# A Phenomenological Approach to Analysis of Maintenance Activities Impact on Interruption Duration in Electricity Distribution Systems, based on Historical Data and Expert Judgment

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## Abstract:

This study intends to quantify, model, and evaluate the impact of preventive maintenance (PM) on interruption duration (IntD) in electricity distribution systems, based on analyzing the data from the dashboard of an electricity distribution company and expert opinions. Following the data cleaning, the data are analyzed to identify the failure modes and their effects, to recognize the critical components (FMEA). Subsequently, the PM activities associated with them are investigated, to analyze the maintenance activities scheduling impact on IntD, employing expert judgment as a decision support. The data analysis reveals that the fuses and fuse holders experience the highest interruption frequencies and durations, nominating them as critical components. Then, the impact of maintenance activity (inspection time) on the IntD percentage change is analyzed, leading to the calculation of the sensitivity of IntD to maintenance activity.

The quasi-linear shape of the IntD and energy not supplied (ENS) percentage decreases versus PM inspection time, i.e. the intended sensitivities are observed, thus two linear models are developed to represent this impact, suitable for maintenance optimization problems which need linear models convexity. Moreover, two indices of $S_{PM}^{IntD}(\alpha)$ and $S_{PM}^{ENS}(\alpha)$ are introduced as maintenance KPIs representing the sensitivities, to prioritize PM actions versus their impact on IntD.

Keywords: Preventive Maintenance, Interruption Duration, Distribution Network, Expert Judgment, Sensitivity Analysis, Failure Mode and Effects Analysis (FMEA).

## 1- Introduction

Customer satisfaction with the offered services is a crucial benchmark for utility companies' competitiveness, especially in a privatized energy system. The factors contributing to customer satisfaction in the electricity distribution sector include the frequency and duration of power interruptions representing system reliability [1-2], the quality of electricity, the level of customer service, and the fairness of pricing. Among these factors, the duration and frequency of power interruptions play a particularly significant role. Consequently, electricity distribution companies devote their efforts to improving system reliability by mitigating power interruptions [2-5], utilizing solutions including distribution automation [6-7], distributed generation (DG) [8-10], demand-side management (DSM) [11-15], and proactively engaging in maintenance activities [16, 17].

Maintenance is conducted in various applications using different strategies like corrective, preventive, predictive, or reliability-centered maintenance [18]. Corrective maintenance (CM) is performed upon detection of a fault or failure. Preventive maintenance (PM) or time-based maintenance (TBM) is performed on a scheduled basis to minimize unexpected failures [19]. Predictive maintenance (PdM) or condition-based maintenance (CBM) intends to monitor the condition of the equipment and identify the need for maintenance [20-22]. The RCM methodology is a framework for developing maintenance programs that concentrate on reliability. The aim is to achieve cost effectiveness by controlling maintenance performance, which implies a trade-off between corrective and preventive maintenance [18,23,24]. PM activities are performed in two stages of inspection and repair, which both need to be scheduled in terms of prioritizing components or feeders to be inspected or repaired/serviced. Table 1 represents a cause and effect mapping of PM activities of inspection and repair as causes to the reliability measures of interruption frequency and duration as the effect.

PM activities play a crucial role in reducing the frequency and duration of interruptions. Research on modeling and prediction of interruption frequency can be categorized into harsh weather conditions [25-28] and normal conditions [29-36]. Reference [33] provides a PM planning based on a risk-based method employing the risk priority number of each equipment. The risk priority number is defined based on interruption frequency or failure rate prediction for each equipment. In [34], the planning of PM activities in the short-term horizon (monthly) has been discussed for four medium voltage feeders. This planning is scheduled based on monthly failure rate estimation, employing the Weibull probability distribution. In [35], recurrent neural networks (RNNs) are proposed to predict failure rates considering random and deteriorating failures. The implementation of this failure rate prediction model on the RCM problem indicates that accounting for random failure rates can aid in preventing financial loss and achieving satisfactory reliability levels. In [36], a maintenance framework based on asset management is presented for overhead lines, which utilizes a developed failure rate model that considers expending cost and other effecting factors. The suggested model can achieve an acceptable reliability level in an asset management-based maintenance strategy.

Despite extensive research on modeling and prediction of the frequency of interruptions [35] and identifying their root causes, there is still a lack of research on modeling and prediction of interruption duration (IntD) [3,5]. Within the research works on IntD modeling and prediction, two main approaches are involved: statistical learning and machine learning.

The IntD modeling and prediction by statistical learning is mostly focused on identifying the most appropriate probability density function by utilizing historical data. The importance of considering the probabilistic nature of IntD is emphasized by [37], as failing to consider this may result in a 40% error in the estimated expected interruption expenses. Researchers in [38] examine the statistical significance of various features without presenting a specific prediction algorithm. A proposed approach in this domain, as outlined in [39], involves utilizing a Weibull-Markov random model to analyze distribution systems reliability. This model overcomes the drawbacks of the homogeneous Markov model while permitting analytic calculations. Another study in [40] investigates beta distribution's potential for modeling reliability indices. The authors compare the beta distribution with seven alternative distributions by emphasizing the advantages of describing reliability indices through their probabilistic distributions rather than relying on single values, such as their mean. Furthermore, [41] focuses specifically on modeling the IntD of primary distribution lines, driven from eight years of data collected from a distribution company.  The investigation in [42] aims to probabilistically model IntD in distribution systems and extract a maintainability function. The authors fit the collected data from a distribution company with eleven different probability distribution functions and evaluate the results. In this study, the generalized extreme value distribution (GEVD) is suggested as the optimal choice for modeling IntD, despite the prevailing recommendation in literature to utilize Burr and Weibull distributions.

The IntD modeling and prediction by machine learning are performed under both harsh weather conditions like [43-45] or normal circumstances like [46-49]. Regarding the latter, normal circumstances, the following papers are considerable: In [46], a fuzzy-heuristic technique is developed, relying on expert knowledge to determine the relative importance of features. The proposed approach combines historical data with engineering expertise, though calibrating this combination proves challenging. Furthermore, reference [47] focuses on utilizing interruption and PM reports alongside using learning and natural language processing methods to predict IntD in real-time. Reference [48] proposes machine learning for IntD prediction utilizing historical and real-time data employing meteorological data and interruption reports. In [49], an IntD model is developed, considering PM action, where linear and nonlinear regression methods are used to model the IntD considering the effect of the repair crew locations and urban traffic, in terms of the repair crew travel time to the accident site.

PM activities consist of inspection and repair, each requiring prioritization of components or feeders to be serviced. PM inspection time plays a key role in reduction of interruption duration and frequency, thus failure costs reduction for the utility company and the customer. In [50], the authors present an optimal visual PM inspection scheduling model for distribution feeders considering it as a stochastic process, and propose a four-state Markov model. Reference [51] schedules the inspection time employing facility defect predictions. First, the effective features are extracted by a relation analysis approach utilizing the chi-square test. Subsequently, the features are employed to predict facility defection, which is utilized in inspection time scheduling. Moreover, several studies have utilized weighting parameters to prioritize feeders for inspection time, based on historical data [52,53].

In this manuscript, an essential practical and industry-striving, yet surprisingly unattended, question is raised as: how much do the prior PM activities affect the IntD time, when a failure occurs on the distribution network. Since, to the best of the authors’ knowledge, no previous study has directly assessed or analyzed the electricity distribution systems PM inspection time impact on IntD. We have devoted an effort to model and predict the IntD, using statistical and machine learning approaches [42, 48-49]. However, in [48], the limited time span of the study (one season) hindered comprehensive modeling of the IntD. In [49], although being successful in modeling the behavior of IntD versus the discrete change of the PM actions, whether being conducted or not in the previous six months, it hardly yielded satisfactory results on the analysis of the IntD behavior versus a continuous change of the PM inspection time. Whereas, finally in the research reported in this paper, a pragmatic phenomenological approach is proposed to achieve this goal, based on historical data and expert judgment, utilizing failure mode and effects analysis (FMEA), yielding satisfactory results. Therefore, the notable contributions of this article can be summarized as follows:

- Proposing a phenomenological sensitivity approach to the analysis of electricity distribution systems maintenance activities impact on IntD, based on historical data and expert judgment,
- Introducing two indices as key performance indicators (KPIs) named “$S_{PM}^{IntD}(\alpha)$” and “$S_{PM}^{ENS}(\alpha)$” to quantify and represent the sensitivity of IntD and energy not supplied (ENS) to PM inspections on each electricity distribution system feeder and in aggregate, which can be utilized as a measure to compare and prioritize PM actions on feeders,
- Conducting failure mode and effects analysis on the electricity distribution systems failures historical data, leading to exploration of fuses and fuse holders in low-voltage distribution network, as critical components,

- Discovering the quasi-linear shape of the IntD and ENS percentage decrease versus inspection time, and developing a linear model to represent the impact of the inspection time on the IntD of each electricity distribution system feeder. This linear model is useful and utilized in maintenance scheduling optimization problem models, where linear models are fruitful due to their convexity.

## 2- Methodology

This research utilizes the operation dashboard of the GTEDC as its data source. Figure 1 illustrates the proposed methodology of this paper, which is inspired by the Crisp methodology [54]. Once the data is collected and explored, the initial step involves preprocessing and cleaning the data to align with the specific problem being investigated. Following the data cleaning process, the next step entails analyzing the historical data using the FMEA tool [23]. FMEA is an effective approach for prioritizing and addressing failures by focusing on the most critical components. By identifying these critical components, the study proceeds to investigate the PM activities associated with them, employing expert judgment as a supportive tool. Consequently, the insights from the historical data exploration, FMEA, and expert judgment are incorporated to analyze the electricity distribution systems maintenance activities scheduling impact on IntD, using a phenomenological sensitivity approach, with its key components elaborated as follows.

### 2-1- Core Business Understanding

The first step of the methodology is business understanding. In this step, researchers should aim to understand the business functions and objectives. The researcher in this field should possess expertise in electricity distribution engineering.

### 2-2- Data Understanding

Available data should be collected, described, and explored. Following data collection and integration from multiple data sources, the acquired data should be described, including the format and the quantity of data. Then the data should be explored using querying, visualization, and reporting techniques considering data mining goals.

### 2-3- Preprocessing and Cleaning of Historical Data

Collected data often contain inconsistencies, such as data entry and measurement errors, missing values, and redundant data. Therefore, in this step, these inconsistencies should be identified and corrected. Subsequently, to evaluate how preventive maintenance actions impact IntD and reliability indices, any irrelevant interruptions to the research goal should be eliminated.

## 2-4- FMEA in distribution systems

In order to prioritize PM activities in the electrical distribution network, it is necessary to identify critical components [55-57]. To analyze and detect critical components, we utilize the historical data, employing the FMEA tool. Figure 2 illustrates the specific area of focus within the scope of the distribution system failures in this study.

### 2-4-1- FMEA Process

The working steps involved in this tool, as described by [23], are as follows:

1- Defining the system under analysis, including boundaries, functions, and failures,

2- Identifying failure modes,

3- Determining failure modes impacts,

4- Ranking failure modes' severity in terms of their impact, and identifying the most critical component,

5 - Identifying the root cause of the critical component failure mode,

6- Determining actions for each root cause that can reduce the severity of its failures.

In order to rank failure modes' impacts, the following formulas are considered:

$$FSh_i = \frac{\sum_{y\in Y}\sum_{f\in F}\lambda_i^{f,y}}{\sum_{i'\in COMP}\sum_{y\in Y}\sum_{f\in F}\lambda_{i'}^{f,y}} \tag{1}$$

$$DSh_i = \frac{\sum_{y\in Y}\sum_{f\in F}U_i^{f,y}}{\sum_{i'\in COMP}\sum_{y\in Y}\sum_{f\in F}U_{i'}^{f,y}} \tag{2}$$

In Eq. (1), the share of the $i^{\text{th}}$ distribution system component in the interruption frequency is calculated in the years under study. This share is calculated through dividing the frequency of interruptions caused by the $i^{\text{th}}$ component failures by the total frequency of interruptions in that feeder. Similarly, in Eq. (2), the share of $i^{\text{th}}$ distribution system component in the IntD is calculated. For employing the FMEA tool, besides the historical data, expert opinions are also required.

### 2-4-2- Expert Judgment as a Source of Phenomenological Rules

Expert opinions are used as a source of phenomenological rules in the FMEA process to provide decision support on root causes and PM activities' impact. Conducting a proper analysis using the FMEA tool requires the accurate identification of root causes for failure modes. Furthermore, expert opinions help identify related PM actions associated with the root causes. However, accurately identifying root causes is not the final step; the expertise of experts is also necessary to quantify the impact of these preventive actions on failures.

## 2-5- Sensitivity Analysis Formulation

A sensitivity analysis is conducted on the inspection time (month) impact on IntD in feeders. The analysis explores the impact of inspection time on IntD. To facilitate this investigation, a yearly time frame has been defined, spanning from the start of July to the end of June in the next year. Calculation of the IntD (MTTR index) involves applying the developed formulation expressed in equations 3 to 6, considering the following two scenarios: In scenario “NPM”, no PM action is performed, and IntD is calculated assuming no PM actions ( $IntD_{NPM}^{f,y}$ ), while in scenario “PM”, IntD is calculated considering PM actions performed on critical components in the $m^{th}$ month ( $IntD_{PM}^{f,m,y}$ ):

$$IntD_{NPM}^{f,y} = \frac{U_{NPM}^{f,y}}{\lambda_{Tot}^{f,y}} \tag{3}$$

$$U_{Mean,Aff}^{f,m,y} = \frac{U_{Aff}^{f,m,y}}{\lambda_{Aff}^{f,m,y}} \tag{4}$$

$$IntD_{PM}^{f,m,y} = \frac{c \times \lambda_{Aff}^{f,m,y} \times U_{Mean,PM} + (1-c) \times \lambda_{Aff}^{f,m,y} \times U_{Mean,Aff}^{f,m,y} + U_{UAff}^{f,m,y}}{\lambda_{Aff}^{f,m,y} + \lambda_{UAff}^{f,m,y}} \tag{5}$$

$$\%\Delta IntD_{PM}^{f,m,y} = \frac{IntD_{NPM}^{f,y} - IntD_{PM}^{f,m,y}}{IntD_{NPM}^{f,y}} \tag{6}$$

In Eq. (3), IntD is calculated considering no PM actions ( $IntD_{NPM}^{f,y}$ ) for feeder $f$ and year $y$. Eq. (4) produces the average duration of interruptions influenced by PM actions in the $m^{th}$ month until the end of that year ( $U_{Mean,Aff}^{f,m,y}$ ). The coefficients $c$ and $U_{Mean,PM}$ are derived from expert judgments and serve specific purposes. The value of coefficient $c$ reflects the level of uncertainty involved in identifying defects in critical components during PM activities. It's represented as a numerical value ranging from zero to one, indicating the average percentage of defect detection during PM inspections. On the other hand, the parameter $U_{Mean,PM}$ refers to the average IntD that would occur in the network if a defective critical component is detected and needs to be repaired or replaced. IntD calculation is performed by Eq. (5), considering introduced coefficients and PM inspection time for each feeder and each year. Lastly, the percentage decrease in IntD with the implementation of PM actions in the $m^{th}$ month ( $\%\Delta IntD_{PM}^{f,m,y}$ ) can be calculated using Eq. (6).

Regarding the calculation of the percentage decrease in ENS resulting from the implementation of PM actions on the critical component in the $m^{th}$ month ( $\%\Delta ENS_{PM}^{f,m,y}$ ), the following formulas can be utilized:

$$ENS_{PM}^{f,y,j} = \frac{U_{Mean,PM}}{U_{NPM}^{f,y,j}} \times ENS_{NPM}^{f,y,j} \tag{7}$$

$$\%\Delta ENS_{PM}^{f,m,y} = \frac{ENS_{NPM}^{f,y} - ENS_{PM}^{f,m,y}}{ENS_{NPM}^{f,y}} \tag{8}$$

Eq. (7) has been employed to determine the amount of ENS when a defective critical component is detected and replaced during an inspection. The ENS in $j^{th}$ interruption ( $ENS_{NPM}^{f,y,j}$ ) is multiplied by the coefficient $\frac{U_{Mean,PM}}{U_{NPM}^{f,y,j}}$ to calculate the ENS of replacing the defective critical component ( $ENS_{PM}^{f,y,j}$ ), considering that the ENS is directly related to the IntD. After calculating $ENS_{PM}^{f,y,j}$ for all interruptions of the feeder, the next step involves applying the uncertainty coefficient $c$ and calculating the ENS that would occur if inspection and repairs were carried out in the $m^{th}$ month ( $ENS_{PM}^{f.m.y}$ ).

Assuming two scenarios for each month results in two outputs that can be employed in interpolation. In the first scenario, no PM action is performed, and in the second scenario, the performance of PM activities is considered with 100% certainty in detecting defective components. By linear interpolation between these two points, considering the value of $c$, the amount of ENS in the event of performing PM actions in $m^{th}$ month can be determined. Consequently, the percentage decrease in ENS with the implementation of PM actions in the $m^{th}$ month can be calculated using Eq. (8).

## 3- Implementation and Results

The proposed methodology is implemented to the operational data of GTEDC company in this section. It begins by describing the distribution system as the core business understanding step in methodology, followed by distribution system failures data description as the data understanding step. Afterward, the data preprocessing is described, followed by presenting the results of applying the FMEA tool to the preprocessed data. Furthermore, this section offers the knowledge derived from expert judgment, which is utilized in the sensitivity analysis.

### 3-1- The Distribution System Under Study

The workflow in the operation practice of the GTEDC PM team is as follows:

1) Annually, an independent team conducts load profiling for each feeder in July. In this study, the Gregorian solar calendar months are approximated with their relevant Jalali solar months.
2) The load profiling results are saved on the company's operational dashboard, which can be accessed by the PM team.
3) The PM team devotes all its effort to inspecting all feeders, but due to the huge network and limited availability of resources, the inspections are prioritized using the historical data and the registered load profiles.
4) These visits are scheduled from August to June of the next year, considering the workload of the team.

Considering these steps, sensitivity analysis of electricity distribution systems maintenance activities impact on IntD based on historical data and expert judgment is defined as the research goal.

## 3-2- Distribution System Failures Data

The operational dashboard of the GTEDC provides a wealth of information for network operators. In this dashboard, the interruption log reports are utilized as the primary data source for this study. These reports meticulously document network interruptions, including interruption initiation time, repair crews' arrival time on site, restoration time, dates, interruption cause, outage groups, IntD, and ENS. PM team utilizes these reports to schedule their activities.

## 3-3- Preprocessing and Cleaning

In the first step, inconsistent data are dropped from the data set, including records with missing values and data entry errors. Secondly, in investigating PM activities concerning IntD and reliability indices, random and unrelated interruptions should be dropped. Accurate analysis of corresponding index changes can only be achieved when statistically irrelevant failure records are removed from the data.

To achieve this, in the recorded columns or different attributes, one should search for random and unrelated factors to PM actions. For instance, in the interruption group column, which records the distribution network section where interruption has occurred, cases such as street lighting and customer connections are considered unrelated data. Other columns, such as interruption cause, contain similar records like equipment theft, digging, external object collision, fire, and animal crossings. The mentioned considerations result from expert consultants on the recorded data over three years. After the pre-processing, 627 interruption records remained for further analysis. In this research, the distribution posts are not limited to a specific type and most of the posts are ground type.

## 3-4- FMEA of Distribution Systems

In this section, the result of the implementation of the FMEA tool on preprocessed data is presented in two sections. The first section illustrates the historical data analysis results, and the second indicates extracted experimental rules from expert judgment.

### 3-4-1- FMEA Process

Figure 3 shows the contribution of each network component to the interruptions frequency that occurred over a three-year period in four specific feeders. To enhance clarity and facilitate understanding, components that resulted in fewer than four interruptions during this period have been categorized as other. The analysis reveals that a significant majority, precisely over 63%, of the failures can be attributed to fuse and fuse holder issues in the first place, while LV cables are in second place with 8%.

Furthermore, Figure 4 displays the temporal distribution of failed components throughout the same three-year period in the investigated feeders. Similarly, components leading to less than two hours of interruption within the three-year timeframe have been categorized as other. Notably, over 57% of the total IntD during these three years can be traced back to the fuses and fuse holders in the first place, while LV cables are in the second place with 9%.

Consequently, the data analysis revealed that the failure incidents attributed to fuse and fuse holders significantly contribute to the frequency and duration of power interruptions by 63% and 57% contribution rates, respectively. Therefore, the fuse and fuse holder are designated as critical components within the electricity distribution system in this research, thus are concentrated in the analysis.

The following section seeks expert opinions to investigate related PM actions and their consequential effects on critical component interruptions.

### 3-4-2- Extracting Experimental Rules from Expert Judgment

This section presents the results from consulting with experts in order to extract rules from expert judgment. The rules and values are obtained by combining the knowledge of a group of experienced experts. This collective approach results in a comprehensive outlook, which helps in making informed decisions. This method also helps in mitigating individual biases and incorporating different perspectives.

To prevent failures in critical components, the electricity distribution system PM team utilizes thermography cameras. These cameras capture thermal images of objects and surfaces employing thermal imaging technology. These images depict temperature distribution on the target surface and, through colorization, highlight points with higher temperatures in brighter colors.

The proficient maintenance team can effectively identify defects by analyzing the obtained thermal images. They promptly solve the issues, thus preventing potential failures. This proactive approach significantly reduces downtime for customers. In the event of a failure, the restoration process involves customer notification, dispatching the maintenance team, diagnosing the fault, performing repairs, and restoring functionality. However, by identifying and addressing these issues proactively, the process is limited to power interruption, repair actions, and power restoration.

According to expert opinion, conducting inspections prior to failures can prevent an average of 80% of interruptions occurring in the critical components until the end of that year. The remaining 20% can be attributed to the inherent uncertainty in detecting defects.

Taking into account the maintenance team's performance and expert opinion, the team prioritizes the inspection of feeders on a monthly basis. By doing so, they anticipate preventing 80% of related interruptions until the next year for that feeder, resulting in a mere 5-minute downtime for each of these incidents as perceived by customers. Furthermore, by leveraging historical data analysis and expert insights, a sensitivity analysis is conducted to assess the impact of PM inspection time on reliability indices.

### 3-5- Sensitivity Analysis Results

A hypothetical scenario is considered where PM inspections are performed on each feeder during the $m^{\text{th}}$ month. Subsequently, using equations 3 to 8, the percentage decrease in IntD and ENS is calculated. For each feeder and every year under study, this process is applied, covering the period from August to June. Figures 5 and 6 provide a representative example of the results for feeder A over a three-year period, as there is limited space to plot all output values for all four feeders. In Figure 5, the horizontal axis represents the month of PM inspection, and the vertical axis represents the percentage decrease in IntD. For example, if PM actions were performed in August for feeder A in the third year, it could decrease IntD by approximately 35 percent. In Figure 6, the horizontal axis represents the month of PM inspection, and the vertical axis represents the percentage decrease in ENS. As an example, this figure shows if PM actions were performed in August for feeder A in the third year, it could decrease ENS by approximately 12 percent.

## 4- Discussions

### 4-1- Meta-analysis

The interesting feature that is visually apparent in Figures 5 and 6 is the quasi-linear shape of the IntD and ENS percentage decrease curves. This quasi-linear shape might be useful and utilized in maintenance scheduling optimization problem models, where linear models are fruitful due to their convexity. Consequently, we fit a linear model to the acquired results of feeder A, employing linear regression, which is visually depicted by the dashed line in figures 5 and 6 and represented for feeders A and B in Eq.s (9) to (12):

$$\%\Delta IntD_{PM}^{A} = -0.023 \cdot m + 0.2978 \tag{9}$$

$$\%\Delta ENS_{PM}^{A} = -0.0042 \cdot m + 0.0586 \tag{10}$$

$$\%\Delta IntD_{PM}^{B} = -0.027 \cdot m + 0.3520 \tag{11}$$

$$\%\Delta ENS_{PM}^{B} = -0.0221 \cdot m + 0.2630 \tag{12}$$

where the percentage decrease in IntD and ENS is represented versus the month of performing PM actions on critical components.

This analysis is also conducted over a three-year period for the feeders B, C, D, which can be observed in figures 7 and 8, expressing the decreasing trend of delayed PM inspection time on IntD and ENS reduction. As observed in Figure 7, the average sensitivity of IntD to PM inspection time in feeder B is higher compared to A, B, and C, expressed as a higher slope of its relevant line. The reason might be that feeder B has the highest percentage share of critical components in the interruption frequency (71.67%) and duration (64.37%) among the feeders.

Moreover, it is noticeable that the average sensitivity of IntD to PM inspection time in feeder A is higher than in feeder D, while the sensitivity of ENS to PM inspection time in feeder D is higher than in feeder A. We may justify this observation as follows: Available statistics indicate that although, on average, one-thirteenth of the feeder failures occur at the medium voltage level in this network, each failure at the medium voltage level results in over 30 times the ENS compared to that of a failure at the low voltage level. Therefore, the lower percentage of medium voltage failures in feeder D compared to feeder A, results in a greater impact in reducing the percentage of ENS in that feeder. In Figure 9 the relation between the percentage decrease of ENS and the percentage decrease of IntD is depicted for each year in feeder A. As anticipated, this relation also follows the quasi-linear shape with a slope of less than one, which means a greater percentage decrease in IntD than ENS would be expected.

Investigation of the average and standard deviation of the percentage decrease in IntD and ENS versus inspection time yields valuable empirical findings for distribution systems maintenance practice regarding the nature of the feeders. Figures 10 and 11 show the average and standard deviation of IntD and ENS for individual feeders, as well as the four feeders aggregated values, serving as an index for each feeder and for the aggregated network of the feeders, represented as [58]:

$$S_{PM}^{IntD}\left(\alpha\right): PM\ \ to\ IntD\ Effectiveness\ Factor = \left[ Average_{S_{PM}^{IntD}} \pm t_{\frac{\alpha}{2}} \frac{SD_{S_{PM}^{IntD}}}{\sqrt{n}} \right] \tag{13}$$

$$S_{PM}^{ENS}\left(\alpha\right): PM\ \ to\ ENS\ Effectiveness\ Factor = \left[ Average_{S_{PM}^{ENS}} \pm t_{\frac{\alpha}{2}} \frac{SD_{S_{PM}^{ENS}}}{\sqrt{n}} \right] \tag{14}$$

Eq.s (13) and (14) provide a $\left(1-\alpha\right)\cdot 100\%$ confidence interval for the average sensitivity of IntD and ENS to PM actions, respectively. These indices can be utilized as a measure to compare and prioritize PM actions on feeders. For instance, in Eq. (13) for the case of thermal imaging of fuses and fuse holders as the proper maintenance action, the corresponding index values are [0.137±0.032] and [0.16±0.053] considering $\alpha$=0.05 significance level for feeders A and B, respectively, which means that we are 95% confident that the average percentage decrease in IntD is between 10.5% and 16.9% for feeder A, and between 10.7% and 21.3% for feeder B.

In Eq. (14), the corresponding index values are [0.029±0.008] and [0.096±0.06] for feeders A and B, respectively, which means that we are 95% confident that the average percentage decrease in ENS is between 2.1% and 3.7% for feeder A, and between 9% and 10.2% for feeder B. The reason for the lower percentage decrease in ENS compared to the IntD, as mentioned earlier, may be justified as the presence of a few medium voltage interruptions with a short duration but high ENS in the electricity distribution system.

## 4-2- Technical Justification for the Critical Components

The primary underlying factors contributing to critical component failures can be attributed to two key events: phase imbalance and loose connections. Phase imbalance refers to issues that lead to an unequal distribution of electrical loads among the three phases of the power system. This phenomenon can be attributed to factors such as uneven load distribution, faulty electrical equipment, improper single-phase load distribution, and voltage fluctuations. In a distribution network, the operator achieves balance by dividing the service cable among the three phases using estimations. However, due to pre-existing disparities in consumer consumption and inaccuracies in this division, one phase may bear a greater burden than the others, resulting in excessive current flow and, over time, causing the fuse to burn out.

Loose connections are another significant factor contributing to the occurrence of interruptions. The root of this issue can be attributed to factors such as improper and loose equipment installation, lack of cleanliness and maintenance of connection surfaces, equipment defects or poor quality, and the presence of mechanical and thermal stresses.

Mechanical stresses, such as vehicle collisions with panels or vibrations and oscillations resulting from construction activities in the vicinity or earthquakes, can cause deformation and looseness in the connections. Thermal stresses can change the size and shape of electrical components. These alterations can stimulate and weaken the connections, resulting in loose connections. The presence of loose connections generates sparks within the panel. The heat generated by these sparks causes deformation and burning of the fuse holder, leading to interruptions. Accordingly, defects in the critical components can be solved by replacement, which can be performed at the time of PM inspection and does not need to be scheduled for other expert teams.

## 5- Conclusions

This paper aimed to assess the sensitivity of IntD to PM actions in electricity distribution system. Accordingly, data collection and analysis were conducted with the help of expert opinion utilizing the operational dashboard of the GTEDC. The data analysis revealed that the fuses and fuse holders exhibit the highest frequency and duration of interruptions among network components, leading to their selection as critical components. Following the study of related preventive actions, the effect of these actions was evaluated based on expert opinions. Subsequently, the quasi-linear shape of the IntD and ENS percentage decrease versus inspection time is discovered, and a linear model is developed to represent the impact of the inspection time on the interruption duration of each electricity distribution system feeder. This linear model might be useful and utilized in maintenance scheduling optimization problem models, where linear models are fruitful due to their convexity.

In addition, two indices were introduced as key performance indicators (KPIs) named " $S_{PM}^{IntD}(\alpha)$ " and " $S_{PM}^{ENS}(\alpha)$ " to quantify and represent the sensitivity of IntD and ENS to PM inspections on each electricity distribution system feeder and in the aggregate, which can be utilized as a measure to compare and prioritize PM actions on feeders.

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## Biographies

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Table 1: Cause and effect mapping of PM activities of inspection and repair

Figure 1: The proposed research methodology of the paper

Figure 2: Research focus based on FMEA results

Figure 3: The share of each network component in the interruption frequency during three years in four feeders

Figure 4: The share of each network component in the interruption durations during three years in four feeders

Figure 5: Percentage decrease of interruption duration regarding month of PM actions on critical components for each year and fitted linear regression

Figure 6: Percentage decrease of ENS regarding month of PM actions on critical components for each year and fitted linear regression

Figure 7: Fitted regression line on percentage decrease of interruption duration by PM actions on the critical component during 3 years for each feeder

Figure 8: Fitted regression line on percentage decrease of ENS by PM actions on the critical component during 3 years for each feeder

Figure 9: Percentage decrease of ENS based on percentage decrease of interruption duration for each year in feeder A

Figure 10: Mean and standard deviation of the percentage decrease of interruption duration by PM actions on critical component during 3 years regarding each feeder and aggregated

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Table 1: Cause and effect mapping of PM activities of inspection and repair

| Effect ↓ / Cause → | | Interruption | |
|---|---|---|---|
| | | Frequency | Duration |
| PM Activities | Inspection | ✓ | ☑ This Paper |
| | Repair | ✓ | ✓ |

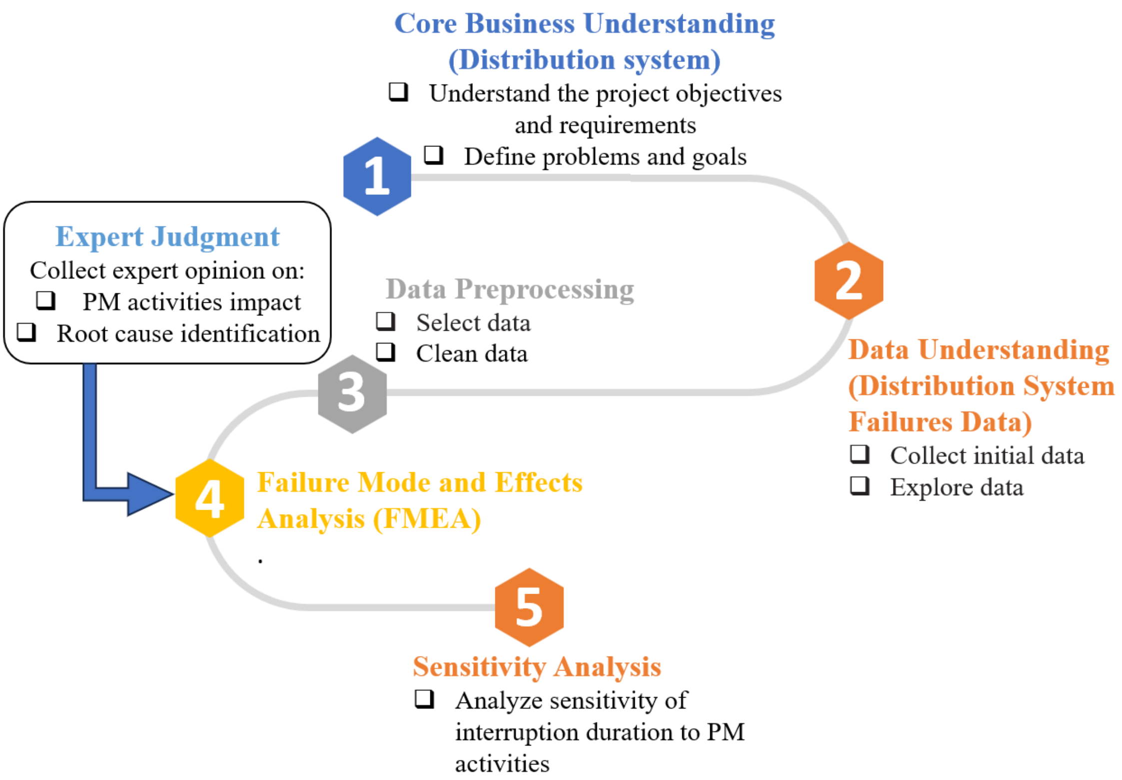


Figure 1: The proposed research methodology of the paper

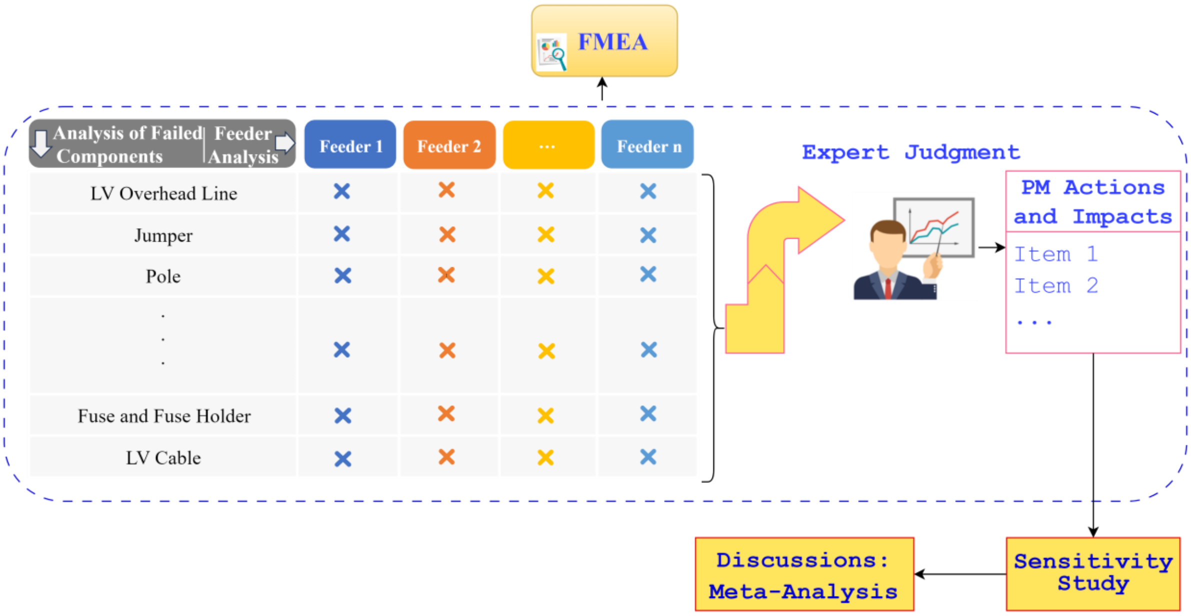


Figure 2: Research focus based on FMEA results

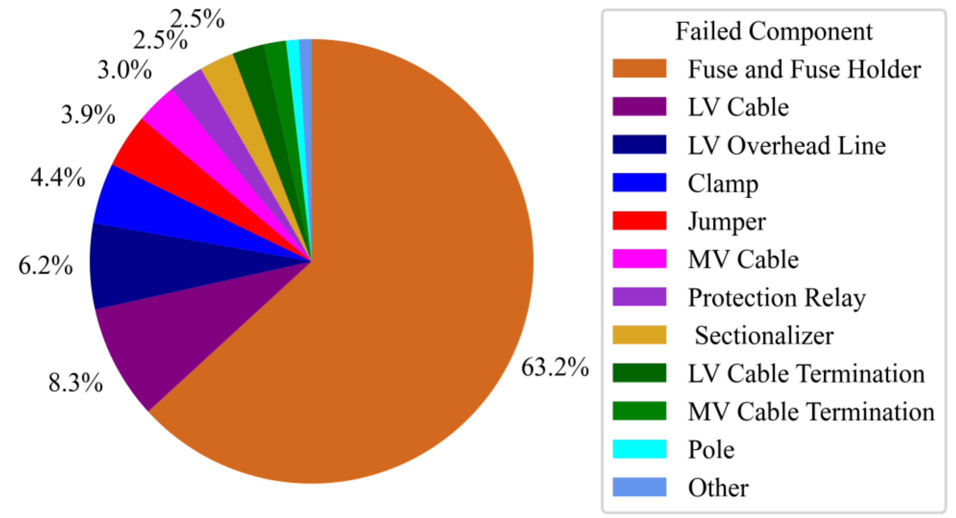


Figure 3: The share of each network component in the interruption frequency during three years in four feeders

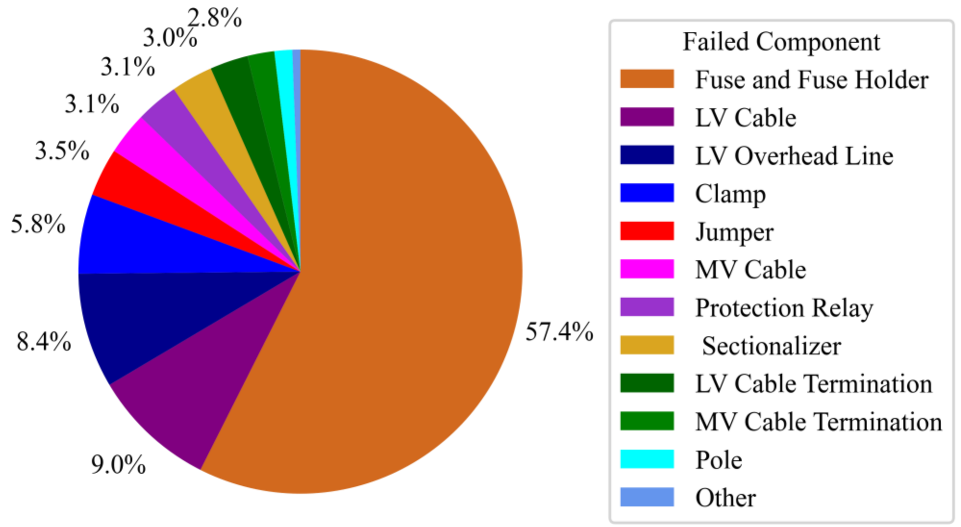


Figure 4: The share of each network component in the interruption durations during three years in four feeders

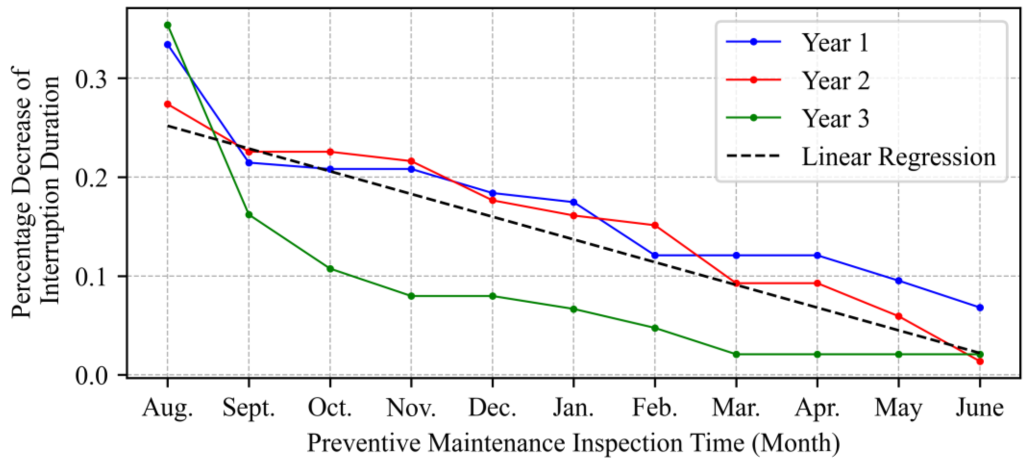


Figure 5: Percentage decrease of interruption duration regarding month of PM actions on critical components for each year and fitted linear regression

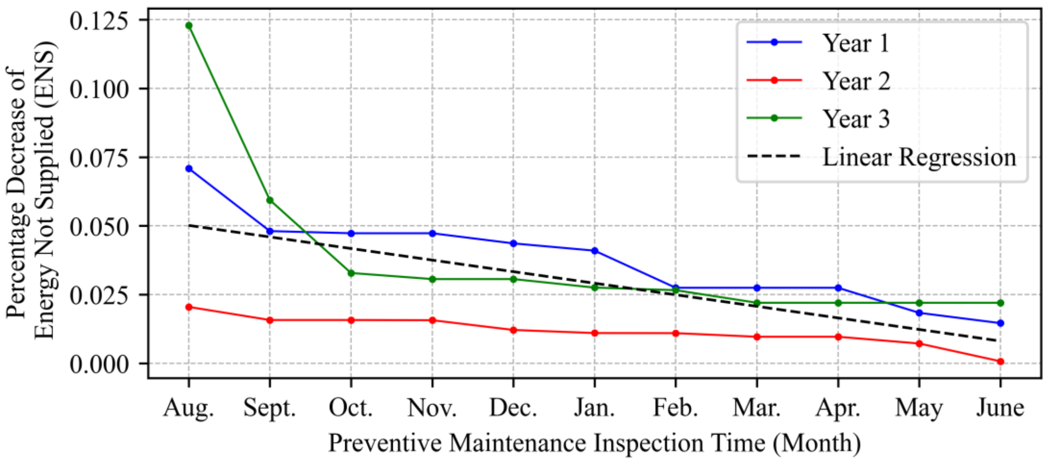


Figure 6: Percentage decrease of ENS regarding month of PM actions on critical components for each year and fitted linear regression

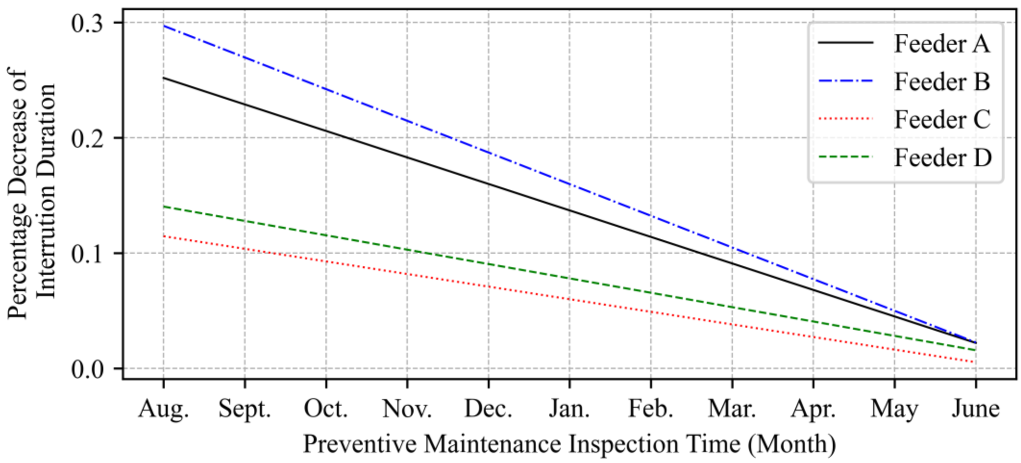


Figure 7: Fitted regression line on percentage decrease of interruption duration by PM actions on the critical component during 3 years for each feeder

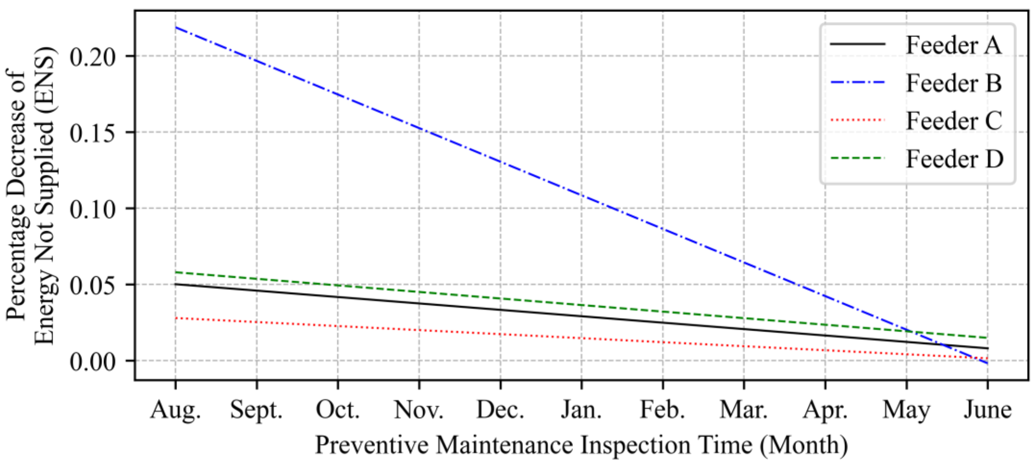


Figure 8: Fitted regression line on percentage decrease of ENS by PM actions on the critical component during 3 years for each feeder

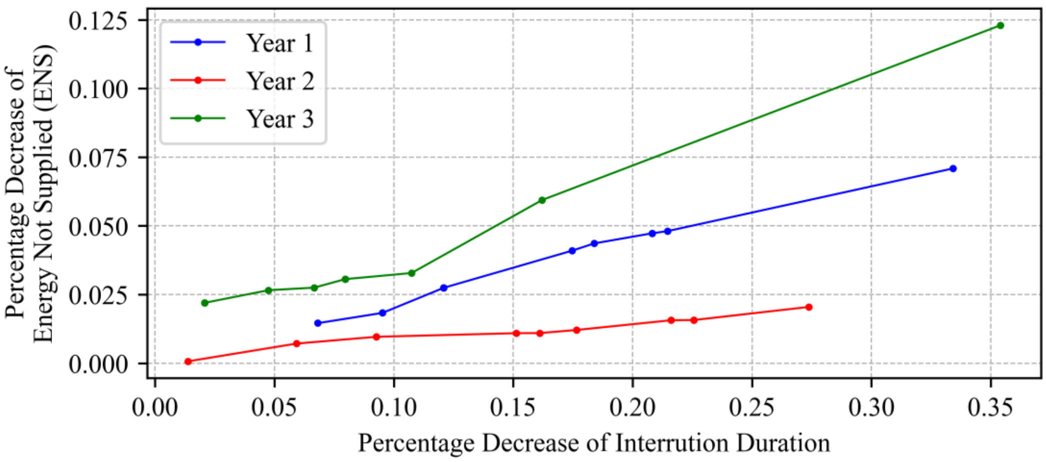


Figure 9: Percentage decrease of ENS based on percentage decrease of interruption duration for each year in feeder A

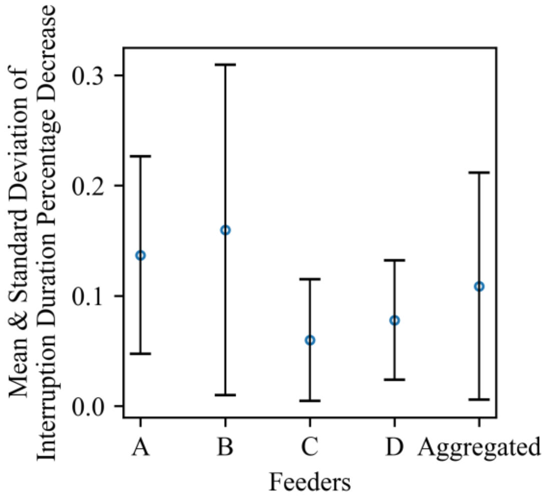


Figure 10: Mean and standard deviation of the percentage decrease of interruption duration by PM actions on critical component during 3 years regarding each feeder and aggregated

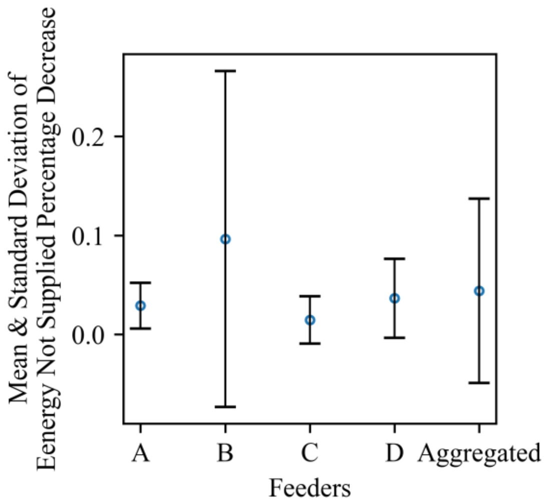


Figure 11: Mean and standard deviation of the percentage decrease of ENS by PM actions on critical component during 3 years regarding each feeder and aggregated

## Nomenclature

**Abbreviations:**

| | |
|---|---|
| KPI | Key performance indicator |
| ENS | Energy not served/supplied/sold |
| FMEA | Failure mode and effects analysis |
| GTEDC | Greater Tehran Electricity Distribution Company |
| IntD | Interruption duration |
| MTTR | Mean time to restoration/repair/replacement |
| DG | Distributed generation |
| DSM | Demand-side management |
| CM | Corrective maintenance |
| PM | Preventive maintenance |
| PdM | Predictive maintenance |
| RCM | Reliability-centered maintenance |
| TBM | Time-based maintenance |
| CBM | Condition based maintenance |
| RNN | Recurrent neural networks |
| GEVD | Generalized extreme value distribution |

**Indices:**

| | |
|---|---|
| *i*, *j*, *m*, *y*, *f* | Index corresponding to a distribution system component type, distribution system interruption, month of PM inspection, year under study, feeder name, respectively |

**Sets:**

| | |
|---|---|
| $Y$ | Set of years under study |
| $M$ | Set of months of PM inspection time |
| $COMP$ | Set of distribution system components |
| $F$ | Set of feeders |

**Constants/Variables:**

| | |
|---|---|
| $c$ | Level of uncertainty involved in identifying defects in critical components during PM activities |
| $U_{Mean,PM}$ | Mean interruption duration for replacement/repair of detected defective critical component |
| $U_{NPM}^{f,y}$ | Sum of interruption durations of, considering no PM actions |
| $U_{NPM}^{f,y,j}$ | Duration of j$^{th}$ interruption, considering no PM actions |
| $U_{i}^{f,y}$ | Sum of interruption durations of i$^{th}$ distribution system component |
| $U_{Mean,Aff}^{f,m,y}$ | Mean duration of interruptions that are affected by PM actions |
| $U_{Aff}^{f,m,y}$ | Sum of interruption durations that are affected by PM actions in the m$^{th}$ month |
| $U_{UAff}^{f,m,y}$ | Sum of interruption durations that are unaffected by PM actions in the m$^{th}$ month |
| $\lambda_{Tot}^{f,y}$ | Total frequency of interruptions |
| $\lambda_{i}^{f,y}$ | Frequency of interruptions of i$^{th}$ distribution system component |
| $\lambda_{Aff}^{f,m,y}$ | Total frequency of interruptions that are affected by PM actions |
| $\lambda_{UAff}^{f,m,y}$ | Total frequency of interruptions that are unaffected by PM actions |
| $ENS_{PM}^{f,y,j}$ | ENS of replacing the detected defective critical component in PM activities, for j$^{th}$ interruption |
| $ENS_{NPM}^{f,y,j}$ | ENS of j$^{th}$ interruption, considering no PM action |
| $ENS_{PM}^{f,m,y}$ | ENS of f$^{th}$ feeder in y$^{th}$ year, considering PM actions in the m$^{th}$ month |
| $ENS_{NPM}^{f,y}$ | ENS of f$^{th}$ feeder, in y$^{th}$ year, considering no PM actions |
| $\%\Delta ENS_{PM}^{f,m,y}$ | Percentage decrease in ENS considering PM actions |
| $IntD_{NPM}^{f,y}$ | Interruption duration for a typical failure considering no PM actions |
| $IntD_{PM}^{f,m,y}$ | Interruption duration for a typical failure considering PM actions |
| $\%\Delta IntD_{PM}^{f,m,y}$ | Percentage decrease in interruption duration for a typical failure considering PM actions |
| $FSh_{i}$ | Share of i$^{th}$ distribution system component in the frequency of interruptions |
| $DSh_{i}$ | Share of i$^{th}$ distribution system component in the duration of interruptions |

| | |
|---|---|
| $S_{PM}^{IntD}(\alpha)$ | PM to IntD effectiveness factor, considering $(1-\alpha)\cdot 100\%$ confidence level |
| $S_{PM}^{ENS}(\alpha)$ | PM to ENS effectiveness factor, considering $(1-\alpha)\cdot 100\%$ confidence level |
| $SD_{S_{PM}^{IntD}}$ | Standard deviation of PM to IntD effectiveness factor |
| $SD_{S_{PM}^{ENS}}$ | Standard deviation of PM to ENS effectiveness factor |
| $\alpha$ | Significance level |
| $t_{\frac{\alpha}{2}}$ | The t distribution critical value with n-1 degrees of freedom |
| $n$ | Sample size |