FINDING ASSIGNABLE CAUSE IN MEDIUM VOLTAGE NETWORK BY STATISTICAL PROCESS CONTROL

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ABSTRACT

The current of outgoing feeders are very important data transmitted over SCADA system. Monitoring of these currents can help dispatching engineers to detect abnormality in energy consumption trend and minor faults in distribution network. Statistical process control (SPC) is one of the capable approaches which can be used for this purpose. Statistical process control is based on categorizing variations into assignable causes and random causes. In current paper we described the methods which were used for finding assignable causes in load trend and short time load variation in Alborz province power distribution company pilot project. Although this approach is not developed completely and some theoretical and practical challenges should be met before extending this project to all feeders, we hope completing this study can help engineers to developing more capable network monitoring softwares.

INTRODUCTION

Medium voltage feeder load fluctuates continuously. Usually, this variation is the result of complex interaction of random causes such as motors inrush current and change of transformers tap position. These variations are normally slight and their sources are not traceable. When only random causes of variations in feeder current are present, the load state is known as ‘in control’ or ‘stable’. But sometimes, feeder load variation is relative large and its source is significant which is called ‘special’ or ‘assignable’ cause and load condition is called, ‘out of control’ or ‘unstable’. Usually, the sources of this variation in medium voltage are high impedance fault and protection device operation like recloser, Sectionalizer and cut-out fuse link. Medium voltage network lacks embedded intelligence and small-scale outages cannot be detected automatically. In addition, some considerable load changes are associated with unauthorized energy consumption. If repetitive momentary assignable causes are detected, it is recommended to detect and eliminate the source of variation by dispatching field technicians.

Statistical process control (SPC) is a set of statistical tools developed for monitoring process variation. SPC can be used for separating assignable causes from random variations. For detecting assignable cause in distribution network, the current of medium voltage feeders are collected and trend and variation components of them are extracted. By plotting proper statistic of these data in control chart, we can distinguish between assignable cause and random variation.

Recent developments in network automation led to renewed interest in finding assignable causes in the distribution network. Although pattern recognition tools like artificial neural network have been used for this purpose, statistical methods can be more applicable approaches because pattern recognition approaches need considerable training data. Although SCADA system collects a lot of recorded data, model training by these data is not practical, especially, if we are not certain when high impedance fault have occurred.

Dispatching department of Alborz province power distribution company has worked on load monitoring for two years. While all high voltage substations in Alborz province and west Tehran region are connected to SCADA data server of Karaj network control center, in pilot project only data of one substation are monitored by statistical load control. In this paper the practical method for detecting assignable cause by control chart has been described and the strengths and weaknesses of using this method have been explained.

STATISTICAL PROCESS CONTROL

Statistical process control (SPC) is a set of tools developed for improving process capability by quality monitoring and process variability reduction. Control chart, also known as process-behaviour chart, is an SPC tool and kind of hypothesis test used for examining whether process is in control or not. Proper control chart can classify any process into three conditions: First, Stable zone (only random causes of variation exist), Second, warning zone (load change may show assignable cause) and third, action zone (assignable cause of variation exists).

There are many control charts for process monitoring. The most famous and simplest control chart have been introduced by Shewhart. Shewhart control chart consists of points representing measurement or statistic of measurement, the centre line drawn at the value of the mean of these measurements and two lines which represent lower and upper control limits [1]. Exponentially-weighted moving average chart (EWMA) is another control chart which uses exponentially weighted average of all prior data as its statistic. EWMA weights decrease geometrically. In

the other word, the most recent sample weight is the largest while the distant samples weight are very little. EWMA control chart can be sensitive to gradual drift in process, if weight factor, which is called lambda, is selected properly. Although EWMA chart is based on the normal distribution, it can be used for monitoring non-normally distributed data too. There is two type of error which may happen when control charts are used for load monitoring. Type I error occurs if the load is in control but control chart indicates assignable cause and type II error happens if the load is not in control but control chart have not detected it. When data are taken in order, there is a risk of serial dependence or autocorrelation [1]. Positive dependency of observations can lead to false alarm in some traditional control charts and the process may appear to be out of control [1], but EWMA can tolerate moderate level of dependency [2].
Control charting has two phases. In phase I, a set of process data is gathered and analyzed in a retrospective test. Control chart in this phase shows that whether the process was in control when the data were collected. The aim of phase one is to determine the possibility of establishing reliable control chart to monitor future data. In phase II control charts are used for testing whether the process remains in control when future data are collected. In other words, phase I is retrospective and phase II is real-time [3].

PROFILE MONITORING

In traditional SPC application a process is measured as a single quality or a vector of quality at a given time or space. In some applications, like load monitoring, a lot of current measurements are collected by SCADA system. Therefore, it is possible to reconstruct load curve by this collected data. Load of feeder can be better modelled by its profile rather than discrete current measurements. Researchers have developed many methods for profile monitoring. Some of simple profiles can be modelled by single linear regression, but more complicated curves can be characterized by a multiple linear or polynomial profile [4]. In addition, there are many profile monitoring methods which are not based on parametric models. In reference 3 many methods developed in recent years have been explained.

SPLINES AND MULTIVARIATE STATISTICAL PROCESS CONTROL

It is not possible to monitor all current samples as vectors, because SCADA system collects numerous samples in a few minutes, so data reduction is necessary. The simplest idea for data reduction is load curve approximation by polynomials, but if we try to approximate data of larger interval, the degree of polynomial may be unacceptably large. The alternative is to divide the interval into few subintervals. It is possible to fit each subinterval with a low degree polynomial. If this piecewise polynomial function satisfies continuity conditions between the pieces, it is called spline.

The position of breaks and coefficients of each polynomial can be monitored by statistical process control. If feeder load is normal or under control, the shape of load profile is similar to previous days shape and the coefficients of spline are in control, but if considerable changes in load profile happen, some of these coefficients will be out of control. Therefore, it is possible to monitor these coefficients instead of all gathered data by SCADA. If these coefficients are correlated, the use of separate control charts for each of them is misleading because type I error and the probability of a point correctly plotting in control are not equal to their expected values. This problem severity increases with the number of measurement variables. For solving this problem, multivariate control charts have been developed.
Applying multivariate control chart has many advantages over using multiple univariate charts: Firstly, it is possible to maintain type I error level. Secondly, a single control determines whether the spline is in control and lastly, the actual ‘in control’ region of the related variables can be represented. Interpreting multivariate control chart is more difficult than univariate one because out-of-control alarms do not reveal which variables are out of control [1]. Multivariate control chart which is based on Hotelling's T^2 statistic is used in this study. The theoretical information which is needed for developing multivariate control charts can be found in reference 1 and 3.

HODRICK-PRESCOTT FILTER

Although, the load of each feeder is rather predictable, many things like change of transformer tap position, customers’ behaviour and random causes lead to load fluctuation. Therefore, a tool which can separate cyclical and trend components of current from raw data collected by SCADA is needed. The Hodrick–Prescott filter is a mathematical tool which can be used for this purpose. Smoothed trend on current which is generated by Hodrick-Prescott filter can be used for next steps of load monitoring.

PROBLEM DEFINITION

SCADA system of Alborz province power distribution company collects data of more than 400 medium voltage feeders in every ten seconds. A reliable method which can detect high impedance fault, changing energy consumption trend and cut-out fuse link operation by monitoring this data is an excellent tool for enhance power quality, reduce ‘energy not supplied’ index and improve customers’ satisfaction.
It is possible to monitor both daily load curve and short time load variation by control charts. While daily load curve monitoring can help control room engineers to detect change in load trend and improper network restoration, short time load monitoring detects network faults which do not activate protection relays.

METHODOLOGY AND RESULT

First stage of monitoring feeder current was data preprocessing. In this stage collected data were analyzed and improper records were eliminated. Then Smoothed load trend and short time variation were separated by Hodrick-Prescott filter. The result of using Hodrick-Prescott filter (smoothing parameter=1,000,000) was shown in figure 1.

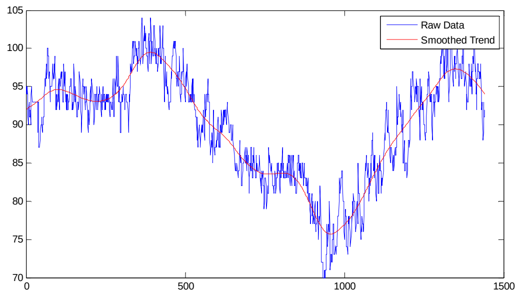

Figure 1: Hodrick-Prescott filter

Normally, Short time variations are highly autocorrelated (Figure 2) and plotting measurements in a control charts leads to false alarms. The part of control chart exceeding red control limits in figure 3 represented 'out of control' point.

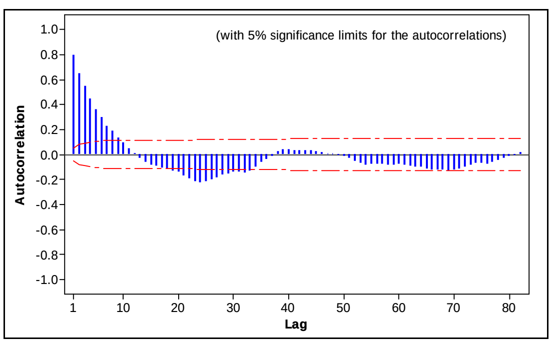

Figure 2: Autocorrelation of short time variation

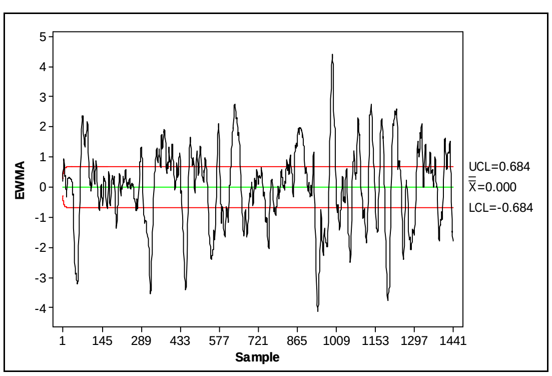

Figure 2: EWMA control chart of short time variation

For solving this problem collected data was grouped into small batches. Then means of each batch were plotted in EWMA control charts (Figure 4). The difference between the smallest and the largest data representing fast current transient change was plotted in other control chart (Figure 5). 'In control' points marked by black circles and 'out of control' one by red squares.

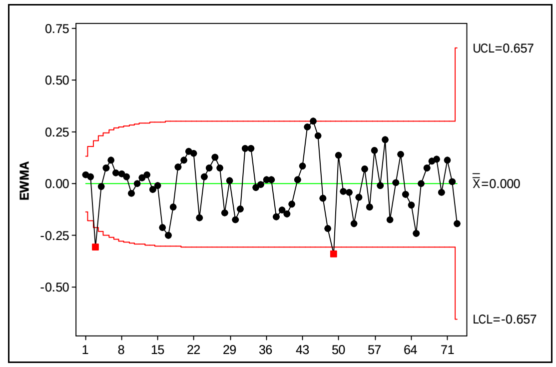

Figure 4: EWMA control chart of short time variation

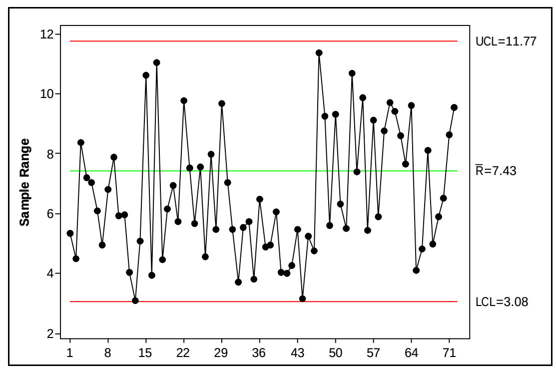

Figure 5: Shewhart control chart of variation range

For monitoring of smoothed load trend, we approximated this curve by spline. Figure 6 and 7 showed two different splines fitted to the collected data of same day. First spline had nine breaks and third order polynomial was fitted to data as accurately as possible. In contrast, second spline had only five breaks and four simple lines were roughly fitted to collected data. Table 1 and 2 represented break points and coefficients of two fitted splines.

For determining whether it is necessary to use multivariate control chart or univariate, we calculated correlation between coefficients. There was considerable correlation between these coefficients (table 3). In the last stage of trend monitoring, multivariate control chart were plotted (Figure 8).

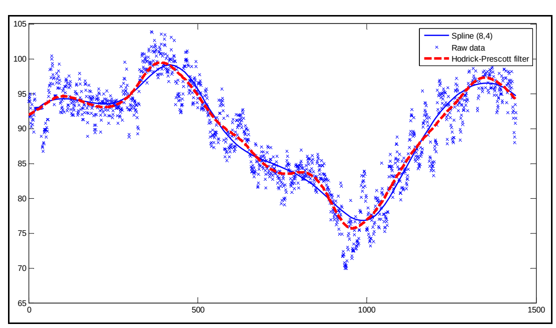

Figure 6: Spline (nine breaks, third order polynomial)

Table 1: Spline coefficients
(nine breaks, third order polynomial)

Break No	Break Point	coefficients			
		X^3	X^2	X^1	X^0
1	1	8.89E-07	-0.00044	0.0615	91.59
2	289	-2.32E-06	0.000333	0.032	94.44
3	433	2.33E-06	-0.00067	-0.0165	99.02
4	577	-8.33E-07	0.000338	-0.0643	89.71
5	721	-2.84E-07	-2.19E-05	-0.0188	84.97
6	865	1.75E-06	-0.00014	-0.0428	80.96
7	1009	-1.85E-06	0.000611	0.0243	77.03
8	1153	-7.33E-08	-0.00019	0.085	87.67

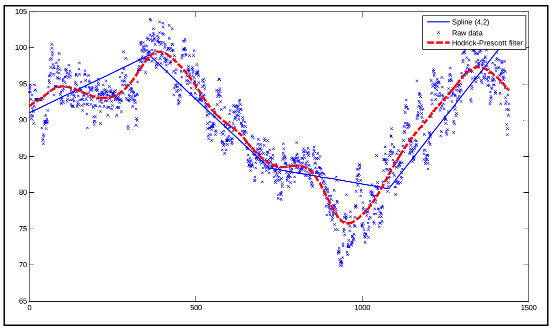

Figure 7: Spline (five breaks, linear)

Table 2: Spline coefficients (five breaks, linear)

Break No	Break Point	coefficients	
		X^1	X^0
1	361	0.0221	91.01
2	721	-0.0433	98.97
3	1081	-0.00788	83.38
4	1441	0.0585	80.54

Table 2: coefficients correlation (five breaks, linear)

	C1	C2	C3	C4	C5	C6	C7	C8
C2	-0.73							
C3	-0.89	0.37						
C4	0.88	-0.30	-0.97					
C5	-0.93	0.60	0.84	-0.88				
C6	0.73	-0.15	-0.78	0.91	-0.81			
C7	-0.12	0.57	-0.17	0.23	-0.01	0.30		
C8	-0.66	0.82	0.45	-0.34	0.67	-0.12	0.36	
C9	0.29	-0.21	-0.30	0.25	-0.29	0.12	0.12	-0.34

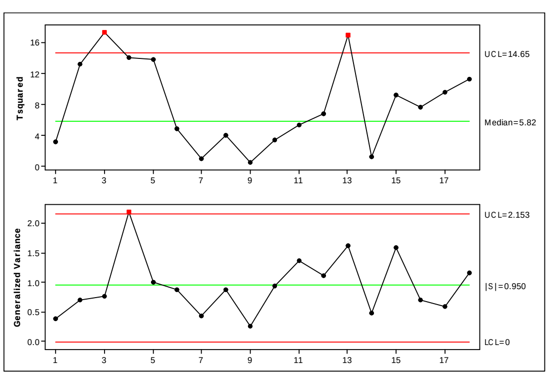

Figure 8: multivariate control chart of spline coefficients

Both control charts were related to phase I. load profile in third, forth and thirteenth days were not in control. For finding reliable control limit which could be used in phase II, the load curve of these day have been replaced with 'in control' load curves and new control chart have been plotted.

One of spline coefficients univariate control chart was shown in figure 9 for comparison. These control chart could not find 'out of control curve' because load abnormality was not affected this coefficient. In addition, two false alarms were generated by this univariate control chart.

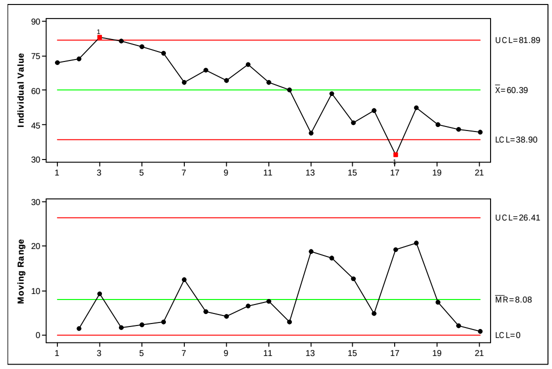

Figure 9: univariate control chart of spline coefficients

CONCLUSION

Finding assignable cause in distribution network is challenging problem. Dispatching department of Alborz province power distribution company have worked on embedded control room software which can help engineers to find abnormal condition in medium voltage network. Finding reliable control limit which can be used in phase II of monitoring can upgrade retrospective approaches to fully real-time ones.

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