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Model Centric Approach for Monte Carlo Assessment of Storm Restoration and Smart Grid Automation

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ABSTRACT
A model centric approach for Monte Carlo simulation for evaluating the economic and reliability benefits of automated switches for storm restoration is presented. A very detailed circuit model with over 20,000 individual customers modeled is used in the simulation. The simulation uses non-constant equipment failure rates based upon actual utility measurements. As part of the Monte Carlo storm simulation, a reconfiguration for restoration algorithm is employed in determining the response to each outage. The reconfiguration for restoration algorithm can work with either manual or automated switches, or both. System reliability with and without automated switching devices is investigated. Cost benefits as well as reliability benefits are considered.

1. INTRODUCTION
Storm response and restoration expenses can be devastating. The data from 14 utilities shows that the average cost is $48.7 million per major storm [6]. This is because the cost of storms involves equipment repairs, logistics, and generally very large man power efforts [1],[5],[7-8],[16-18]. When a major storm hits, utilities have to rely on their support network of contractors and often, borrowed crews from other utilities, if they are available. Insufficient outside resources or inefficient crew dispatching can lead to a much larger price tag for the utility, which turns into to a surcharge to customers, and has a negative impact on the reputation of the utility management.

Quantitatively evaluating the economic worth of distribution automation and the impacts on reliability under storm restoration has not been addressed in previous literature. In this paper, a model-centric simulation approach that provides a quantifiable assessment for both reliability and economic benefits obtainable from distribution automation is presented. Monte Carlo simulations of storm restoration coupled with automated system reconfiguration is employed. Traditionally, in previous work it has often been assumed that the failure rate of equipment during adverse weather conditions is a constant [17-19] for each weather stage, but this assumption does not agree with real storm data. Therefore, the simulation we performs here takes into account that the number of equipment failures fluctuates as a function of the hour of the storm[2,16]. The simulation results benefit from the detailed, multiphase distribution network model with all individual customers modeled, which has not been considered in previous studies.

The highlights of the study reported in this paper is as below:

- Given an automation design plan for a distribution system, a software simulation approach for evaluating the economic and reliability benefits of the automation is presented
- Commonly existing utility data is used to perform the storm simulations
- A very detailed model of the distribution network is used in the analysis
- A unique model centric approach is used to make the fast computation possible, which involves large amount of data and real-world size system model

- The simulation uses non-constant equipment failure rates, which are based upon actual utility measurements, for the storm simulation
- As part of a Monte Carlo storm simulation, a reconfiguration for restoration algorithm is employed in determining the response to each outage

2. MODEL CENTRIC APPROACH

The model centric approach considered here integrates a detailed physical network model, multiple sets of data , and interacting, computational algorithms into one simulation architecture. In Fig. 1 the Integrated System Model (ISM) Container includes all components in the distribution network, from substations to all customers. Load modeling for each customer is based on customer class load profiles and customer kWHr measurements. Parameters such as weather based failure rates can be attached to each component. The container manages system topology by maintaining topology iterators for all components. The topology iterators offered by the container are employed by algorithms, such as reconfiguration for restoration [20-23]. All calculations are based on **G**raph **T**race **A**nalysis [22] and object oriented programming. GTA can be viewed as a combination of ideas from physical network modeling, graph theory, and generic programming. By utilizing topology iterators, fast traversing of ISM system components to determine reconfiguration strategies is possible. Changes in topology, such as occur when components are failed by the Monte Carlo or when switches are operated, do not take any additional processing time with GTA.

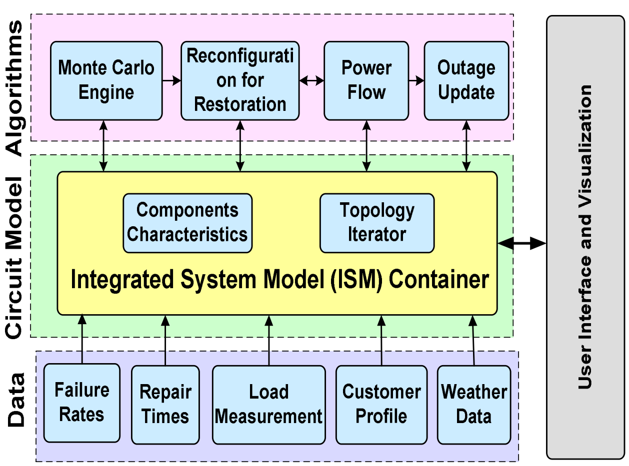

Fig. 1. Monte Carlo Simulation Architecture

3. STORM MODELING AND RESTORATION SIMULATION

In our work here historical Outage Management System data are mined to extract the data needed for the storm related outage simulations. The weather data was obtained from weather stations located in this distribution system. Weather conditions such as wind speed, temperature and others are recorded at least every hour at both weather stations. In the outage data, outages are associated with the weather measurements from the closest weather station.

Storms are classified by temperature and wind speeds as shown in Table I based on our previous study [2].

TABLE I
STORM CLASSIFICATION

Storm Type	Description	Temperature Range(°F)	Wind Speed Range (mph)
H	High temperature, no strong wind	MaxT > 80	WS <= 20
HS	High temperature, strong wind	MaxT > 80	WS > 20
L	Low temperature, no strong wind	MinT < 32	WS <= 20
LS	Low temperature, strong wind	MinT < 32	WS > 20
M	Moderate temperature, no strong wind	MaxT <= 80 MinT >= 32	WS <= 20
MS	Moderate temperature, strong wind	MaxT <= 80 MinT >= 32	WS > 20

MaxT: maximum temperature; **MinT**: minimum temperature; **WS:** wind speed

The study here provides a simulation that mimics what is observed during each type of storm. For each storm hour, the Monte Carlo simulation randomly picks components to fail, based on measured, weather related failure statistics as a function of the hour of the storm. The reconfiguration algorithm then operates sectionalizing devices to restore power, where the type of sectionalizing devices used in the reconfiguration may be specified, such as automated or manual devices of certain types. After isolating failures, the algorithm illustrated in Fig. 2 tracks and updates a list of devices bordering the outage area (OA). If closing a device in the list results in over currents or under-voltages, the algorithm re-opens the device and removes it from the list. This process is repeated until either the outage area is fully restored or until there are no devices which can be closed to restore power. The final list of devices reported by the algorithm includes the isolating devices, and the list of boundary devices that can be closed to restore power without violating system constraints.

Therefore, the simulation approach we presented here considers the alleviation of the original storm failure events destructive impact by performing reconfiguration for restoration, which is what utilities practice during storms. The customers lost power information is then collected after performing reconfiguration for restoration. Monte Carlo simulations are built on the principle that a random sampling tends to show the same properties as populations from which it is drawn [15,18]. In our study we simulate 6000 storms for each type of storm.

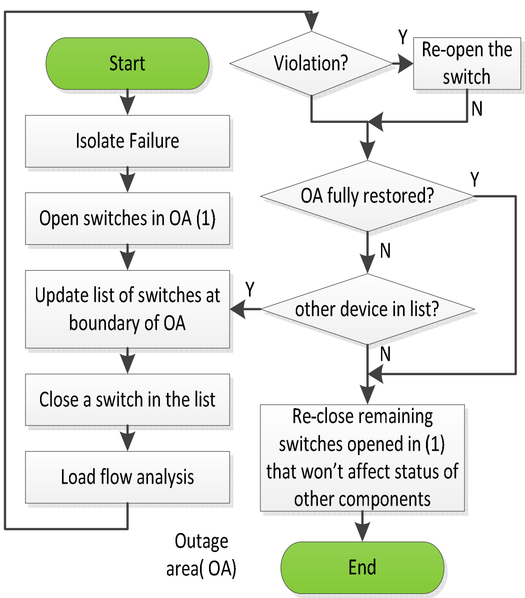

Fig.2. Reconfiguration for restoration algorithm

3. SIMULATION APPLICATION

A sufficiently large system is needed to test the reconfiguration capabilities of the distribution automation. The system used in the study is shown in Fig. 3 and includes seven substations and fourteen feeders with ten different types of customers.

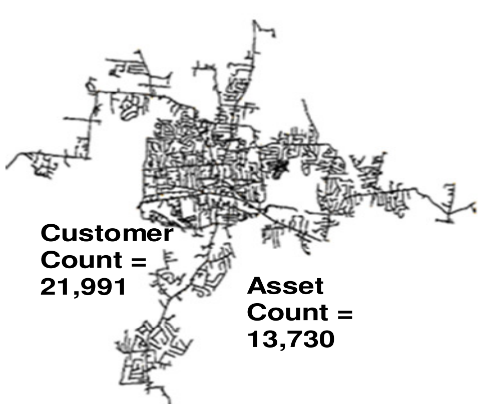

Fig.3. 7 Substations and 14 feeders model

The simulation compares the relative effectiveness of using automated switching devices over manual operations under different storm conditions. The simulation of the non-automated design allows all sectionalizing devices except protective devices to be operated, were manual switching operations are simulated.

The automated design includes SCADA operable devices that are the only switches operated in the restoration simulation. The automated design attempts to place an automated switch for each 250 customers. It is assumed that the automated device operation takes 0 hours. From utility operating experience with manual switching operations for a given outage, it takes 1 hour for the crew to operate the first switch and 15 minutes for each additional switch operation.

Since all individual customers are modeled, the reliability calculations are performed in terms of customer hours of interruption, and reliability parameters are a function of storm type. As shown in Fig. 4, the automation design considered reduces the number of customer hours for all types of storms.

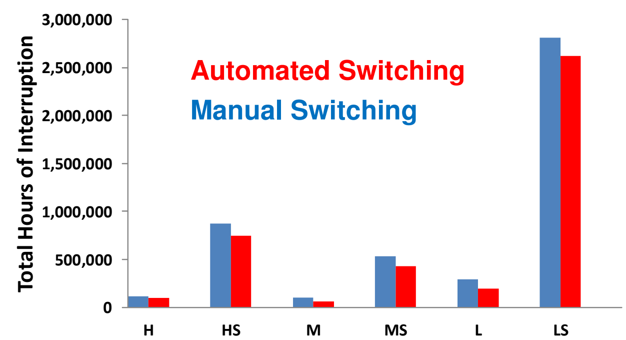

Fig. 4. Comparison of interruption Hours by storm type

The economic evaluation is performed by comparing the operating costs of the alternative designs – manual operation versus automated operation. Table II shows the 10 year estimated savings across storm types extrapolated to the entire utility, which consists of 260 feeders. The number of crews and hourly storm cost come from utility practical experience. The number of storms are the average number of storms for each type in 10 years period.

For example, consider the high temperature (H) storm. For the storm restoration the manual design requires 40 crew hours more than the automated design. During a high temperature storm there are on average about 100 crews employed for the storm restoration, with a restoration cost of about $70k per hour. On average there are 13 high temperature storms over a 10 year period, and thus the non-discounted savings are about $364k. For all 6 storm types, the automated design has a savings of about 9 million in storm restoration over the non-automated design. Thus, the study shows that deploying automated restoration procedures can bring the system back faster with significant economic benefits.

TABLE II
10 YEAR SAVINGS ACROSS STORM TYPES

Storm Type	Manually Switching Crew Hours	Number of Crews	Hourly Storm Cost ($k)	Number of Storms	Non-discounted Savings ($k)
H	40	100	70	13	364
M	60			12	504
HS	213	142	100	17	2,550
MS	168			23	2,721
L	127	171	120	7	624
LS	403			10	2,828
				Total Savings	9,592

4. CONCLUSIONS

The deployment of automated switches can benefit the utility by decreasing storm restoration hours. In this paper a model centric approach is proposed to provide quantifiable benefit evaluation. A Monte Carlo simulation is used to mimic storm equipment failure events, followed by reconfiguration for restoration and power flow evaluations. The customer outage status and duration are examined. Changes in reliability for the system with and without automated switching devices are investigated. Operating cost benefits of utilizing smart grid automated devices are considered. A large system model was used to determine the benefits of the reconfiguration, where each individual customer is modeled. Reliability statistics were determined by counting customers without power and using statistics from utility operating experience. Improvements in reliability and operating costs are shown to be significant for the automated design. Finally, it should be noted that there are other value streams for automated switches beyond storm restoration, including blue sky operations and reconfiguration for minimum loss.

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