

# **Attachment E**

# Effect of Outage Management System Implementation on Reliability Indices

M. McGranaghan, *Senior Member, IEEE*, A. Maitra, *Member, IEEE*, C. Perry, *Senior Member, IEEE*,  
A. Gaikwad, *Member, IEEE*

**Abstract**— This paper describes the issue of how the implementation of automated Outage Management Systems (OMS) can influence the accuracy of reliability indices. Approaches for analyzing the influence of the OMS implementation on the accuracy of reported reliability indices are described. An example is provided of a systematic evaluation of reliability indices calculation before and after implementation of an automated system. The paper illustrates the importance of considering these effects if reported indices are used as the basis for benchmarking of reliability performance incentives.

**Index Terms**—Outage management system, reliability indices, reliability

## I. INTRODUCTION

Distribution reliability statistics are the primary benchmark used by utilities and regulators to identify service quality and to measure performance. Over 20 states in the United States now require some level of annual reporting of the quality of service in terms of frequency and duration of sustained interruptions. This reporting is usually in the form of specific distribution reliability indices such as System Average Interruption Frequency Index (SAIFI) and System Average Interruption Duration Index (SAIDI). [1]

## II. OMS IMPLEMENTATION

Utilities continue to implement automated outage management and reporting systems that are designed to improve the response to outages and management of system reliability. These systems incorporate automated call systems that handle very large volumes of calls, geographic information systems that manage information about the electrical system, and customer information systems that contain connectivity information relating customers to the electrical equipment in the GIS system [2]. Combining all these systems with logic to automatically identify the portion of the circuit that is most likely to be out of service provides utilities with the capability to locate problems more quickly, efficiently assign crews to repair problems, and get customers back in service faster. The result should be improved reliability performance.

These systems also result in much more accurate calculation of the reliability indices themselves. Customer calls are managed more efficiently and accurately. The durations of interruptions are calculated very accurately by the system based on the initial customer calls and the time of restoration (often obtained directly from SCADA systems). The number of customers interrupted in each case is also determined automatically from the customer information system and geographical information systems (GIS) databases.

However, the implementation of OMS systems can result in unexpected changes in the reported reliability due to these more accurate calculations. Older methods for call management, manual recording of information in paper form and then entering data into disturbance recording systems, and trouble men estimating customer counts and duration times of outages have inherent errors and can result in inaccurate calculations and reporting of reliability performance indices. The differences in reported reliability levels before and after implementation of automated systems can cause difficulties in assessing the actual changes in reliability levels.

Following implementation of OMS, many utilities have reported that their reported SAIDI and SAIFI numbers have increased. [3,4,5,6] This may be misconstrued as indicative of a decline in reliability, even as other indications suggest improved reliability. However, the apparent decline in indicators is often the result of more accurate indices calculation, and not actual deterioration of system reliability. It is important to understand and quantify these expected changes in reliability indices as a result of more automated and accurate information for such items as customer connectivity, outage start time, and restoration time.

## III. EXAMPLE CASE STUDY

The analysis in this paper focuses on a specific evaluation for an example utility using actual reliability data. Reliability levels reported by this utility and benchmarks for future performance evaluation are established based on historical reliability levels. Therefore, it is important that the calculation of historical reliability levels be consistent with the ongoing calculations. The analysis evaluates the reported reliability levels prior to implementation of automated OMS to see if there are inconsistencies with the calculation of reliability levels after OMS implementation.

Implementation of the various components of an

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M. McGranaghan ([mmcgranaghan@epriolutions.com](mailto:mmcgranaghan@epriolutions.com)), A. Maitra ([amaitra@epriolutions.com](mailto:amaitra@epriolutions.com)), C. Perry ([cperry@epriolutions.com](mailto:cperry@epriolutions.com)) and A. Gaikwad ([agaikwad@epriolutions.com](mailto:agaikwad@epriolutions.com)) are with EPRI Solutions, Inc. in Knoxville, TN 37932 USA.

automated system (call handling systems, improved databases describing the electrical system and customer connectivity, and automated outage analysis systems) does not occur in one simple step. These systems evolve over time and may include different versions of the systems. However, it is usually possible to identify the period of time where the most important changes occurred in the management and analysis of outage information. For the example utility in this case, the most important implementation period is from 1999-2000.

Prior to this period, important characteristics of outage information management included:

- Mainframe-based disturbance recording system (DRS)
- Device causing the outage was identified by the lineman based on his best estimate
- Trouble tickets filled out manually based on information from the line crews
- Trouble tickets recorded manually into the DRS, often many days after the event (there is an issue of whether or not every event actually gets entered into the DRS)
- No information about the number of customers connected on individual phases for three phase events

After implementation of the OMS and improvements in the underlying connectivity database (including full three phase representation with data about customers connected to each phase), calculation of the number of customers interrupted is completely automated and the accuracy is substantially improved. Equally important, the system assures that every event is entered into the outage database and included in the calculation of reliability indices.

#### A. Data Analysis Technique

The statistical analysis used the entire database of reliability data. A database of actual customer calls (CC) received each day provides the basis of the customer call statistics. The reliability statistics that provided a strong correlation with customer call statistics, were customers interrupted (CI) and customer minutes interrupted (CMI) for each day. Typically, customer calls on a certain date is either due to outage reporting or due to other causes such as billing inquiries, etc. Most utilities (including the example utility) have found a consistent relationship between the number of customer calls for an outage and the actual number of customers interrupted. The data was analyzed in two primary datasets: the “post-OMS” dataset included the years 2000-2003 and the “pre-OMS” dataset included the years 1994-1999.

In order to improve the accuracy of the correlation, the analysis was done by separating the Customer call data and the associated CI/CMI data into separate bins representing different average levels of customer calls/day. This allows for different correlations between CC and CI/CMI at different

call volumes. The objective was to obtain a better correlation between reliability levels during the post-OMS as well as pre-OMS period if the reliability levels in the individual years are divided into smaller subsets/bins.

A method was developed to systematically select the number of the bins as well as the ranges of customer calls/day for each bin. The range of CC/day for each bin is obtained by evaluating the cumulative distribution functions (CDFs) for the 25th, 50th, and 75th percentiles. Daily data of CC/day during the 2000-2003 period is used for this purpose. For example, if the distribution that best describes reliability performance of Customer Calls (CC), Customer Interruptions (CI), Customer Minutes Interrupted (CMI) is lognormal, then the CDF for CC/day is obtained using the Lognormal Maximum Likelihood Estimation based technique. Reliability distributions of daily as well as weekly CC/day, CI/day, and CMI/day, for the two operating companies revealed that lognormal distribution fits the data better than other likely distributions including Normal (Gaussian) and Weibull. Four bins based on this lognormal CDF corresponding to 25th, 50th, and 75th percentiles were used.

The weekly data from 2000-2003 is then used to establish the relationship between CC and CI/CMI. This relationship is assumed to apply in the years prior to OMS implementation (1994-1999) and adjustment factors are calculated for the previously reported data so that it can be compared directly with more recent data and used for establishing benchmarks.

#### B. Analysis Results

The initial analysis of the data clearly indicated a need for an adjustment for the effects of OMS implementation. This is illustrated by the graphs in Figure 1 and Figure 2. Figure 1 shows the daily customer call data for the two periods evaluated. Notice that the entire distribution of customer calls/day for the post-OMS period is below the distribution of the customer calls/day for the pre-OMS period. This indicates that there were fewer customer calls/day after OMS implementation, indicating that reliability levels should have been better in this period (assuming correlation between customer calls and customers interrupted). However, Figure 2 shows that the reported data of customers interrupted per day shows the opposite relationship – there are more customers interrupted per day for the post-OMS period. The analysis is used to determine the corrections required to the pre-OMS implementation reliability data (CI and CMI).

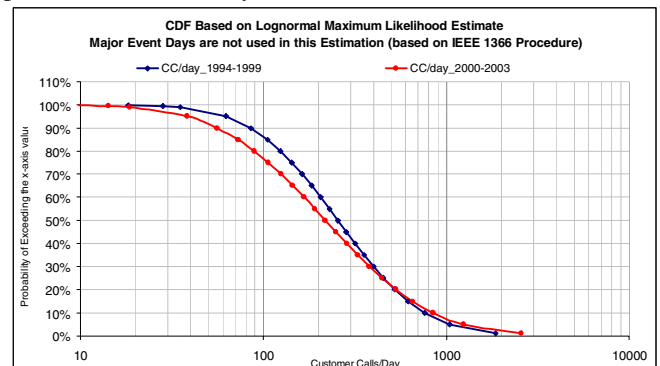


Figure 1. Lognormal representation of customer call data showing a comparison of pre-OMS and post-OMS data.

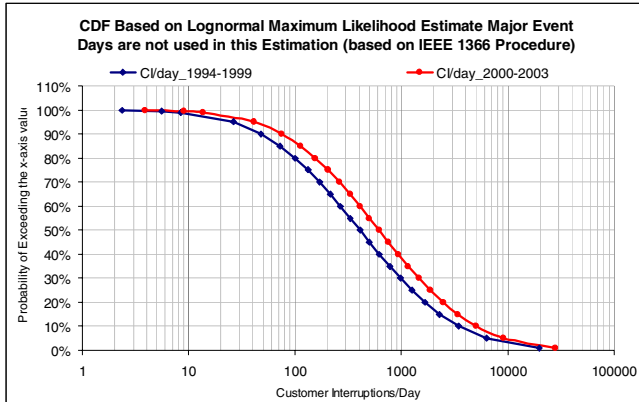


Figure 2. Lognormal representation of customer interruption data showing a comparison of pre-OMS and post-OMS data.

For calculation of the adjustment factors, the correlation between customers interrupted and customer calls is evaluated in each of four different bins of customer call volumes. The correlations are performed for the data in the years 2000-2003. Figure 3 illustrates the results.

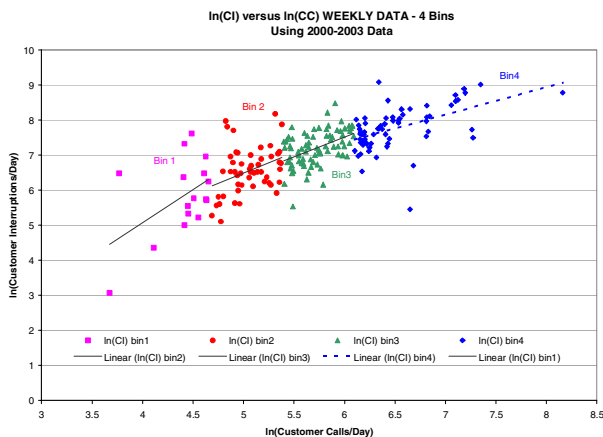


Figure 3. Illustration of the regression analysis for determination of relationship between customer calls and customer interruptions for four different bins representing four different categories of daily call volumes.

The relationship between customer calls and customer interruptions was calculated for each of the four bins. This factor is then used to re-estimate the customer interruptions (CI) for each day in the pre-OMS years. The new values of CI are summed and compared with the previously reported values of CI to develop an average adjustment factor that applies to the pre-OMS years. A similar procedure is used to develop the adjustment factor for customer minutes interrupted. The results are summarized in Table I.

TABLE I

EXAMPLE CASE ADJUSTMENT FACTORS FOR PRE-OMS RELIABILITY INDICES

Indice	Adjustment Factor for Pre-OMS Data
SAIFI	26%
SAIDI	53%

#### IV. SUMMARY

OMS implementation, combined with improved databases of customer connectivity information, can result in much more accurate calculation of reliability indices. However, this can make comparison with previously reported reliability levels very difficult. This paper presents a method that can be used to adjust pre-OMS reliability data using correlation of reliability indices with customer call data. The results allow a consistent comparison of reliability performance data and more accurate establishment of benchmarks for future performance evaluation.

#### V. REFERENCES

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#### VI. BIOGRAPHIES

**Charles H. Perry, Jr. P.E.** is Lab Manager at the EPRI Solutions, Inc. office in Knoxville, TN. His activities include power system studies in power quality, reliability, metering, relaying and distributed generation. Before joining EPRI Solutions, Inc. in 2000, he worked for American Electric Power for ten years. Mr. Perry has a Master's of Science degree in Engineering from West Virginia Graduate College (1996) and a Bachelor's degree in Electrical Engineering from West Virginia University (1989). Mr. Perry is a registered Professional Engineer in the State of West Virginia.

**Mark F. McGranaghan** is a Vice President with EPRI Solutions, Inc. in Knoxville, TN. He works with electric utilities worldwide in the areas of reliability and power quality assessments, system monitoring, transient and harmonic studies, and economic evaluations. He is a co-author of the book *Electric Power Systems Quality* and has written numerous IEEE papers. Before EPRI Solutions, Mr. McGranaghan worked for Electrotek Concepts and Cooper Power. He has BSEE and MSEE degrees from the University of Toledo and MBA from University of Pittsburgh. He is active in many IEEE and IEC Standards activities.

**Arindam Maitra (M'1995)** received his BSEE, MS, and Ph.D. degrees from R.E.C. Nagpur and Mississippi State University in 1995, 1997 and 2002, respectively. He is currently a senior engineer at EPRI Solutions, Inc. in Knoxville, Tennessee where he is responsible for conducting and managing research activities associated with power quality and reliability. His research interests are in the areas of modeling and simulation techniques for power system harmonics, power system transients, distribution reliability, load modeling, computer applications in power systems, and power system control and

protection. He has authored and co-authored numerous technical papers on such topics.

**Anish Gaikwad** (M'2002) received his BSEE, and MS degrees from R.E.C. Nagpur and Mississippi State University in 1997, and 2002, respectively. He is currently an engineer at EPRI Solutions, Inc. in Knoxville, Tennessee. His main areas of focus are computer applications in power systems, statistical and reliability methods applied to power systems, load modeling and data acquisition systems. He has written various technical papers and articles.