ASSESSING VOLTAGE CONFORMITY BY CAPABILITY ANALYSIS

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ABSTRACT

Power distribution companies should supply electric power to the customers with predefined voltage level. Thus, a proper method that can evaluate the capability of distribution network to provide electricity with suitable voltage level is absolutely helpful. Capability analysis is a set of techniques that can be used to assess whether a system is statistically able to meet its requirements or not. This approach was used to evaluate the voltage conformity in a power distribution network. The assumption of normality which is used in the previous study may be violated in the real world, especially in the presence of distributed generation. In this case the result of capability study can be misleading. In current study we used more reliable nonparametric technique to solve this problem. Finally, the voltage conformity was assessed in a few nodes of Alborz power distribution network using this approach.

INTRODUCTION

Suitability of electrical power for consumer devices is defined by many factors. Voltage level is the most important factor and should be maintained in the predefined range. Many indices, based on average or minimum of voltage level, have been introduced by engineers in order to representing voltage deviation in the power distribution design stage. These indices basically describe quality of design. Quality of design is the quality decided to be provided for customers and represents how well the service is designed to meet customers' need. But there is another aspect which is called quality of conformance. Quality of conformance represents how the real service matches the design specification. Most studies are based on quality of design and quality of conformance analysis has been neglected. Although appropriate design and utilization of power distribution network improves voltage profile, we cannot be certain that the power quality perceived by customers matches the design specification without proper approach. Capability study is used to evaluate quality of conformance and variability of the process output. The result of capability study helps engineers judge whether the process is statistically able to meet requirements or not.

Using capability study to assess voltage conformity was introduced by Dr Saghaei et al in CIRED 2012 [1]. Their study was based on normal distribution assumption. When there is a considerable difference between observation distribution and normal distribution, calculating process capability with suggested equations can be misleading.

Two years work on applying suggested algorithm to Alborz province power distribution company data, have shown that sometimes voltage profile does not follow a normal distribution and the distribution is skewed or bimodal, especially in the presence of distributed generation. Distribution generators are not always in service. These units are shut down for overhaul, maintenance or even protection device trip. In addition, output of wind turbines is erratic and it is not reasonable to consider their output constant. Seasonal network reconfiguration and fluctuating loads like arc furnaces are other reasons of voltage non-normality.

A few approaches have been introduced for calculating capability indices of skewed observation which can be categorized in three groups: First, Using flexible distributions like Gamma, Pearson, Johnson and Burr. Second, Converting non-normal data to normal data by Cox-Box or Johnson transformation and finally, nonparametric techniques. The voltage level in power distribution network in the presence of distributed generation is not only skewed but also bimodal. In current study non-parametric technique has been modified for bimodal distribution. Then, the voltage conformity in a few nodes in Alborz power distribution network was assessed using proper approaches.

CAPABILITY OF NETWORK TO MAINTAIN VOLTAGE LEVEL

Using standard capability analysis equations relies on normal statistical distribution. Therefore, normality test is the first step of capability analysis in voltage distribution network. There are many tools that can be used for normality test. Kolmogorov-Smirnov normality test which was selected for this study compares the empirical cumulative distribution function of sample data with the distribution expected if the data was normal. If the difference is large enough and p-value of the test is less than chosen significance level α, the null hypothesis of population normality is rejected and the non-normality of the population is concluded.

If voltage level follows normal distribution, capability indices can be calculated by simple equations 1-3 used in

previous study [1]

$C_P = \frac{USL-LSL}{6S}$ (1)

$C_{PU} = \frac{USL-Mean}{3S}$, $C_{PL} = \frac{Mean-LSL}{3S}$ (2)

$C_{PK} = Min(C_{PU}, C_{PL})$ (3)

Where:

USL = Maximum acceptable voltage

LSL = Minimum acceptable voltage

S = Data standard deviation

Mean = Data average

C_{PL} = Distribution network capability of maintaining voltage level above minimum acceptable voltage

C_{PU} = Distribution network capability of maintaining voltage level below maximum acceptable voltage

C_{PK} = Distribution network capability of maintaining voltage level in the predefine voltage range

There is a relationship between capability indices and the expected rate of over voltage/ under voltage. If C_{PK} value is less than one, distribution network is not capable of maintaining voltage level and customers will suffer from over voltage/under voltage but if C_{PK} is more than two the network is capable of maintaining voltage in the predefined range. In table 1 relation between capability indices and over/under voltage rate was shown. If the capability index is more than 2 the network is capable of maintaining voltage level in the predefine range, if the index is less than 2 the risk of over/under voltage increases and if the index is below 1 the distribution network is almost incapables of maintaining voltage level.

Table 1: Relation between C_{PK} and the expected rate of exceeding the voltage level (Over voltage and under voltage)

over voltage/ under voltage Rate	C_{PK}	over voltage/ under voltage Rate	C_{PK}
%50	___	400 PPM	1.18
%31.73	0.33	200 PPM	1.24
%4.55	0.67	100 PPM	1.30
%2	0.79	63 PPM	1.33
%0.27	1.00	20 PPM	1.42
%0.18	1.04	10 PPM	1.47
%0.14	1.06	3.4 PPM	1.5
%0.12	1.08	1 PPM	1.63
%0.10	1.10	0.6 PPM	1.67
800 PPM	1.12	0.0002 PPM	2.00

Using equations 1-3 is not applicable if the voltage level distribution does not follow a normal distribution function. Using more flexible distributions such as gamma (equation 4) and Weibull (equation 5) is the first technique of solving this problem. There are other distributions like Burr, Delta, Johnson and Pearson which can be applied for this purpose.

$f(x;k,\theta) = \frac{x^k e^{\frac{-x}{\theta}}}{\theta^k \Gamma(k)}$ $x \geq 0$ (4)

$f(x;k,\lambda) = \frac{k}{\lambda}(\frac{x}{\lambda})^{k-1} e^{-(\frac{x}{\lambda})^k}$ $x \geq 0$ (5)

Transforming the non-normal data to the normal one is another approach that can be put into use, if voltage observation does not follow normal distribution. Box-Cox is a famous transformation which is shown in equation 6. Johnson is another transformation that has three classes: bounded system (equation 7), log-normal system (equation 8) and unbounded system (equation 9).

$$y_i = \begin{cases} \frac{x_i^{\lambda}-1}{\lambda} & \lambda \neq 0 \\ \log x_i & \lambda = 0 \end{cases} \quad (6)$$

$y_{i,SB} = \gamma + \eta \ln(\frac{x_i-\varepsilon}{\lambda+\varepsilon-x_i})$ (7)

$y_{i,SL} = \gamma + \eta \ln(\frac{x_i-\varepsilon}{\lambda})$ (8)

$y_{i,SU} = \gamma + \eta \sinh^{-1}(\frac{x_i-\varepsilon}{\lambda})$ (9)

There is no guarantee that using flexible distribution or transformation is successful, especially when the voltage distribution is bimodal that may occur in the presence of distributed generators. Researchers have introduced nonparametric techniques for solving this problem [2], [3], [4] and [5]. The first step of Ramanathan method is defining a class of interval I and corresponding distance (equations 10 and 11).

$I = \{(x,y): F(y) - F(x) = 0.9973$ (10)

$D = \{d_{xy}: d_{xy} = y - x, (x,y) \in I\}$ (11)

For unimodal distribution, Ramanathan have defined non-parametric capability index by (12) and (13)[4].

$C_P^* = \frac{USL-LSL}{d^*}$ (12)

$C_{pk}^* = \min(\frac{USL-m}{y^*-m}, \frac{m-LSL}{m-x^*})$ (13)

Where:

m= mode $F(x)$

$d^* = \inf D$

When F is a normal distribution, $C_p^* = C_p$ and $C_{pk}^* = C_{pk}$. Capability indices defined by Ramanathan cannot be applied to multimodal distribution. Therefore, we extended this definition in order to use it for multimodal distribution.

Let m_L be a smallest and m_U be a largest mode and $LSL \leq m_L \leq m_U \leq USL$. C_{pk}^{**} in (14) represents modified definition of non-parametric capability index.

$C_{pk}^{**} = \min(\frac{USL-m_U}{y^*-m_U}, \frac{m_L-LSL}{m_L-x^*})$ (14)

In unimodal distribution $m_L = m_U$ and $C_{pk}^{**} = C_{pk}^*$.

The current study was conducted in four stages. The summary of current study was represented in figure 1. At the first stage data was collected by power analyzers, collected data was cleaned by pre-processing techniques and then the normality of the observed voltage distribution was tested using Kolmogorov-Smirnov method. Capability indices of normal distribution observations were calculated using equations 1-3. For non-normal data we tried to use transformation, flexible distributions and nonparametric to calculate capability indices.

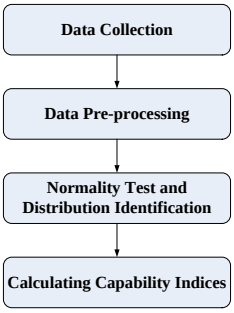

Figure 1: stage of calculating capability indices in power distribution network

CASE STUDY

In the paper given in 2012 CIRED workshop, one of the Nazarabad region medium voltage feeders was chosen as case study and total study was conducted by simulation. Although, simulation was helped authors to understand the behaviour of voltage profile in the medium voltage feeders, there is no guarantee that simulation result matches the real voltage profile. Therefore, in the current study we used real data collected by power analyzers from the electricity supplied to the five industrial power customers. In this study minimum acceptable voltage (LSL) was 0.95 and maximum acceptable voltage (USL) was 1.05 per unit.

RESULT

In table 2 descriptive statistics of voltage level and normality test results were shown. (All voltage is per unit.) We didn't find considerable difference between voltages of phases. Therefore, only voltage of phase A are inserted in the table. The result of normality test and histogram of voltage phase A in node 1 were shown in figure 2 and figure 3. The result of normality test in table 2 showed that voltage of all nodes did not follow normal distribution and using standard equations 1-3 was not applicable.

Table 2: Descriptive statistics of voltage level and normality test results

	Node 1	Node 2	Node 3	Node 4	Node 5
Sample frequency	10 min	10 min	10 min	10 min	10 min
Number of sample	576	432	560	983	983
mean	0.9883	1.0541	0.9879	0.9892	0.9927
Standard deviation	0.0158	0.0246	0.01918	0.0122	0.0323
min	0.9561	0.9994	0.9171	0.9544	0.9080
median	0.9864	1.0459	0.9877	0.9894	1.0050
max	1.0314	1.0981	1.0388	1.0193	1.0327
Kolmogorov-Smirnov test p-value	<0.010	<0.010	<0.010	<0.010	<0.010
Result of normality test	Rejected	Rejected	Rejected	Rejected	Rejected
Number of mode	2	2	1	1	2

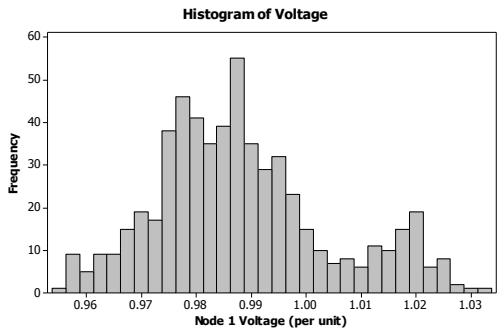

Figure 2: Histogram of voltage in node 1 (Phase A)

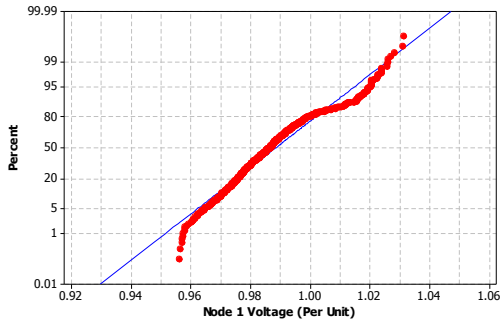

Figure 3: Result of normality test of node 1 (Phase A)

Anderson-Darling statistic measures how well the data follow a particular distribution (The better the distribution fits the data, the smaller this statistic is). In table 3 the results of Cox-Box and Johnson transformation and fitting observations to a few famous non-normal distributions were shown. Both Cox-Box and Johnson transformation were failed in all nodes as well as fitting famous distributions to observed data.

Table 3: Result of transformation and fitting observations to non-normal distributions (NA=not available)

	Node1	Node2	Node3	Node4	Node5
Johnson transformation	Failed	Failed	Failed	Failed	Failed
Cox-Box transformation	Failed	Failed	Failed	Failed	Failed
3-parameter lognormal test p-value	NA	NA	NA	NA	NA
3-parameter lognormal Anderson-Darling	1.974	10.749	1.004	3.820	58.743
3-parameter Gamma test p-value	NA	NA	NA	NA	NA
3-parameter Gamma Anderson-Darling	2.148	10.514	1.293	4.224	61.723
3-parameter Weibull test p-value	<0.005	<0.005	<0.005	<0.005	<0.005
3-parameter Weibull Anderson-Darling	5.368	13.294	1.008	2.856	34.994
3-parameter loglogistic test p-value	NA	NA	NA	NA	NA
3-parameter loglogistic Anderson-Darling	1.268	9.728	1.665	6.012	49.767

Although calculating capability indices using a distribution that does not fit observation is not technically correct, we calculated them in nodes 1 and 3 only for comparison (Table 4). In figure 4 the results of Cox-Box transformation (node 1 voltage) and in figure 5 and 6

probability plot of 3-parameter loglogistic (node 3 and 5 voltage) were shown. In table 5 capability indices calculated using non-parametric technique were shown.

Table 4: Capability indices estimated with the assumption that a famous distribution was fitted to observation data.

	Index	Node 1	Node 3
3-parameter lognormal	C_{PL}	1.09	0.66
	C_{PU}	0.97	1.08
	C_{PK}	0.97	0.66
3-parameter Gamma	C_{PL}	1.11	0.69
	C_{PU}	1.01	1.01
	C_{PK}	1.01	0.69
3-parameter loglogistic	C_{PL}	1.00	0.52
	C_{PU}	0.64	0.85
	C_{PK}	0.64	0.52

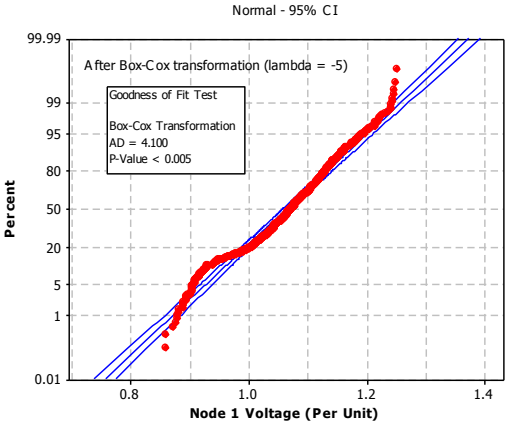

Figure 4: Result of Cox-Box transformation node 1 (Phase A)

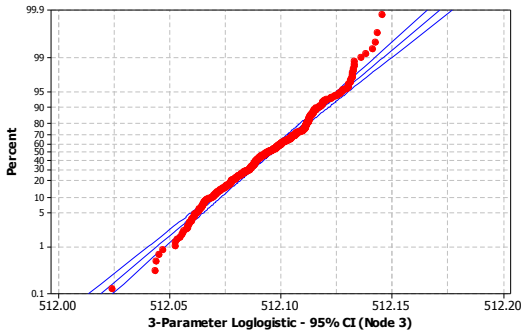

Figure 5: probability plot of 3-parameter Weibull (Node 3 voltage phase A)

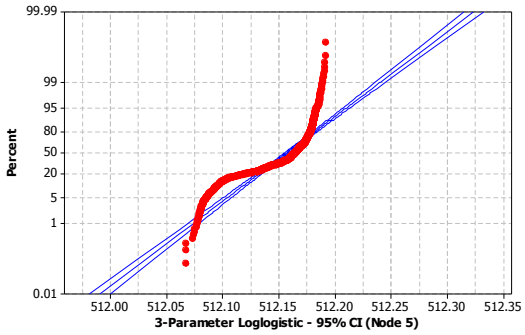

Figure 6: probability plot of 3-parameter Weibull (Node 5 voltage phase A)

Table 5: Capability indices calculated using non-parametric technique

	Node 1	Node 2	Node 3	Node 4	Node 5
x^*	0.9565	0.999	0.9366	0.9586	0.908
y^*	1.0310	1.098	1.0366	1.018	1.033
m_U	1.012	1.081	0.984	0.993	1.011
m_L	0.979	1.034			0.930
C_{PU}^{**}	2.02	___	1.25	2.26	1.78
C_{PL}^{**}	1.28	2.42	0.72	1.25	___
C_{PK}^{**}	1.28	___	0.72	1.25	___

The m_U in node 2 in larger than USL .Therefore, the rate of over voltage in this node is so high that it was not possible to calculate the network capability of maintaining voltage level below maximum acceptable voltage (C_{PU}^{**}) using non-parameter technique. Similarly, the (C_{PL}^{**}) in node 5 was not calculated. The comparison between table 4 and table 5 showed that if voltage profile does not follow a known distribution, calculating capability indices with the assumption that the data follow it can lead to misleading result.

CONCLUSSION

In current study, we introduced non-parametric technique that can be used for calculating the capability indices. This indices represent the capability of power distribution network to maintain voltage level in the predefine range. This study showed that in real world voltage profile may not follow a well-known distribution, so using a method that is not based on a specific distribution can help engineers to calculate capability indices.

Acknowledgments

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REFERENCES

[1] Saghaei A, Jamshidi B, Zare A, Safari M and Golmohamadi A, 2012 "Voltage Profile Quality of Conformance Evaluation with Process Capability Analysis in the Presence of Distributed Generation,", *CIRED workshop, Lisbon*,

[2] Polansky A.M., 2001"A Smooth Nonparametric Approach to Multivariate Process Capability", *Technometrics*, Vol. 43, No. 2, 199-211

[3] Lovelacea C.R. Swaina J. J., 2009 "Process Capability Analysis Methodologies for Zero-Bound, Non-Normal Process Data Process Capability Analysis Methodologies for Zero-Bound, Non-Normal Process Data" *Quality Engineering*, Vol. 21, Issue 2, 190-202

[4] Ramanathan T. V., Dharmadhikari A.D. and Bovas A., 2003,"Nonparametric Capability Indices," *Economic Quality Control*, Vol.18, No.1, 31-41

[5] Bong-Jin and Kwan-Woo, 2011," A bibliography of the literature on process capability indices: 2000–2009," *Quality and Reliability Engineering International*, Vol. 27, Issue 3, 251–268