J Electr Eng Technol.2017; 12(5): 1764-1776
http://doi.org/10.5370/JEET.2017.12.5.1764

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Visibility of Electric Distribution Utility Performance to Manage Loss and Reliability Indices

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Abstract – To achieve economic stability, distribution Company as an economic institution should be managed by various processes. In this way, knowledge of different processes is the first step. Furthermore, expectations, outputs, requirement data, and sub-processes should be extracted and determined. Accordingly, to assign the performance responsibility of each process, the decision-making points must be introduced and, the deviation or change in set-points should be investigated into processes. Also, the performance of processes could be monitored by introducing of the sub-indictors. In this study, a practical method is presented for monitoring of reliability and power loss indices from viewpoint components' supply chain into the distribution network. At first, the visibility model of the supply chain is illustrated by focus group and the sub-indicators are extracted for each process of this chain. Then, validation and verification of the sub-indicators are accomplished by the Delphi method and, an information dashboard is presented by confirmed the sub-indicators and statistics methods. Finally, the proposed method is investigated by real data in a typical network and the results are analyzed.

Keywords: Distribution system performance, Power loss, Reliability, Statistical method, Delphi method, Visibility model

1. Introduction

A vital link between customers and the bulk power system is the distribution system. The power distribution utility confronts with the ongoing challenges such as aging infrastructures, increasing customer demands for higher reliability and power quality and budget constraints. With regard to a deregulated environment, electrical utilities are under pressure to reduce operating costs, enhancing the components availability, improving service power and quality for customers. Statistics represented that the distribution system is responsible for a large percentage of electricity costs, the vast majority of customer interruptions and power loss in system [1]. The significant characteristics of electric distribution industry are the natural monopoly of electricity supply chain, low intrinsic efficiency of network in comparison with others, high arrival rate of new technologies, major focus of power industry assets and, having expanded and complicated financial system. Accordingly, the opportunities and threats of long- and short-term planning should be ascertained in this industry and to predict assets treats, enhancement of system efficiency must be undertaken. Therefore, actions analysis, renewing structure of distribution management and extraction of regulation-based indicators for each process are of the activities that have a crucial role to improve distribution system performance.

On other hand, a set of independent or isolated parts in a system cannot guarantee success of distribution system. Furthermore, the process attitude not only in providing the requisition of shareholders but also in speed and agility of these utilities for responsibility of demands is more effective. In this case, how to work original processes as a comprehensive system should be distinguished by a company. As a result, from subjects of crucial in efficiency enhancement of a distribution company are to identify, to control, to manage and to conduct of processes performance using data flows.

At present, general indicates such as power loss, failure rate, etc are used for monitoring of distribution utility performance that these are an abstract of different processes performance. For instance, modeling of failure rate has been used for analysis of reliability in various articles. In order to overcome data deficiency and population variability in reliability data, various methods have been proposed for constant failure rate estimation in [2]. In this method, the operation performance of feeder is monitored by classification of feeder failures based on average load, age and tree density. In [3], Bayesian modeling techniques, such as HBM is employed for

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Received: November 12, 2016; Accepted: May 29, 2017

survey of reliability to group failures of feeder. A study of planned and unplanned medium voltage outages has been presented by Artificial Neural Network in [4]. A comprehensive model for forecasting reliability is proposed by component failures and planned outages in distribution system. In this article, influencing factors of failures as neuron in the ANN input layer are considered and is trained using historical reliability data. Also, a new component outage model is introduced in [5]. The proposed time-varying outage model is able to reflect the effects of component aging and repair activities on the failure rate. The model is obtained by renewal-process and Weibull distribution function to classify failures of an actual transformer. In [6], a statistical methodology is proposed for end-of-life studies of aging populations of electric components. The time-varying failure rate of a component, such as circuit breaker is estimated by different parametric distributions, and to choose the one that best describes the data. The age-based failures classification is used to this reference and end-of-life of electric power component is assessed by this method. A probabilistic methodology has been developed to achieve quantification of maintenance in [7]. Various performance indices are defined to investigate the condition of breaker using probability distributions and Bayesian approach utilizing its control circuit data. In [8], a fault prediction model to detect transformers' potential failure under various operating conditions is presented by real-time monitoring of key parameters and data mining. A systematic and generic approach is used to manage the on-line diagnostic tools which monitor, access information, and recommend maintenance strategies in this article. These analyses are concentrated on failures from viewpoint the operation of component and the operation performance revises for system improvement only, therefore the fails origin would not be investigated into system processes.

Also, various studies have been performed to calculate power loss indicator for different purposes, such as network planning, calculating the nontechnical losses, assessing the network efficiency and operational decisions. These articles are classified to different groups. The first group, a method of calculation or estimation of power loss is introduced. In these studies, methods of technical losses calculation have been demonstrated to different techniques such as fuzzy sets and clustering [9], top-down approach [10], network simulation [11] and ANN-based modeling [12] and so on. In this case, a network analyst has only the amount of power loss and then, a method should be found to manage it. Another set of articles proposes methods to optimize network performance from viewpoint power loss, such as network reconfiguration [13-15]. Generally, they optimize the power loss based on present load and network structure therefore, regarding variation of network parameters, improvement in the network performance should be investigated again. A third group of articles try to employ the components such as capacitor or generation distributed, the power loss manages in present network [16-19]. These researchers have concentrated on the optimum operation of network and assumed that the other processes of network establishment have been assigned perfectly from viewpoint power loss.

In spite of the fact that the general indices can illustrate the performance of distribution utility but the process-centered controllability and visibility never has been looked as a method of the performances improvement. Indeed, all of processes, relation between these and data flows should been introduced and extracted in order to the process-centered controllability of general indicators. This condition should been performed to each company regarding the different geography location, variety in procedures and views of giving service and also, varied ways of the operation.

In this study, the performance of distribution utility is investigated from viewpoint reliability and power loss indices, but the process-centered performance is monitored here. In a distribution company, some of the processes can be defined as a specific activity that here, the processes of components' supply chain are used for analysis of these indices. Accordingly, improvement of system performance is planned to improve overall indices. But from the viewpoint process, these indices are monitored to consider the effect of each process.

In this case, the processes visibility model is introduced by data flows between different processes and defined new sub-indicators, and then the processes controllability is presented to inspect into each process. Therefore, to describe the processes of components' supply chain by distribution system experts, new sub-indicators are extracted from viewpoint reliability and power loss. Theses sub-indicators are used for monitoring and visibility of process performance, thus the control of distribution system is performed by historical data and experience of experts. Accordingly, the effective factors of each process on these sub-indicators should be identified and the relation between these with other factors of different processes should be assigned. Also, a threshold value is defined which has been approved by distribution company as the desired value of the sub-indictor. On this base, the threshold value can be equal to the desired value. This value should be selected regarding geography condition, type of load and network, human resource and facilities. The documents, standards, evidences and expert experiences are used for selection of the desired value. Finally, the performance gap and improvement methods of each process should be assessed in consultation with the managers and experts involved. As a result, an asset manager can provide a complete evaluation of the processes performance by this visibility.

2. Proposed Method

Electrical distribution utilities have to employ appropriate assets in order to manage their flows including energy, cash, and data flows and realize their targets [20]. Accordingly, asset manager plays a key role in administration of various processes in order to achieve system targets in long term, so that the performance of utility has to analyze by monitoring of new components inserting into network. A new components' supply chain includes four processes namely the design process (DE), the purchase process (CP), the installation process (IE) and the operation process (OP).

A new component is inserted into network by above processes. Therefore, the deviation of process performance can affect the performance indices of system. Generally, the system reliability is affected by inserting of new component but the reliability and the loss indices could be affected coincidentally by the components which are in line of current flow. As a result, when the performance of each process would be monitored by both indices, the supply chain of components such as transformer, cable, wire, switches and accessories has to investigate. Fig. 1 illustrates the general effect of the components' supply chain in typical distribution utility on the reliability and the power loss indices. The components are selected and inserted into the network by input data and, the processes performance would be affected output indices. The basic idea is that visibility is related to the ability of the company to access the significant, reliable and meaningful data owned, neglecting additional data that is not useful in the decision-making. Fig. 2 depicts the procedures that supported each phase of research. These phases include; (1) extracting effective factors of each process, assigning relation between factors and introducing of new sub-indicators; (2) confirming candidate sub-indicators, and (3) obtaining probability trend of confirmed sub-indicators.

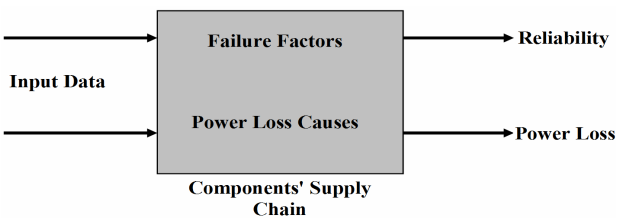

Fig. 1. The effect of components' supply chain in typical distribution utility on reliability and power loss indices

2.1 Focus group

In initiation of the research, a model is obtained on the basis of main findings in the literatures, documents and surveys regarding the variables and factors that affect the supply chain performance from viewpoint reliability and loss, and also relation between factors and data flows to their. Here, a principle question is propounded that 'what factors would be both indices affected in each process?'. Therefore, a primary model would be obtained to extract these factors. Then, a focus group is organized to investigate model that includes experts of distribution utility, and ultimately, a final model is introduced based on changing or revising of primary scheme. On the whole, four meetings were arranged, each of which lasted two hours. During the meetings, the factors and relations between these were shared and discussed in detail with the experts.

In the study, the focus group was relatively homogenous in terms of representative organizations to prevent dominant voices, as participants with relatively homogeneous backgrounds normally have similar perceptions and experiences related to the same topic. There were 12 participants in total, and the experts in each group were working experience 15-20 years. The participants were working in designing, commerce, supervision and operation departments. At first, the effective factors of each process were extracted and identified from viewpoint both indices in two meetings and subsequently, relation between factors and nominated sub-indicators were investigated. The meetings were begun to questions such as 'what are the effective factors of component failure in the DE process?' and then, the opinions of participants were collected and surveyed. Each session was recorded and summarized in the form of a report, and in new meeting, the subjects of former session were read to remember participants. Interviews were conducted to senior managers of utility for controlling the final model and in last meeting, the result obtained were shared to participants in order to obtain

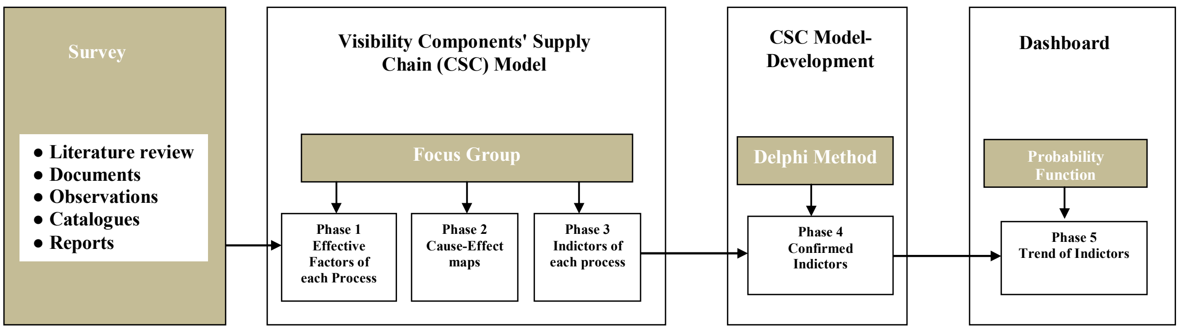

Fig. 2. Research procedures and related methodologies

feedback and improving model validity. Output of this phase includes a model is that shows relation between the effective factors of the supply chain process and the overall proposed sub-indicators introduce for processes visibility.

Generally, the focus group is considered to be an appropriate methodology for the fine-tuning and validation of a model, as it allows viewpoints that are in agreement with the primary views of the interviewer, as well as those that are not, to be grasped [21].

2.2 Use of the Delphi method

The set of the sub-indicators pre-selected should been validated by a valid technique that the Delphi method is used to assess in this study. We chose the Delphi method because it meets the challenge of generating a set of balanced indicators by integrating the knowledge of a group of various industry experts with different opinions. The Delphi method was used according to the methodology applied by the following procedure: (a) compiling a set of reference the sub-indicators through literature review and experts; (b) using these previously selected the sub-indicators for a presentation to the researchers using the Delphi method; (c) from this presentation, researchers will give grade the relevance of the sub-indicators using a Likert scale.

Before submitting the set of the sub-indicators to researchers at surveys, the purpose of the study was described, containing: (a) the origin of the pre-selected sub-indicators; (b) the selecting procedure and application method of the sub-indicators in departments of distribution utility; (c) the benefits to utilize these for monitoring of various processes performance; (d) procedures to survey experts and reasons to select the reference sub-indicators.

The survey respondents were experts from different areas of distribution utility such as engineering, commercial, operation and executive departments that have distinctive experiences. The analysis of the sub-indicators assessed by the researchers was based on statistics, analysis of Weighted Average (WA) and the level of consensus (LC) [22]. In various studies, these cut-off parameters are validated that the LC can range from 0.5 to 0.8, thus the sub-indicators can be validated at the first round as long as there in a desirable LC in the answers. Therefore, the sub-indicators that had WA $\geq$ 0.7 and LC $\geq$ 4.5 were selected by respondents to monitor the processes.

2.3 Statistical distribution of the sub-indicators trend

From the past, most frequently various probability functions have been used for modeling of reliability in electrical power system. These functions are employed regarding type of system, application and analysis requirements. Furthermore, application of probability functions were in other subjects such as load forecasting, impacts of electric vehicle on network and electricity market. In all cases try that a probability model obtains for better analysis using set of historical and measurable data [23].

In this study, the probability function distribution has been used to investigate the sub-indictors trend regarding nature of non-negative measures. For probability modeling of system behavior, various probability functions exist that are proposed as candidate regarding set of data in each the sub-indicator. Then, data on each probability distribution is fitted and the goodness of fit of a statistical model describes how well it fits a set of data.

The selection of an appropriate statistical distribution which describes the observed data is based on several goodness-of-fit tests. With these tests it is determined how well the model actually reflects the data. A goodness-of-fit test refers to a hypothesis test in which the null hypothesis is that the population has a specific probability distribution, such as a normal probability distribution. Some of available tests such as likelihood ratio, Kolmogorov-Smirnov, Chi-squared, and for small samples, Anderson-Darling (AD), are used for goodness-of-fit of model. If the statistical distributions are confirmed then the statistical distribution with the greatest p-value is selected. This value determines the appropriateness of rejecting the null hypothesis in a hypothesis test. The p-values range from 0 to 1 and this is the probability of obtaining a test statistic that is at least as extreme as the calculated value if the null hypothesis is true. Before conducting any analyses should be selected (α) level. Here α is a number selected independently of the data, usually 0.05 or 0.01. If the p-value of a test statistic is less than α, this can reject the null hypothesis [24-25].

3. Model of Components' Supply Chain Visibility

3.1 Evaluation tools

The components' supply chain in an electrical distribution company is responsible to inset new components regarding variation in network and load requirement. This chain institutes different processes that include:

- Design process (DE); selecting different components for a new network and investigating method of link to network.
- Purchase process (CP); selecting appropriate component between presented samples by vendors regarding defined characteristics in the DE process.
- Installation process (IE); executing and linking purchased components to network based on principle of designed.
- Operation process (OP); charging new network and monitoring it in the period of operation.

In this research, the effective factors on the reliability and the loss in each process are extracted and verified to

Table 1. Extracted factors for each process

Process	Factor	Comments
Designing	Fitting	Selection of component regarding condition of position and environment
	Sizing	Selection of component regarding load forecasting
	Siting	Install location of component regarding geography position
Purchase	Component manufacture	Construct of component correctly
	Component material	Proper used material in component
Installation	Connection installation	To connect component into network
	Component installation	To transport and to install in position
Operation	Inspection	To survey external form of component
	Monitoring	To survey electrical performance of component

Table 2. Relation of the factors with each other

Process		DE			CP		IE		OP	
	Factors	*Fitting*	*Sizing*	*Siting*	*Manufacture*	*Material*	*Connection In.*	*Component In.*	*Inspection*	*Monitoring*
DE	*Fitting*	o	-	-	x	x	x	-	-	-
	Sizing	-	o	x	x	x	x	x	x	x
	Siting	-	x	o	-	-	-	x	-	-
CP	*Manufacture*	-	-	-	o	-	x	x	-	-
	Material	-	-	-	x	o	x	x	-	-
IE	*Connection In.*	-	-	-	-	-	o	-	x	x
	Component In.	-	-	-	-	-	-	o	x	x
OP	*Inspection*	-	-	-	-	-	-	-	o	-
	Monitoring	-	-	-	-	-	-	-	-	o

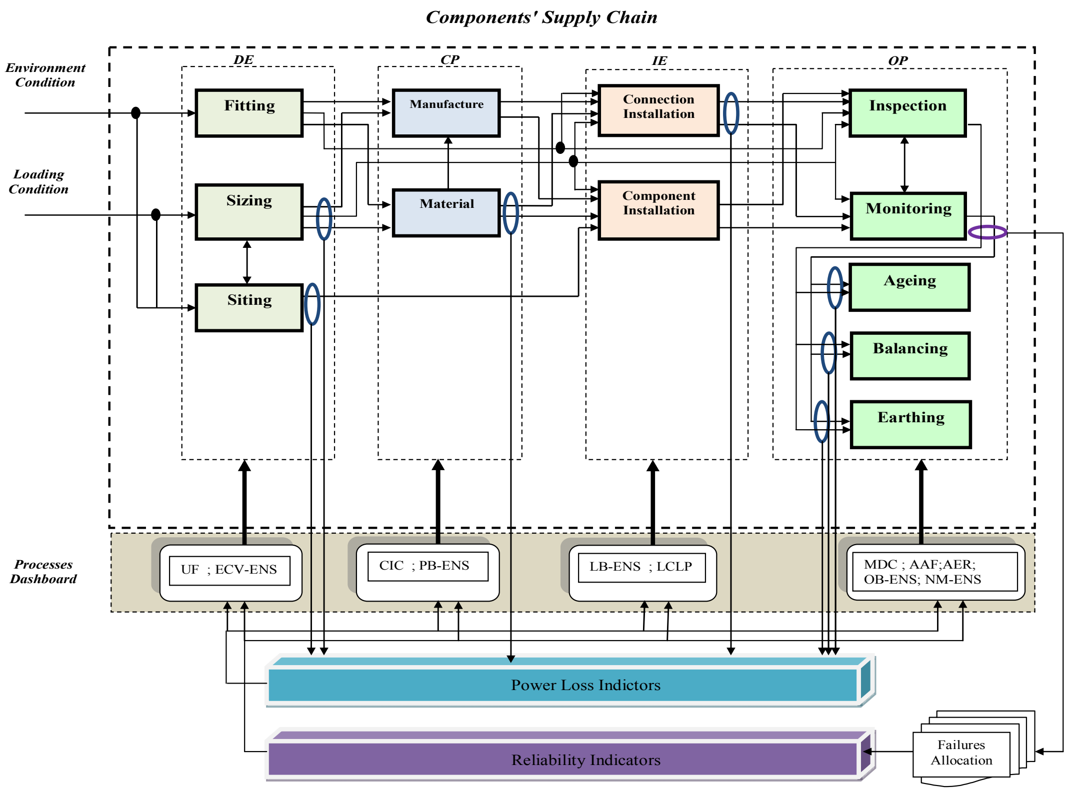

Fig. 3. Model of distribution utility performance visibility for reliability and power loss indices

survey and to argue in focus group. Table 1 summarizes the results and the explanations of the extracted factors. Three supplementary factors i.e. aging, unbalancing and grounding resistance have been used to analyze loss power in the OP process.

In order to better survey data flow, a new model has been introduced that shows the influence of various factors on each other. This model can help to asset manager in qualitative and quantitative improvement of the supply chain performance. Furthermore, the model has a twofold purpose: that allows the identification of the effective factors route in processes for improvement of reliability and loss indices, and explains the reasons why these improvements are generated to introduce new indicators for visibility of process performance into the supply chain.

Therefore, the model of performance visibility and relation between factors is prepared using Table 2. This table is completed based on the influences of columns factors on rows factors. In the table, the signs of "x" and "o" indicate influences of two factors on each other and similar factors, respectively and have been completed by focus group. Accordingly, the final model was obtained by this table as Fig. 3. For instance, the component sizing in the DE process can affect the sitting factor. Also, the manufacturing component and materials it would be affected by this factor.

In order to measure the level of visibility on the processes performance of the supply chain, the new sub-indicators are introduced from viewpoint reliability and power loss. On the basis of process targets and practical experiences, new sub-indicators were suggested by focus group to study documents, standards, observations and literature review. Therefore, in a first meeting with the experts a list of various data and data flows in the distribution utility that may use to visibility was identified as shown in Table 3. Furthermore, a subset of the new sub-indicators were recognized and categorized in accordance with the processes to which they relate, as shown in Table 4. The sub-indicators included in Table 4 were selected from viewpoint reliability and loss indices and were validated by focus group. In addition, in order to assign importance of each sub-indicator, the weight of influence on the process were provided by the Delphi method; the weights must sum to 100%. In Table 4, the importance of each sub-indicator is shown individually for reliability and loss. A brainstorm session with five company expert was conducted in order to ensure the consistency of the results. For example, the sub-indicators of DE process i.e. UF and LD have an importance 12% and 10% respectively for power loss index.

Table 3. Types of data and data flow

Type of data	Data flow
Electrical data	Electrical Power
	Energy Consumer
	Power Quality
Events data	Failures Data
	Outages Data
Monitoring data	Maintenance Data
	Inspection Data
Physical measures	Quantity data
Master data	Characteristic
	Installer
Status data	Position

Then, for each data flow, a map was created that shows the sub-indicators affected by an improvement in the quality and quantity of the company's performance visibility on that data flow in the components' supply chain for both indices. Such maps have two targets. Firstly, the improvement of visibility is identified potentially by the effective sub-indicators, secondly, the reasons of improvement and raising confidence in the quality of the results can explain. The sub-indicators related to data flows were created so as to be applicable to present processes performance, and should therefore be confirmed through direct interviews with the company's managers before being used. For this purpose, the cause-effect map related to the DE process data flow regarding the proposed sub-indicators is shown in Fig. 4, that data flow is illustrated by grey boxes, the proposed sub-indicators by black boxes and types of data within dotted boxes. The other cause-effect maps were obtained that they are not mentioned to avoid prolonged here. In model, the information dashboard based on the final sub-indicators has been obtained that is explained as follows.

Table 4. The new sub-indicators extracted by focus group and relative importance

Process	Sub-indicator	Importance obtained	Sub-indicator	Importance obtained
	Power loss		***Reliability***	
DE	Utilization Factor(UF)	12%	Failure rate-based the DE	10%
	Load Density(LD)	10%	Electrical condition variation- based ENS (ECV-ENS)	20%
CP	Weighted substituent numbers (WSN)	5%	Purchase-based ENS (PB-ENS)	25%
	Changing in component Characteristics (CIC)	3%	Feeder failure rate	5%
			Component failure rate	10%
IE	Loose connection power loss (LCLP)	5%	Loose connection-based ENS (LB-ENS)	5%
	Weighted loose connection number (LWN)	3%	Loose failure rate	3%
			Installation-based ENS	2%
OP	Maximum deviation from mean of current (MDC)	25%	Operation-based ENS (OP-ENS)	5%
	Average failure age (AFA)	17%	Non-monitoring-based ENS (NM-ENS)	5%
	Average grounding resistance (AGR)	20%	Operation-based feeder failure rate	3%
			Non- monitoring feeder failure rate	2%
			Operation-based component failure rate	3%
			Non- monitoring component failure rate	2%

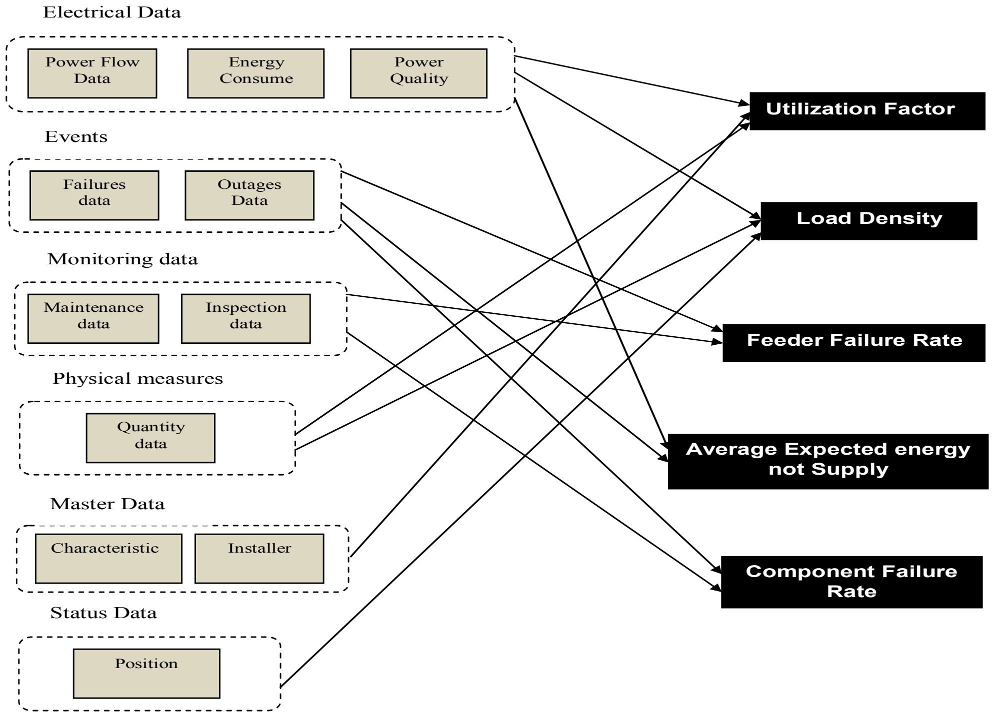

Fig. 4. Cause-effect map for the DE process

Table 5. The final sub-indicators assigned by the Delphi method

Sub-indicator	Likert Scale						
Designing	**5**	**4**	**3**	**2**	**1**	**LC**	**WA**
UF	12	2	1	-	-	0.8	4.7
ECV-ENS	11	2	2	-	-	0.73	4.6
Purchase							
CIC	11	3	1	-	-	0.73	4.7
PB-ENS	11	2	2	-	-	0.73	4.6
Installation							
LB-ENS	12	2	1	-	-	0.8	4.7
LCLP	13	2	-	-	-	0.9	4.9
Operation							
MDC	12	2	1	-	-	0.8	4.7
AFA	11	3	1	-	-	0.73	4.7
AGR	11	3	1	-	-	0.73	4.7
OB-ENS	13	2	0	-	-	0.9	4.9
NM-ENS	12	2	1	-	-	0.8	4.7

3.2 Evaluation technique

To obtain the components supply chain visibility by the proposed sub-indicators, which have been introduced previously, the final sub-indicators should be selected. We chose the Delphi method because it meets the challenge of generating a set of proper sub-indicators by integrating the knowledge of a group of researchers with different opinions. The Delphi technique is generally a kind of multilevel, structured group interaction process, in which individuals are required to give numerical judgments over a number of rounds. Between rounds, intermediate anonymous feedback is provided from the panel [26]. It is conceived to obtain consensual expert opinions or to identify needs for action in case of dissent.

On this base, applying the Delphi method to the 15 experts for assessing the proposed sub-indicators from Table 4 resulted in the selection of the final sub-indicators that obtained a LC ≥ 0.7 with a WA ≥ 4.5, as shown in Table 5. The resulting sub-indicators comprise two confirmed the sub-indicators for each of the DE, CP and IE processes, and also five sub-indicators for the OP process. The utilization factor (UF), changing in component characteristics (CIC) and loose connection power loss (LCLP) are introduced for the DE, CP and IE processes respectively, and the maximum deviation process. Furthermore, the influence of failures in process is considered as expected energy not supply (ENS), therefore for example, the ENS due to the electrical condition variation (ECV) for the DE process is defined as ECV-ENS. Also, the purchase-based ENS (PB-ENS), the loose-based ENS (LB-ENS), the operation-based ENS (OB-ENS) and the non-monitoring-based ENS (NM-ENS) are assigned for the CP, IE and OP processes, respectively.

In the following the evaluation of components' supply chain visibility will be characterized in more detail from the viewpoint reliability and power loss:

Step 1: Data preparation. To obtain data of the final sub-indicators, stages of data preparation should be conducted. A part of data such as feeder length that in database of each distribution company has been registered, are utilizable but some data consist of component failure should been allocated to each process of the supply chain. Some component failures such as the incident by car, human error or theft are separated from event database because these failures are not used in analysis. In this case is assumed that the components' supply chain is not influence on these. Because historical failure data has been not registered based on obtained failure factors, so these preparation need to be done carefully.

Step 2: Probability function selection. To select probability distribution function, type of data distribution should been assigned. In reliability studies, the statistical modeling methods based on type of system, repairable and non-repairable, are used. In this way, the proper probability distribution such as Poisson process for repairable system or Weibull distribution for non-repairable system is employed regarding the nature of system. For instance, the advantage of Weibull distribution is the ability to provide reasonably accurate failure analysis and failure forecasts with extremely small samples. In this study, various probability functions as candidate have been used for final sub-indicators regarding type of data as shown in Table 6, and then to fit data, the best probability function is introduced.

Step 3: Fitting validation. The crucial step in selection and confirmation of the sub-indicators probability function is the fitting validation. Various methods are used for goodness of fit tests that here among those, the different theoretical tests have been suggested regarding type of candidate probability function.

For instance, two stages are conducted to validate model of the DE process sub-indicators. The Weibull and Log-Normal distributions are used for the UF sub-indicator and Anderson-darling (AD) test is employed to validate goodness of fit. If both the statistical distributions are confirmed then the statistical distribution with the greatest *p*-value is selected. This value determines the appropriateness of rejecting the null hypothesis in a hypothesis test. The *p*-values range from 0 to 1 and this is the probability of obtaining a test statistic that is at least as extreme as the calculated value if the null hypothesis is true.

Step 4: Trend investigation. The influence of different factors in each process is illustrated by model of the supply chain visibility so that to assess trend of each sub-indicator, the effective factors of improvement is distinguished and the effect of theses in the supply chain is assigned. Also, data flow of model can help to analyze the effect of factors on each other. In this way, the sub-indicators that have the most effect on reliability and power loss indices, are explored and planned for the improvement of the overall system performance. Accordingly, the target measures of distribution utility are assigned for each the sub-indicator. Furthermore, the performance gap shows the different between the current performance level and the target. This gap often exists for reasons that the cause-effect maps are intended to help managers identify the causes of the gap. Therefore, the performance gap between the current value and the desired one was identified through interviews so that to analyze the cause-effect maps again, until these causes were assigned. Then, the AHP methodology is used to allocate the weight of influence on the causes of gap. Also, data flows that can reduce the causes of the gap are identified and the expected reduction in the occurrence of each cause would be calculated. The weighted average of the cause reductions for each the sub-indicator is defined as the performance deviation, follows:

$$\Delta \text{Div} = \sum_{i=1}^{n} P_i \Delta C_i \tag{1}$$

where P_i is the weight of influence to the cause i; ΔC_i is the percentage reduction (or increase) in the cause i due to improved visibility and ΔDiv is the percentage deviation. On this way, in order to achieve the target value, the influence of different factors is investigated to obtain the performance gap reduction in each process.

4. Numerical Example

The purpose of the numerical example was to explore the applicability of the visibility in a practical context by assessing the benefits that a distribution company can gain through better visibility on the data flows in its supply chain. To perform numerical study, Gilan Distribution

Table 6. The final sub-indicators, candidate probability functions and tests

Process	Sub-indicator	Probability function	Tests
Designing	UF	Weibull, Log-Normal	AD, *p*-value
	ECV-ENS	Intensity functions NHPP	LR, Chi-squared
Purchase	CIC	Weibull, Log-Normal	AD, *p*-value
	PB-ENS	Intensity functions NHPP	LR, Chi-squared
Installation	LCLP	Weibull, Log-Normal	AD, *p*-value
	LB-ENS	Weibull, Log-Normal	AD, *p*-value
Operation	MDC	Weibull, Log-Normal	AD, *p*-value
	AFA	Weibull, Log-Normal	AD, *p*-value
	AGR	Weibull, Log-Normal	AD, *p*-value
	OB-ENS	Intensity functions NHPP	LR, Chi-squared
	NM-ENS	Intensity functions NHPP	LR, Chi-squared

Company with an approximate of 18000 transformer units and about 1.3 million customers was chosen. This company is responsible to provide distribution services for Gilan province in south of Caspian Sea, Iran. Due to the lack of data, this study is performed only from viewpoint inserting a component such as the transformer. Therefore, the transformers data of the case study network about 686 units were collected and used. The following the main steps are summarized here for completeness.

4.1 Data collection and preparation

Due to registered data in different database, the preparation phases were performed in two parts.

a) The main data source was the outage management database. Therefore, to extract and to classify data of the transformers in related network, the preparation phase is initiated. These data can include load average and grounding resistance. But the transformer failures were registered for overall network, thus these failures should be allocated to each process by interview, observations and registered reasons. Also, to analyze the OP process, the age of failures related to this process was used.

b) Data related to the loose connections have been registered into the inspection database. Therefore, the loss of loose connections and the failures related to the transformer should be provided using these data.

The frequencies of obtained data are displayed in Fig. 5. Due to the lack of registered data, the sub-indicators of the CIC and ECV-ENS were not calculated. The measures of the UF, MDC, LCLP and AGR sub-indicators are illustrated in Figs. 5(a) and 5(b). The age of failed transformers related to the OP process is shown in Fig. 5(c) and the allocated failure data to processes is observed in Fig. 5(d). Generally, 96 transformer failures were allocated to each process for the years 2009-2013, but the transformer failures related to the DE process was not identified. Also, due to lack of historical data, 228 units were used to calculate the sub-indicators.

4.2 Probability function selection and validation

In this step, the probability function of the sub-indicators is introduced by obtained data in previous part and its fitting is validated by different tests. Due to the data nature and type of candidate probability functions, these phases have been performed in two stages.

Following for instance, these stages for two of the sub-indicators i.e. the UF and PB-ENS, are explained. The AD test is employed to validate goodness of fit for both the statistical distributions and because the test measure is smaller than the critical value, the candidate probability functions are confirmed. Then, the *p*-value of the statistical distributions is calculated and the confirmed model i.e. Weibull function, is selected with the greatest *p*-value. Accordingly, the average and the standard deviation of measures are calculated for the confirmed probability function so that the overall attitude of network designers is seen as the average UF of the transformers and the statistical distribution of the designing attitude is considered as the standard deviation of the UF value. In last case, all of the designers have a tendency toward the average UF regarding being small of this measure, thus the average measure is proper from the viewpoint they. The summary of results is shown in Table 7(a).

The parameters of candidate probability functions and the tests of reliability-based sub-indicators of each process is presented in Table 7-b. In general, the non-homogeneous Poisson process (NHPP) is used to model the transformer failures data. This modeling for the intensity functions of

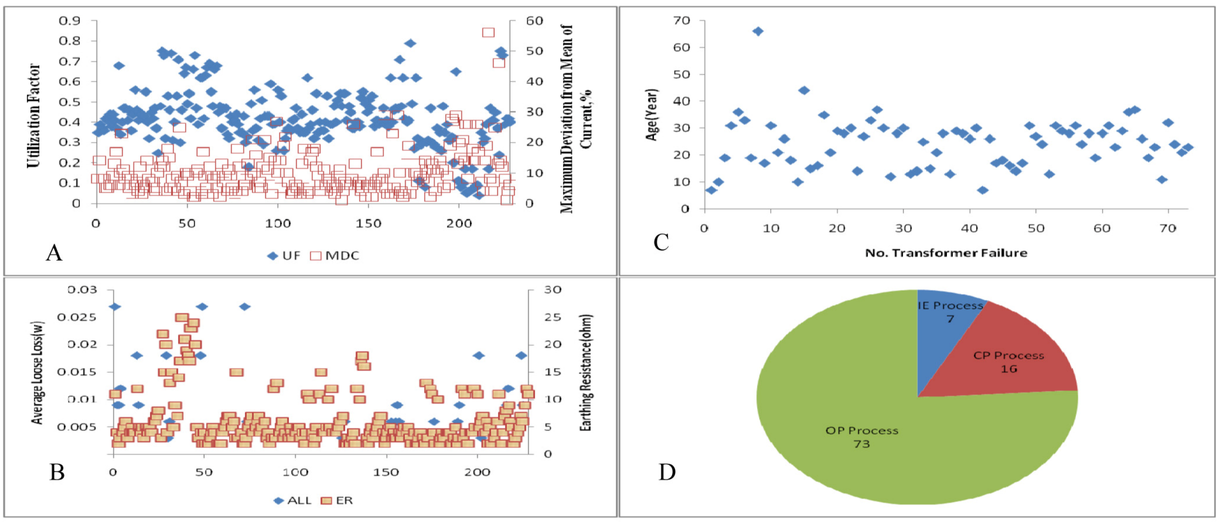

Fig. 5. Data of case study network

Table 7. The parameters and testes of probability function for each the sub-indicator

A.

Sub-indicator	Weiball function				Log-Normal Function			
	Shape	Scale	AD	*p*-value	Location	Scale	AD	*p*-value
UF	3.148	0.4605	0.73	< 0.01	-0.9661	0.4807	0.45	< 0.005
MDC	1.506	11.23	0.609	< 0.01	2.079	0.685	0.637	0.096
LCLP	1.543	0.1085	0.697	< 0.01	-2.559	0.6709	0.313	< 0.005
AGR	1.474	6.776	0.481	< 0.01	1.583	0.6276	0.335	< 0.005
AFA	2.693	27.32	0.965	0.015	3.114	0.4155	0.563	< 0.005

B.

Sub-indicator	Power Law			Log-Linear		
	λ	β	Chi-Sq.	δ	η	Chi-Sq.
PB-ENS	3.87e-3	1.007	7.087	0.762	6.13e-3	6.69
LB-ENS	0.649e-3	1.09	0.6728	-0.152	4.95e-3	0.4828
OB-ENS	5.315e-3	1.654	0.7594	0.2467	0.99e-4	0.544
NM-ENS	0.608e-3	1.974	4.547	0.732	0.12e-3	10.42

Table 8. The overall results of average and standard deviation of the sub-indicators

Process	Sub-indicator	Average	Standard deviation
Designing	UF	0.412	0.143
Purchase	PB-ENS	5.19e-3 PU	256 days
Installation	LCLP	0.0097 kW	0.064 kW
	LB-ENS	0.395e-3 PU	5 years
Operation	MDC	10%	6.85%
	AGR	6.13 ohm	4.22 ohm
	AFA	24 years	9.7 years
	OB-ENS	0.2124e-3 PU	14.6 years
	NM-ENS	0.2595e-3 PU	11 years

Table 9. The summary of visibility results for case study

Sub-ind.	Gap reduction	Desire value	Data flows
UF	38%	0.57	Electrical, Physical measures, Position, master, events data
PB-ENS	12%	4.567e-3 PU	Events, monitoring, master, Physical measures
LCLP	27%	0.0071 kW	Electrical, events, monitoring data
LB-ENS	27%	0.288e-3 PU	Electrical, events, monitoring data
MDC	21%	7.9%	Electrical, events, master data
AGR	24%	4.66 ohm	Electrical, monitoring data, Physical measures
AFA	14%	27 years	Electrical, events, master, monitoring data
OB-ENS	23%	0.1635e-3 PU	Electrical, events, master, monitoring data
NM-ENS	27%	0.1894e-3 PU	Electrical, events, master, monitoring data

the power law $\lambda(t) = \lambda\beta t^{\beta-1}$ $\beta > 0,\ t \geq 0$ and the log-linear $\lambda(t) = e^{\delta+\eta t}$ $-\infty < \delta,\ \eta < \infty,\ t \geq 0$ were concluded. Therefore, the parameters of both functions are calculated and the intensity function with lower chi-squared value is confirmed. For instance in modeling of the failures of the CP process, the log-linear function is selected. The PB-ENS sub-indicator may be calculated as a per-unit value using this curve, the average failure rate and the average utilization factor. Briefly, the results of average and standard deviation of the sub-indicators are presented in Table 8.

4.3 Assessing the sub-indicators performance

For each of the sub-indictor, the performance gap between the current value and the desired one was assigned through direct interviews with the company's managers and experts. Accordingly, for the sake of brevity, only the analysis carried out for two the sub-indicators, the UF and PB-ENS, are described in detail, although the results obtained for all of the sub-indicators are summarized in Table 9.

To analyze the effective factors on the deviation of the UF from the desired value, four main causes are identified (see Fig. 6); these causes comprise lack of precision in load data registration, imprecise load forecasting, selection of higher transformers capacity for reliability enhancement and mistake transformer placement are that directly related to electrical data, and can therefore be improved through better visibility on this data. Then, to survey company's experts for improvement in the UF sub-indicator, this visibility improvement would enable a 30% reduction in imprecise load forecasting, a 70% increase in load data registration and a 40% reduction in mistake transformer placement, and accordingly, the combination of these effects leads to a 38% expected reduction in the causes. This assessment showed that the transformer utilization factor can be increased toward the target value to 0.57 by improving visibility on the supply chain. The small standard deviation of this sub-indicator shows that overall attitude of planners is similar to another, therefore the overall improvement should be considered in all of company.

Similarly, the PB-ENS sub-indicator is negatively affected by three main causes i.e. defect in construct, wrong technical characteristics and incorrect environment condition. The interviewees believe that visibility on events

		UF				PB-ENS		
		Causes of the gap				Causes of the gap		
		Sizing			Siting	Manufacture	Material	
		Lack of precision in load registration	Load imprecise forecasting	Selection of higher transformer capacity	Mistake transformer placement	Defect in construct	Wrong technical characteristics	Incorrect condition environment
Cause weight (%)		25%	15%	50%	10%	45%	25%	30%
Data flow	Electrical data	×	×	×	×			
	Events data				×	×		×
	Monitoring data					×	×	×
	Physical measures	×		×	×			
	Master data	×	×				×	
	Status data		×	×				×
Reduction in the cause occurrence (%)		30%	70%	40%	0%	20%	0%	10%
Weighted reduction of cause occurrence (%)		38%				12%		

Fig. 6. Assessing of two the sub-indicators- UF and PB-ENS

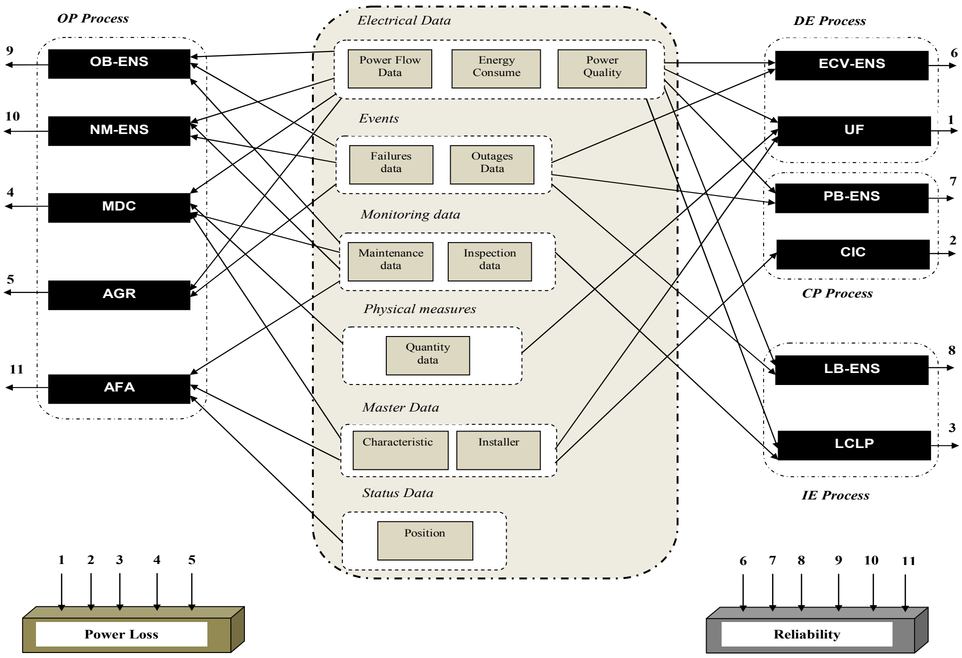

Fig. 7. The overall cause-effect map for final the sub-indicators

data can improve this sub-indicator because this visibility improvement can enhance a 20% in precision of component purchase and 10% in selection of environment condition. Moreover, the weighted reduction of causes leads to a expected reduction of 1.567e-7 PU per each transformer in the PB-ENS sub-indicator.

Table 9 summarizes the results of visibility assessment for the case study. The evaluation shows that the deviation of the sub-indicators can be reduced toward 12-38% by improving visibility on the components' supply chain. By analyzing the data flows which have a greater impact on the sub-indicators, electrical data was shown to have an impact on all of the sub-indictors from viewpoint reliability and power loss. In addition, data flow of monitoring and inspection have a high impact on the final sub-indictors. This issue shows that electrical distribution utility should focus on those data flows when investing in improving visibility on the component's supply chain.

This insight illustrates in Fig. 7. The cause-effect map of the final sub-indicators shows a high influence of the event and electrical data on the sub-indicators. Finally, using Tables 4 and 8, a 16% expected reduction in power loss and 20% expected improvement in reliability would be obtained by reduction in the performance gap from viewpoint the transformer inserting to network.

5. Conclusions

The proposed method in this study can easily show the desired level of distribution utility performance visibility. This level specifically focuses on the development of continual improvement in the effective factors of the reliability and the power loss indices. Also, the results show that this method can identify the priorities of increase the level of supply chain visibility for future projects. The results are based on the main findings of expert interviews in distribution utility, thus the direct involvement of experts in the analysis and critical discussion of the results facilitated the review of the draft case and the gathering of feedback.

Moreover, the new model was shown that the cause-effect maps and the sub-indicators can help to asset manager identify how and why the benefits might be achieved. Therefore, the effectiveness on the final sub-indictors and as a result, on the reliability and power loss indices has been presented in each level regarding the desired value. In other words, the method can be used to provide a good approximation of the benefits visibility with a limited amount of effort, and can then be refined to obtain more reliable results.

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