**S**	**P**	**S**
	0.140	1	0.160	1	0.080	1	0.080	1	0.080	1	0.340	1	0.160	1
	0.520	2	0.420	2	0.440	2	0.500	2	0.480	2	0.380	2	0.540	2
	0.340	3	0.420	3	0.480	3	0.420	3	0.440	3	0.280	3	0.300	3
	2.200		**2.260**		**2.400**		**2.340**		**2.360**		**1.940**		**2.140**	
Ranking	7		6		2		4		3		11		9	

Level 1												
	D8		**D9**		**D10**		**D11**		**D12**		**D13**	
	P	**S**	**P**	**S**	**P**	**S**	**P**	**S**	**P**	**S**	**P**	**S**
	0.220	1	0.220	1	0.160	1	0.280	1	0.120	1	0.120	1
	0.480	2	0.400	2	0.520	2	0.500	2	0.440	2	0.300	2
	0.300	3	0.380	3	0.320	3	0.220	3	0.440	3	0.580	3
	2.080		**2.160**		**2.160**		**1.940**		**2.320**		**2.460**	
Ranking	10		8		8		11		5		1	

Table 6. Probability and Expected Value Disruption Events for Level 2, 3, and 4

Level 2									**Level 3**				**Level 4**	
	PB1		**PB2**		**PB3**		**PB4**		**OU**		**PP**		**DI**	
	P	**S**	**P**	**S**	**P**	**S**	**P**	**S**	**P**	**S**	**P**	**S**	**P**	**S**
	0.235	1	0.268	1	0.270	1	0.260	1	0.247	1	0.263	1	0.254	1
	0.395	2	0.395	2	0.397	2	0.370	2	0.396	2	0.384	2	0.391	2
	0.370	3	0.336	3	0.333	3	0.370	3	0.356	3	0.352	3	0.355	3
	2.135		**2.068**		**2.063**		**2.109**		**2.109**		**2.089**		**2.101**	
Ranking	1		3		4		2		1		2		1	

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The highest-priority disruptions were identified as being related to increased customer complaints, network operation and maintenance disruptions, substation and distribution network damage or disturbances, restricted technical team mobility, and prolonged outage durations. The high-priority status assigned to customer complaints suggests that the effects of flooding are being strongly felt from a customer service perspective, especially when restoration efforts are prolonged and customers require clear information about ongoing disruptions. In addition, the results also show that flooding can significantly affect the operational activities of PLN Customer Service Units (ULPs). Road access disruptions and challenging field conditions can slow down the mobilization of technical teams and material distribution, leading to longer network recovery times. To provide a clearer comparison of the priority levels among disruption events, the expected value rankings are presented in Table 7.

Table 7. Ranking of Disruption Events Based on Expected Value

Rank	Code	Disruption Event	Low	Medium	High	Expected Value
1	D13	Increased customer complaints	0.180	0.180	0.640	2.460
2	D3	Delays in network operation and maintenance activities	0.200	0.200	0.600	2.400
3	D5	Affected substations/distribution networks	0.220	0.200	0.580	2.360
4	D4	Limited mobility of technical teams	0.080	0.500	0.420	2.340
5	D12	Longer outage durations	0.230	0.220	0.550	2.320
6	D2	P2TL activities cannot be performed	0.160	0.420	0.420	2.260
7	D1	kWh meter maintenance cannot be performed	0.140	0.520	0.340	2.200
8	D9	Billing and disconnection activities are disrupted	0.220	0.400	0.380	2.160
8	D10	Meter recording activities are delayed	0.160	0.520	0.320	2.160
9	D7	Distribution material logistics disruptions	0.160	0.540	0.300	2.140
10	D8	Marketing activities cannot be carried out	0.220	0.480	0.300	2.080
11	D6	Damaged kWh meters/APP	0.340	0.380	0.280	1.940
11	D11	Slow response from field personnel	0.340	0.380	0.280	1.940

SCRes Capability Mapping Results

This study also identified SCRes capabilities relevant to the operational conditions of PLN Customer Service Units (ULPs) during flood events, in addition to analysing disruption events. The capabilities were grouped into four key areas: readiness, flexibility, integration, and response and recovery. Furthermore, a relationship matrix between SCRes capabilities and disruption events was developed based on the interview results with the interviewees. The purpose of this matrix analysis was to identify which capabilities were considered influential in helping reduce or manage flood-related disruption events within the electricity distribution system. At this stage, the interviewee assessments were compiled into a capability–disruption matrix. The impact of each capability on a disruption event was assessed based on the number of interviewees who reported that the capability had an effect on the related disruption. The values in the capability–disruption matrix range from 0 to 3, with the interpretation of each value presented in Table 8 below:

Table 8. SCRes Capability–Disruption Matrix

Value	Interpretation
0	No interviewee stated that the capability influences the disruption
1	One interviewee stated that the capability influences the disruption
2	Two interviewees stated that the capability influences the disruption
3	All interviewees stated that the capability influences the disruption

In this study, the values in the capability–disruption matrix were not used as weighting factors to represent the strength of the relationships. Instead, they were used to reflect the level of agreement among interviewees regarding the influence of each capability in reducing disruption events. The results of the capability–disruption mapping are presented in Table 9.

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Table 9 SCRes Capability–Disruption Matrix

SCRes Capabilities	Disruption Events												
	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**D11**	**D12**	**D13**
F1	1	2	3	1	1	1	1	2	0	0	3	2	3
F2	1	2	2	1	3	0	0	1	0	1	2	3	2
F3	3	3	3	3	2	1	2	3	0	3	3	3	3
R1	1	2	3	1	3	3	3	1	0	0	2	3	2
R2	0	3	3	3	3	0	3	2	0	0	3	3	3
R3	1	3	3	3	2	2	3	1	0	1	3	3	3
I1	3	3	3	3	3	0	3	1	1	1	3	3	3
I2	3	3	3	3	3	1	3	2	1	2	3	3	3
I3	3	3	3	3	2	1	3	2	1	1	3	3	3
RR1	2	3	3	3	3	3	2	1	0	1	3	3	3
RR2	2	3	3	3	3	1	3	1	1	1	3	3	3
RR3	3	3	3	3	2	2	3	1	0	0	3	3	3
RR4	3	3	3	3	3	3	3	3	1	2	3	3	3

Note: F = Flexibility, R = Readiness, I = Integration, and RR = Response and Recovery capabilities

Based on the calculation results, Learning and Improvement Capability showed the highest contribution to reducing flood-related disruptions. This capability is associated with the organization's ability to conduct post-disruption evaluations, learn from previous incidents, and continuously improve disturbance-handling procedures. The results suggest that operational experience and organizational learning contribute significantly to improving the resilience of PLN Customer Service Units (ULPs) when responding to flood-related disruptions. The next highest-ranked capabilities were coordination among ULP–UP3–UID during disruptions and Operational Flexibility. Effective coordination across organizational units supports faster decision-making, resource mobilization, material distribution, and cooperation among units during disruption events. Meanwhile, Operational Flexibility highlights the importance of an organization's ability to adapt working patterns and operational priorities according to field conditions.

Ranking of SCRes Capabilities

The SCRes capability values were calculated based on the accumulated expected values of the disruption events multiplied by the relationship values in the capability–disruption matrix. The calculation results were then used to determine the priority ranking of the capabilities. The ranking of SCRes capabilities is presented in Table 10.

Table 10. Ranking of SCRes Capabilities

Rank	SCRes Capability	Dimension	Capability Score
1	Learning and improvement capability	RR4	79.80
2	Coordination among ULP–UP3–UID during disruptions	I2	73.84
3	Operational flexibility	F3	71.42
4	External collaboration	I3	69.32
5	Information sharing	I1	67.66
6	Recovery capability	RR2	67.40
7	Disaster Response Team	RR1	66.98
8	Prioritization of vital facility restoration	RR3	64.86
9	Resource readiness	R3	62.62
10	Flood Emergency Response Post	R2	58.82
11	Inventory readiness	R1	53.42
12	Workforce flexibility	F1	44.70

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13	Temporary network switching/maneuver	F2	40.94

The calculation results revealed that Learning and Improvement Capability had the greatest impact on minimising flood-related disruptions. This capability is closely related to the organization's ability to evaluate post-disruption conditions, learn from previous incidents, and improve disruption-handling procedures over time. The results also indicate that operational experience and organizational learning play an important role in strengthening the resilience of PLN Customer Service Units (ULPs) during flood-related disruptions. Other capabilities that also showed strong contributions include coordination among ULP–UP3–UID units during disruptions and Operational Flexibility. Effective coordination across organizational units supports faster decision-making, resource mobilization, material distribution, and cooperation during flood-related disruptions. Meanwhile, Operational Flexibility reflects an organization's ability to adjust working patterns and response priorities according to actual field conditions.

The results show that Learning and Improvement Capability achieved the highest score among the identified SCRes capabilities. This capability is closely related to post-disruption evaluation and continuous improvement activities that help PLN Customer Service Units strengthen their operational resilience during flood events. Unlike capabilities that mainly address specific operational disruptions, Learning and Improvement Capability contributes to a wider range of resilience activities by helping organisations capture lessons learned, refine operational procedures, improve coordination mechanisms, and strengthen preparedness for future disruptions. Flood-related disruptions often recur and may affect operational activities in different ways depending on local conditions. Therefore, the ability to evaluate previous disruption responses and implement corrective actions contributes not only to improving future response and recovery performance but also to enhancing the effectiveness of other resilience capabilities. This explains why Learning and Improvement Capability demonstrated a higher overall contribution in the capability–disruption mapping results.

This study also offers practical insights for PLN. Strengthening post-disruption evaluation and continuous improvement practices, cross-unit coordination, and operational flexibility can help improve operational resilience during flood events. These capabilities can support better preparedness, facilitate coordination and decision-making during emergency situations, and enhance the effectiveness of response and recovery activities within the electricity distribution system.

Capability Gap Analysis

The results indicate that several disruption events still cannot be effectively mitigated by the capabilities currently available within PLN Customer Service Units (ULPs). In this study, capability gaps were identified through disruption events that exhibited relatively low levels of connectivity with existing SCRes capabilities, as indicated by the dominance of relationship scores of 0 or 1 in the capability–disruption matrix. These low relationship scores suggest that the currently available capabilities are not yet able to optimally mitigate the impacts of certain disruptions. The capability–disruption mapping results show that disruptions related to damaged customer kWh meters or APP equipment (D6), disrupted billing and disconnection activities (D9), and delayed meter recording activities (D10) exhibit relatively lower levels of connectivity with existing SCRes capabilities compared with other disruption events. These disruption events show that the existing capabilities provide limited support for customer service processes and field administrative activities during flood conditions. Some disruptions remain challenging to manage because they are affected by field operational constraints, restricted accessibility, and flood-related conditions that disrupt normal service activities. As a result, these disruption events may be viewed as potential capability gaps within PLN ULPs and point to areas where additional capability development could be beneficial.

Limitation of the Study

This study has several limitations that should be considered when interpreting the results. The Bayesian Network model was developed using expert judgement and questionnaire-based probability assessments because

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comprehensive historical disruption data were not available. Although this approach is commonly used in resilience and risk assessment studies, the resulting probabilities may still reflect the experience and perspectives of the respondents involved in the study. This research focused on flood-related disruptions within PLN Customer Service Units (ULPs) located in the Distribution Main Unit of South Sumatra, Jambi, and Bengkulu. As a result, the findings should be interpreted within the context of the study area and may not fully represent operational conditions in other PLN distribution regions or under different types of natural disasters. The capability–disruption relationships were assessed through a qualitative mapping process based on expert evaluations. Therefore, the resulting capability scores represent perceived relationships between capabilities and disruption events rather than direct measurements of operational performance. In addition, both the Bayesian Network structure and the capability mapping framework were developed using several modelling assumptions and simplifications to represent actual operational conditions. Future studies may strengthen the model by incorporating more detailed historical data, involving additional experts, and exploring alternative analytical approaches.

CONCLUSION

This study developed a Supply Chain Resilience (SCRes) model to analyze flood-related disruptions at PLN Customer Service Units (ULPs) by integrating Bayesian Network analysis with SCRes capability mapping. The validation and identification process uncovered 13 disruption events associated with flood-related disturbances in the electricity distribution network. The results of the Bayesian Network modeling showed that the highest-priority disruptions were associated with increased customer complaints, disruptions to network operation and maintenance activities, disturbances affecting substations or distribution networks, limited mobility of technical teams, and longer outage durations. These findings indicate that the impact of flooding extends beyond technical network issues and also significantly affects operational activities and customer service performance.

The SCRes capability mapping results showed that Learning and Improvement Capability, coordination among ULP–UP3–UID during disruptions, and Operational Flexibility were the key capabilities that contributed most to minimising flood-related disruptions. However, the study also found that several disruption events still cannot be optimally mitigated by the existing capabilities currently available within PLN ULPs. Improving the operational resilience of PLN ULPs against flood-related disruptions should focus on enhancing capabilities such as post-disruption learning, cross-unit coordination, operational flexibility, information sharing, and response and recovery within the electricity distribution system.

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