Model-Based Grid Modernization Economic Evaluation Framework

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ABSTRACT

A smart grid cost/benefit analysis answers a series of economic questions that address the incremental benefits of each stage or decision point. Each stage of the economic analysis provides information about the incremental benefits of that stage with respect to the previous stage. With this approach stages that provide little or no economic benefits can be identified. In this study there are series of applications,- including quasi-steady state power flows over time-varying loads and costs of service, Monte Carlo simulations, reconfiguration for restoration, and coordinated control - that are used to evaluate the cost-benefits of a series of smart grid investments.

In the electric power system planning process, engineers seek to identify the most cost-effective means of serving the load within reliability and power quality criteria. In order to accurately assess the cost of a given project, the feeder losses must be calculated. In the past, the feeder losses were estimated based upon the peak load and a calculated load factor for the year. The cost of these losses would then be calculated based upon an expected, fixed per-kWh generation cost. This dissertation presents a more accurate means of calculating the cost of losses, using hourly feeder load information and time-varying electric energy cost data. The work here attempts to quantify the improvement in high accuracy and presents an example where the economic evaluation of a planning project requires the more accurate loss calculation.

Smart grid investments can also affect response to equipment failures where there are two types of responses to consider -blue-sky day and storm. Storm response and power restoration can be very expensive for electric utilities. The deployment of automated switches can benefit the utility by

decreasing storm restoration hours. The automated switches also improve system reliably by decreasing customer interruption duration. In this dissertation a Monte Carlo simulation is used to mimic storm equipment failure events, followed by reconfiguration for restoration and power flow evaluations. The Monte Carlo simulation is driven by actual storm statistics taken from 89 different storms, where equipment failure rates are time varying. The customer outage status and durations are examined. Changes in reliability for the system with and without automated switching devices are investigated.

Time varying coordinated control of Conservation Voltage Reduction (CVR) is implemented. The coordinated control runs in the control center and makes use of measurements from throughout the system to determine control settings that move the system toward optimum performance as the load varies. The coordinated control provides set points to local controllers. A major difference between the coordinated control and local control is the set points provided by the coordinated control are time varying. Reduction of energy and losses of coordinated control are compared with local control. Also eliminating low voltage problems with coordinated control are addressed.

An overall economic study is implemented in the final stage of the work. A series of five evaluations of the economic benefits of smart grid automation investments are investigated. Here benefits that can be quantified in terms of dollar savings are considered here referred to as “hard dollar” benefits. Smart Grid investment evaluations to be considered include investments in improved efficiency, more cost effective use of existing system capacity with automated switches, and coordinated control of capacitor banks and voltage regulators. These Smart Grid evaluations are sequentially ordered, resulting in a series of incremental hard dollar benefits. Hard dollar benefits come from improved efficiency, delaying large capital equipment investments, shortened storm restoration times, and reduced customer energy use. The evaluation shows that when time varying loads are considered in the design, investments in automation can improve performance and significantly lower costs resulting in “hard dollar” savings.

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Chapter 1 Introduction

1.1. Introduction

Calculation of losses and loads with high accuracy are critical for power system planning. If losses, cost and energy are not calculated correctly, planning engineers may make the wrong decision whether to go ahead with a decision or not. For example, in calculating losses with high accuracy, two quantities must be known: the energy (kWh) of the losses and the cost of those losses ($/kWh). Generally these quantities are not available for each hour of analysis and estimated either based on load factor method or averaged. Even though, load factor method is used by the utilities today, high accurate calculation would provide better understanding of power system and also provide better planning decision options. This high accuracy is also need at the stage of implementing smart grid to be able to say whether smart grid is cost effective.

Smart grid technologies have recently garnered significant attention among researchers in academia and industry. Many questions remain unanswered and more questions are sure to come .While regulations provide much incentive for technological advancement, utilities may find the economic incentives to be more than adequate even when regulation requirements are met without upgrades.

Smart grid cost-benefit evaluation can be categorized in four sections including:

1. Smart Grid Assets
2. Smart Grid Algorithms
3. Smart Grid Metrics
4. Monetization of Smart Grid Metrics.

In this dissertation, these four categories will be evaluated and demonstrated to prove that smart grid is efficient, reliable and cost effective.

Smart Grid assets are the key elements needed to build smart grid circuits. Without these devices or technologies, smart applications cannot be implemented. These *smart assets* include smart meters, automated switches, electronic reclosers, communication modules, smart capacitors, renewable technologies.

The smart grid does not need new devices to be “smart,” however. Old devices can be controlled using *smart algorithms* that make use of SCADA data and detailed system models. The smart algorithms considered in this dissertation include (1) coordinated control of Volt/Var devices and (2) system reconfiguration for restoration and contingencies. Besides using algorithms for real-time control smart algorithms help design the system under more static conditions. These applications include phase balancing, capacitor placement.

Once we have smart assets and algorithms, then we need to compare these smart grid systems with our existing system (base case) to prove that the new system (smart grid) is better than old system (base case). This introduces the need for *smart grid metrics* such as kWh energy reduction, peak kW reduction, loss reduction, restoration time reduction, and overall efficiency and reliability.

The final step for smart grid economic evaluation is to *monetize* these metrics. Without this final step, utilities cannot know whether the smart grid is cost effective nor can regulators understand whether their regulations are reasonable. Table 1-1 below shows the monetization of the metrics listed above.

Table 1-1. Monetization of the metrics

Electrical System Metric	Monetization
Reduction in Energy Delivered	Cost of Energy
Reduction in Peak KW	Equipment Deferral; Congestion Costs
Reduction in Energy Losses	Cost of Energy
Reduction in Restoration Time	Crew Labor Costs
Improvement in Reliability	Deferral of Equipment Needed to Meet Reliability Requirement

1.2. Dissertation Objectives and Research Questions

The objective of this dissertation is to help utilities better understand the economic potential of smart grid projects by answering the following questions:

Question 1: Where do the trade-offs lie between investment in capital equipment and investment in control algorithms?

Vendors always want to sell utilities new equipment. Automation, on the other hand, can help the utility make better use of existing equipment, though implementing such automation also costs money. This dissertation seeks to help utilities understand this trade-off.

Question 2: At what point are smart grid investments economically justifiable?

Since smart grid technologies are often new and unproven, utilities are justifiably wary of proceeding. Simplistic assumptions about power system operation and energy costs only increase their skepticism. In contrast with this skepticism stand researchers and vendors promising huge savings. This dissertation seeks to remove some of the uncertainty by using detailed load and price data together with detailed models and algorithms to produce more accurate estimates of economic savings in terms of both year-to-year operation costs and one-time capital costs.

Question 3: Can utilities achieve significant capital deferral through smart grid reliability improvements?

The purpose of this study was to simulate the effect of automation on radial distribution circuits during a station transformer failure at peak load. The ultimate goal was to determine if this automation could be used to defer the construction of a new distribution substation by satisfying planning criteria for customer interruption hours in the event of a failure of this nature. As a result of the study, it can be observed that the automation of the pilot substation yielded a 10,000 customer interruption hour decrease on each transformer bank when compared to the results run for the manual switching models. The absence of switching time in the automated scenario is the reason for the decrease. By automating circuits, with their respective adjacent tie circuits, it is possible to eliminate or reduce customer interruption hours resulting from manual switching.

Question 4: How can smart grid investments affect the cost of storm response?

Storms cause failures across large power systems, resulting in widespread customer interruptions. The power system can be divided into the segments so that power can be rerouted when one feeder path is lost, thereby reducing the number of customers affected by each outages piece of equipment. Besides allowing the switching/rerouting to occur faster, distribution automation also provides faster notification to system operators of equipment outages. Automation therefore helps the utility meet reliability criteria without building more redundancy into the system. Additionally, reductions in labor costs can be in the neighborhood of $25 to $35 million dollars.

Question 5: What are the economics of Conservation Voltage Reduction?

Some loads, such as incandescent light bulbs draw less energy when the supply voltage is lowered. The attempt to reduce loading by lowering voltage is called conservation voltage reduction (CVR). Most of the past research into CVR has focused on reducing loading at peak for the sake of avoiding capital equipment upgrades. The reduction in energy, however, also has economic value, but this reduction will vary throughout the year as the loads increase and decrease. This dissertation uses detailed historical load data to calculate the savings that might have been realized over the course of a year using a coordinated control algorithm to perform CVR.

Question 6: How much investment in efficiency should be made before investment in automation?

Automation does not preclude investment in the static performance of the circuit. This dissertation considers investments in phase balancing and capacitor placement in addition to smart grid investments, seeking to determine how much attention should be given to the efficiency of the static system before analyzing an automated system.

1.3. The Contents of Dissertation

The dissertation chapters are organized as follows. Chapter 2 introduces how time varying algorithm is different than traditional way of calculation. Chapter 3 is centralized control of Volt/Var devices for CVR and efficiency and Chapter 4 is centralized switching and reconfiguration for restoration. Chapter 5 considers the sequence in which these automation options should be considered together with traditional distribution system planning. Chapter 6 describes the hard dollar evaluation of the planning considerations addressed in Chapters 3, 4 and 5 with several case studies using detailed models of real power systems and actual historical load and energy price data. The final section provides the conclusions of dissertation and presents future work.

1.4. Published Works Related to the Dissertation

1.4.1. Publications for Coordinated Control for power distribution system and its economy

1. [Journal] Ahmet Onen, D.Cheng, R. Arghandeh, J. Jung, J. Woyak, M. Dilek, R. Broadwater, "***Smart Model-based coordinated control based on feeder losses, energy consumption, and voltage violations***," Electric power system component and system, vol. 41, issue 16, pages 1686-1696, August, 2013.

1.4.2. Publications for Storm Restoration and its economy

2. [Journal] Danling Cheng, Ahmet Onen, Dan Zhu, David Kleppinger, Reza Arghandeh, Robert P. Broadwater, Charlie Scirbona "***Automation Effects on Reliability and Operation Costs in Storm Restoration***", accepted for publication in International Journal of Electrical power and Energy Systems, Elsevier.

3. [Conference] Danling Cheng, Ahmet Onen, Robert P. Broadwater and Charlie Scirbona, "***Model Centric Approach for Monte Carlo Assesment of Storm Restoration and Smart Grid Automation***," submitted in for publication in ASME 2014 Power.

1.4.3. Publications for Distribution Automation and its economy for Capacity, Reliability and Efficiency

4. [Journal] Ahmet Onen, Jaesung Jung, D. Cheng, and Robert P. Broadwater, "***Model-Centric Distribution Automation: Capacity, Reliability, and Efficiency***", submitted for publication in IEEE Smart Grid Transaction.

5. [Journal] Ahmet Onen, Danling Cheng, Robert P. Broadwater, Charlie Scirbona, George Cocks, Stephanie Hamilton, Xiaoyu Wang, Jeffrey Roark "***Economic Evaluation of Distribution System Smart Grid Investments***," submitted for publication in Electric Power System Research, Elsevier.

1.4.4. Publications for Accurate Loss Calculation Methods

6. [Journal] Ahmet Onen, Jeremy Woyak, Reza Arghandeh, Jaesung Jung, and Robert P. Broadwater, "***Time-varying Cost of Loss Evaluation in Distribution Networks Using Market Marginal Price***", submitted for publication in International Journal of Electrical power and Energy Systems, Elsevier.

Chapter 2 Time-varying Cost of Loss Evaluation in Distribution Networks Using Market Marginal Price

2.1. Introduction

In almost any power system planning project, the cost of electric energy losses represents a significant cost factor, whether the planning engineer faces the task of laying out new feeders or resolving an overload or low voltage on an existing feeder. When laying new conductor or reconductoring, the lower losses of a larger conductor may offset the cost of the larger conductor. When evaluating a phase move to reduce flow imbalance on an existing feeder, the reduction of losses alone may be sufficient reason to perform the phase move. On the other hand, if losses are not calculated correctly, planning engineers may make poor choices of conductor size or may make the wrong decision whether to go ahead with a phase move or not.

In calculating losses accurately, two quantities must be known: the energy (kWh) of the losses and the cost of those losses ($/kWh). Methods for cost of loss calculation are well-established in literature. In the past, planning engineers often only had estimates of the peak load on a feeder and the total annual consumption on the feeder. With only this information, the total annual losses were calculated based upon the peak losses and a load factor calculation [1]. Furthermore, many distribution utilities also owned their own generation or else had fixed per-kilowatt-hour costs of electric energy. In [2], authors use peak load losses and diversity factor for loss cost calculation. Authors in [3] used average loading on transformers for the cost of loss calculations to avoid using the peak load approximation. In [4], the costs of losses are divided in two categories, fixed loss and dynamic loss. Fixed loss is independent of the load level and variable loss depends on the square of the load profile. A statistically based method is presented in [5] to calculate loss with the help of Time of Use (TOU) tariffs and daily load profiles. Reference [6] explains a marginal loss calculation that used an incremental approach and Newton's method.

In the past decade, two changes have brought about the need for more detailed loss calculations. First, advancements in telecommunication and computing technology have made it much less expensive for utilities to acquire hourly flow measurements at each of their feeders and make these measurements available to their engineers [7, 8]. These hourly feeder flow measurements can greatly improve the calculation of losses at each hour of the year. Second, the deregulation of the industry has changed the way many power distribution companies pay for the energy they deliver to their customers. The actual price of energy is no longer fixed, but rather changes hourly (or more often), determined by the real-time bidding managed by the regional transmission organization (RTO) or independent system operator (ISO) and are published as the real-time locational marginal price (LMP) [9]. Authors in [10] used hourly power flow analysis and hourly load data to calculate annual line loss cost. Reference [11] explains marginal loss calculation that is independent of reference bus.

Thus, to get a more accurate evaluation of the annual losses on a feeder, the losses may be calculated for every hour of the year and then paired up with hourly energy prices to determine the actual cost of the losses.

This chapter is organized as follows: Comparison of old and new methodology is discussed in Section 2.2. The differences in accuracy are quantified for a 31-feeder system in section 2.3. In Section 2.4 an example is presented of how calculating the cost of losses more accurately may sway the decision to accept or reject a project. Finally, conclusions of chapter 2 are drawn in section 2.5.

Nomenclatures of Chapter 2

P_{avg}	: Average Load (kW)
E_{annual}	: The total annual energy consumption (kW)
8760	: Total number of hours in a year
P_{peak}	: Peak Load (kW)
LF	: Load Factor
$Loss_{peak}$	: Peak Loss (kW)
$Loss_{avg}$	: Average Loss (kW)

$Loss_{total}$	: Total Loss (kW)
$C_{expected}$	: The expected cost of a kilowatt of energy ($/kWh)
C_{total}	: Total Cost of Losses ($)
C_{alpha}^{i}	: The Coefficient for each customer type
C_{kWh}	: The monthly consumption (kWhr)
$C_{kWh}^{expected(i)}$	: The expected hourly demand for customer (kWhr)
$Fkw_{expected}^{i}$	: Total expected feeder demand at a given hour (kWhr)
$Fkw_{measured}^{i}$	: The measured demand at the start of the feeder (kWhr)
$Ckw_{expected}^{i}$	: The expected customer's demand (kWhr)
Ckw_{scaled}^{i}	: The scaled customer's demand (kWhr)
P_{loss_i}	: The losses at hour t (KW)

2.2. Old Methodology and New Methodology

2.2.1. Load Factor Loss (LFL) Method

With only peak demand information and annual energy consumption information available, the planning engineer may use a method of calculating losses that is designated the "load factor" method. The method works as follows. The total annual energy consumption (total kilowatt-hours consumed by all customers on the feeder during the course of a year) is determined by totaling the meter readings of all customer meters on the circuit. This energy consumption is then divided by the number of hours in a year (8760 if not a leap year) to get the average load:

$$P_{avg} = \frac{E_{annual}}{8760} \tag{2-1}$$

For a long time, for many feeders, the only demand data available to a planning engineer was the maximum demand on the feeder (taken from the maximum value on a circle chart reading), and perhaps the maximum demand at certain large customers who had demand meters. With the peak load known, a "load factor" may be calculated as follows:

$$LF = \frac{P_{avg}}{P_{peak}} \tag{2-2}$$

A load flow analysis program can calculate the losses on the feeder at peak. Since the losses through a conductor are proportional to the square of the current, the average losses are estimated using the square of the load factor.

$$Loss_{avg} = Loss_{peak} * LF^2 \tag{2-3}$$

Then, the total losses may be calculated by multiplying the average hourly losses by the number of hours in the year.

$$Loss_{total} = Loss_{avg} * 8760 \tag{2-4}$$

Finally, the cost of these losses would be calculated based upon the expected cost of a kilowatt-hour of energy which is the LMP in this paper. $C_{\exp ected}$ in \$/kWh

$$C_{total} = Loss_{total} * C_{\exp ected} \tag{2-5}$$

The most significant problem with this calculation appears in equation 2-3. Willis notes that this equation will "underestimate losses' costs slightly" [12]. Although Willis himself does not stop to explain the reason for his statement, the reason may be seen as follows. While it is true that the losses are proportional to the square of the current, accurately calculating the total losses would require applying the square at each hour and then averaging the results (square-then-average), rather than the opposite sequence of average-then-square used in the load factor calculation. The difference in computation can be seen in Table 2-1.

Table 2-1. Comparison of methods

Method	Formulation
Square-then-Average	$\frac{\sum x_i^2}{n}$
Average-then-Square	$(\frac{\sum x_i}{n})^2$

Averaging and then squaring can be proven by induction to always produce a smaller value than squaring and then averaging, represented in Equation (2-6).

$$\frac{\sum x_i^2}{n} \geq (\frac{\sum x_i}{n})^2 \tag{2-6}$$

The proof by induction would normally start with *n*=1, but, as that would leave $x_2 = x_2$, we will show the *n*=2 case,

$$\frac{x_1^2 + x_2^2}{2} \geq (\frac{x_1 + x_2}{2})^2 \tag{2-7}$$

to demonstrate the inequality. First, expanding the terms yields

$$2(x_1^2 + x_2^2) \geq x_1^2 + 2x_1x_2 + x_2^2 \tag{2-8}$$

Moving all of the terms to the left produces

$$x_1^2 - 2x_1x_2 + x_2^2 \geq 0 \tag{2-9}$$

Finally, factoring gives us an inequality known to be true, as the square of any quantity is always ≥ 0:

$$(x_1 - x_2)^2 \geq 0 \tag{2-10}$$

Given that the inequality is true for n = 1 or 2, the inequality will be true for all n if it can be shown that, given the inequality for any n, it holds true for n+1. The inequality for the n+1 case may be written as follows:

$$\frac{\sum_{i=1}^{n+1} x_i^2}{n+1} \geq \left(\frac{\sum_{i=1}^{n+1} x_i}{n+1}\right)^2 \tag{2-11}$$

Multiplying through by (n+1) and separating out the n+1st variable yields

$$x_{n+1}^2 + \sum_{i=1}^{n} x_i^{\ 2} \geq \frac{((\sum_{i=1}^{n} x_i) + x_{n+1})^2}{n+1} \tag{2-12}$$

Multiplying again by (n+1) and expanding the right-hand side yields

$$(n+1)x_{n+1}^2 + (n+1)\sum_{i=1}^{n} x_i^{\ 2} \geq (\sum_{i=1}^{n} x_i)^2 + 2x_{n+1}\sum_{i=1}^{n} x_i + x_{n+1}^2 \tag{2-13}$$

A x_{n+1}^2 term may be subtracted from both sides:

$$n\sum_{i=1}^{n} x_i^{\ 2} + nx_{n+1}^2 + \sum_{i=1}^{n} x_i^{\ 2} \geq (\sum_{i=1}^{n} x_i)^2 + 2x_{n+1}\sum_{i=1}^{n} x_i \tag{2-14}$$

If the general inequality from Equation 2-6 holds true, then, multiplying both sides of Equation 2-6 by n^2, we have the inequality

$$n\sum_{i=1}^{n} x_i^{\ 2} \geq (\sum_{i=1}^{n} x_i)^2 \tag{2-15}$$

Therefore these two terms may be removed from Equation 2-15 and the inequality is not lost, resulting in the following inequality to be proven:

$$nx_{n+1}^2 + \sum_{i=1}^{n} x_i^{\,2} \geq 2x_{n+1} \sum_{i=1}^{n} x_i \tag{2-16}$$

The x_{n+1}^2 terms may be grouped into the summation terms as follows:

$$\sum_{i=1}^{n} (x_i^{\,2} + x_{n+1}^2) \geq 2 \sum_{i=1}^{n} x_i x_{n+1} \tag{2-17}$$

The square can be factored, resulting in an inequality known to hold true:

$$\sum_{i=1}^{n} (x_i - x_{n+1})^2 \geq 0 \tag{2-18}$$

2.2.2. Measurement Based Loss (MBL) Calculation

To avoid the problem of averaging-then-squaring, one would simply need to calculate the losses at every hour. With all of these "square" terms, one could use Equation 2-4 above to calculate the total annual losses. Of course, there is no need to average and then multiply by the number of hours—one could sum the individual hourly losses directly to get the same result.

Of course, calculating the losses at every hour would require knowing the load at every hour. While a small yet growing number of feeders have advanced metering infrastructure which provides the demand at each load point at each hour (or higher resolution), such detailed load information will not be available on all feeders at many utilities. However, if the total feeder load is available at each hour (through flow measurements at that feeder), the load may be divided among the customers on the feeder based upon the type of customer and the monthly meter readings at those customers.

By researching the typical load patterns for each customer type, a series of coefficients C_{alpha}^{i} can be obtained which, when multiplied by the monthly consumption C_{kWh} give the expected demand for that customer at that hour [13]

$$C_{kWh}^{\text{expected}(i)} = C_{alpha}^{i} * C_{kWh} \tag{2-19}$$

For a given hour and day in a month, the customer load curve and customer kWh sales for that month provide us with an expected kW demand for that customer at that hour. These expected kW demands can be totaled for the feeder to produce a total expected feeder demand at a given hour

$$Fkw_{\text{expected}}^{i} = \sum overallcustomer(C_{kWh}) \tag{2-20}$$

This feeder demand can be used to find a scaling factor that would match the measured demand from a meter at the start of the feeder

$$Scaling_{factor} = Fkw_{measured}^{i} / Fkw_{\text{expected}}^{i} \tag{2-21}$$

This scaling factor can be used at each customer to adjust that customer's demand

$$Ckw_{scaled}^{i} = Ckw_{\text{expected}}^{i} * Scaling_{factor} \tag{2-22}$$

With this load estimation a power flow algorithm more accurately calculates the losses throughout a feeder at a time point [14, 15]

Furthermore, by estimating the losses at each individual hour, the utility may assign different costs to those hours, using the LMP data available from the ISO to which they belong. Equation 2-5 is then replaced with the following:

$$C_{total} = \sum P_{loss_i} * LMP_i \tag{2-23}$$

2.3. System Model

The circuit for testing the accuracy of the loss calculation is shown in Figure 2-1. The circuit has seven substations which feed 31 feeders. The feeders cover residential and small commercial type customers' area. The circuit serves 11174 load points with a variety of sizes.

Figure 2-1. Test circuit

The test circuit also consists of 54777 components, which are mainly lines, breakers, fuses, busses, switched and fixed capacitors, voltage regulators, switches and transformers. Detailed component information for the test circuit is given in the Table 2-2.

Table 2-2. Component types and numbers

Component Type	Numbers for 31 Feeders Model
Primary Overhead Line	19797
Overhead Line Cutout	2701
Overhead Distribution Transformer	7087
Overhead Step Transformer	60
Voltage Regulator	2
Recloser	22
Capacitor	61
GOAB	171
Disconnect Switches	297
Underground Cable (Primary)	9164
Underground Distribution Transformer	3988
Underground switches	132
Busses (transmission/distribution)	24
Substation Transformer	11
Load service points	11174

2.4. Quantification of Differences between Loss and Cost Calculations

2.4.1. Improved accuracy in loss calculation

In this chapter of dissertation, a system of 31 feeders in the northeastern United States is analyzed to compare the accuracy of the two approaches to calculating losses.

The two approaches were used as described above to calculate the total annual losses (kWh) for each feeder. Figure 2-2 below shows the differences in loss calculation.

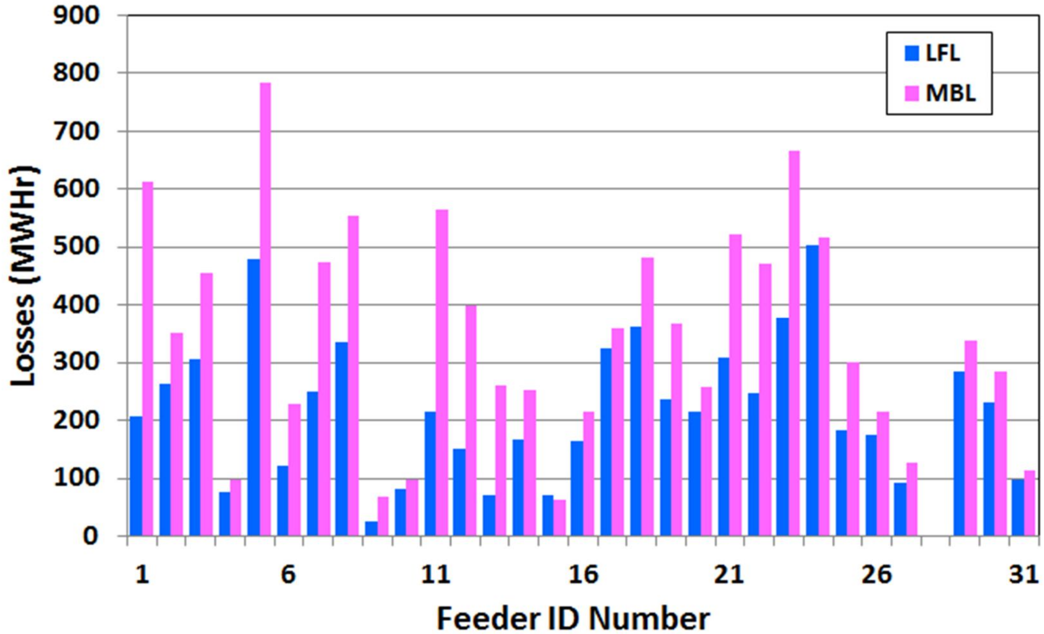


Figure 2-2. Comparison of calculated loss and measured loss

As discussed earlier, using the load factor method significantly underestimates losses on most of the feeders. The loss information can be collected into a histogram to show the under-estimation of losses on these feeders. Figure 2-3 provides histograms showing the number of feeders falling within ranges associated with the percentage ratio of load factor loss calculation to measured loss calculation.

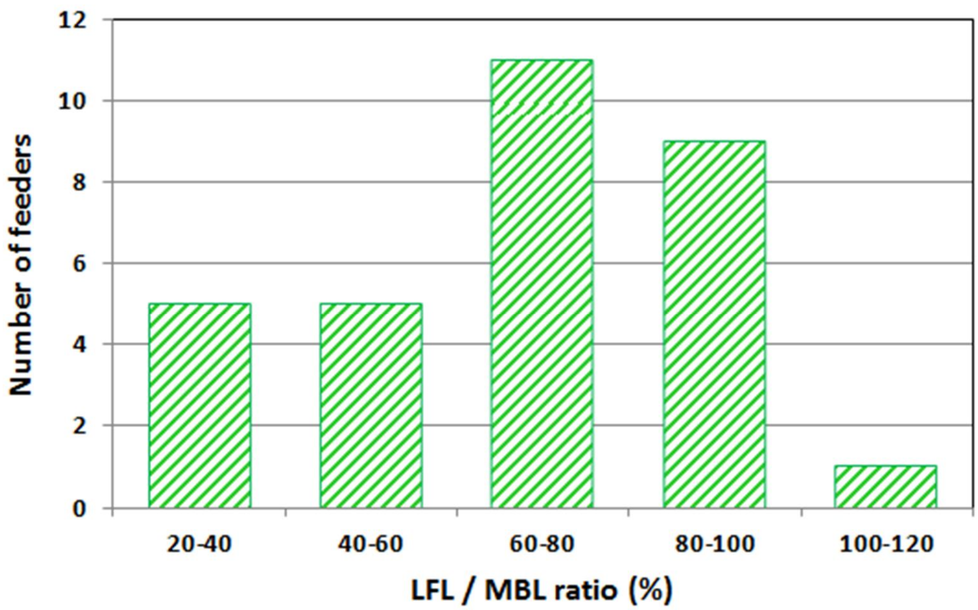


Figure 2-3. Histogram illustrating LFL/MBL ratio percentages

The underestimation due to averaging-then-squaring rather than squaring-then-averaging is only one cause of error. The two methods also differ in how they model other time-varying information such as capacitor switching. Different capacitor configurations and controllers may result in a given feeder being relatively more efficient off-peak or relatively less efficient off-peak. For example, if the utility were to leave capacitors on year-round that provide a good power factor at peak, the circuit may suffer a poor, leading power factor during periods of light load. Similarly, turning capacitors off too early or too frequently may also result in worse efficiency off-peak. In either of these cases, since the load factor calculation only evaluates the circuit at peak, it may be overly optimistic about the efficiency during the rest of the year. On the other hand, if the capacitors are switched well, the efficiency may be much better off-peak, and the load factor method may be pessimistic about the circuit efficiency and might actually overestimate losses, in spite of the fact that averaging-then-squaring tends to underestimate losses. Another factor affecting the accuracy of the load factor method is that the circuit may not be balanced the same off-peak as it is on-peak.

2.4.2. Improved accuracy in cost calculation

The problem of underestimating losses using the load factor method is further exacerbated by the problem of typically underestimating costs by using average costs rather than hourly costs. Typically, the cost of energy is higher at peak than off-peak. Thus, the utility pays more during periods of higher losses, further driving the cost of losses above the "average" expected cost.

A single day may serve as an example. In Figure 2-4, the losses and LMPs are given for one day, using LMP data from NYISO and a feeder in the ISO's region [16]. Using the cost and losses at every hour, the total actual price of losses for the day is $11.10. Using the average price and average losses, however, results in a cost estimate of $10.57, which is about 5% below the actual price.

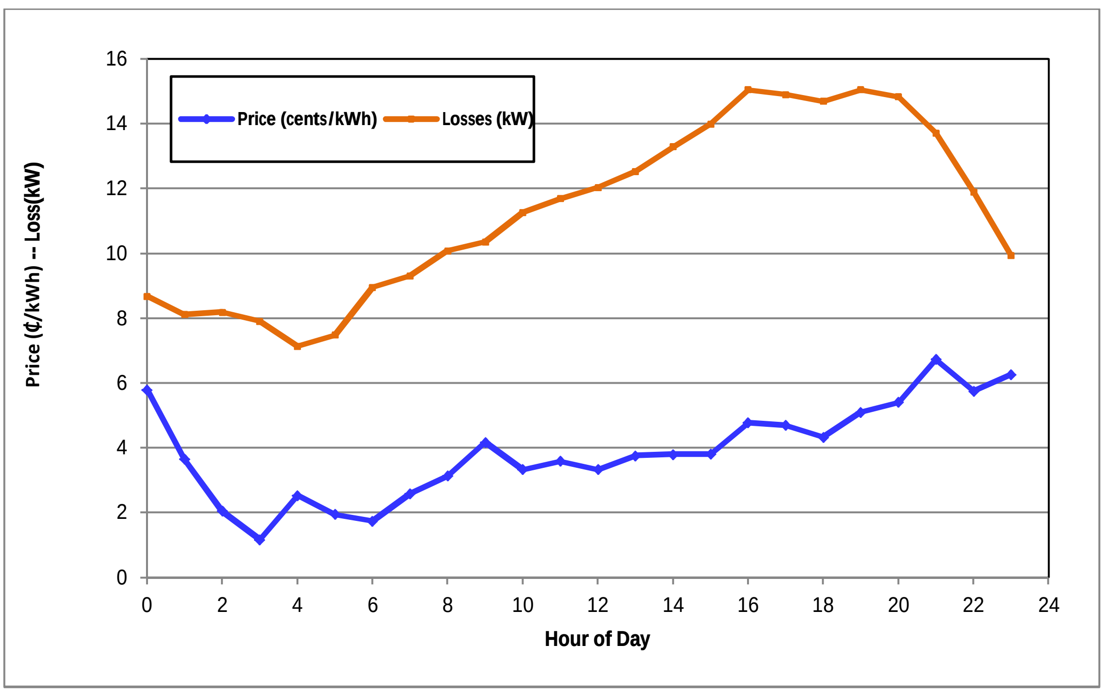


Figure 2-4. LMP and losses for one day

To further investigate the difference between using the average LMP cost and the hourly LMP data, the more accurate hourly loss calculation was used on the 31 feeder system with both an average price and an hourly price to calculate the total annual cost of losses, as shown in Figure 2-5.

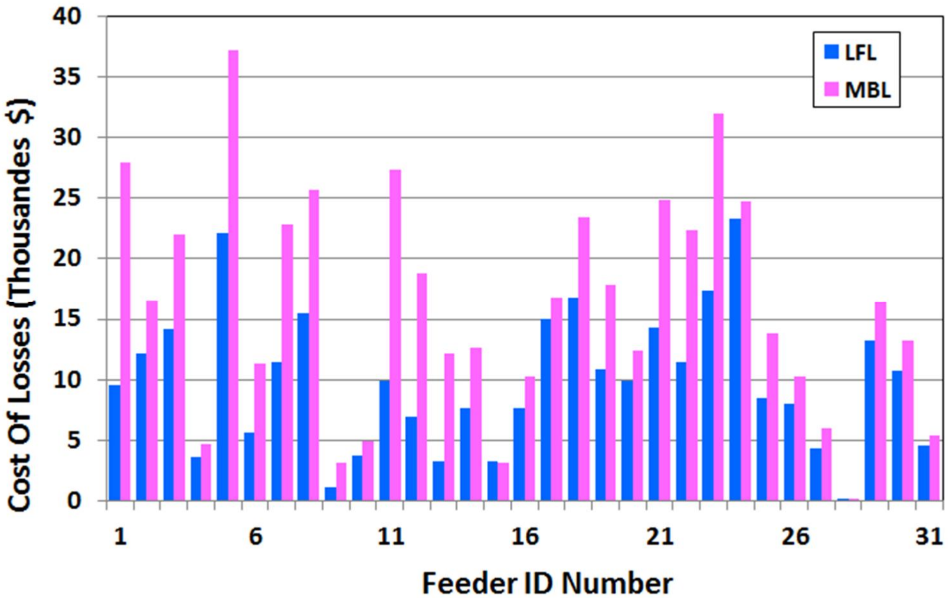


Figure 2-5. Comparison of average LMP cost and the hourly LMP cost

Figure 2-6 shows that the inaccuracy of the average costs is close to a Gaussian distribution centered around 97%.

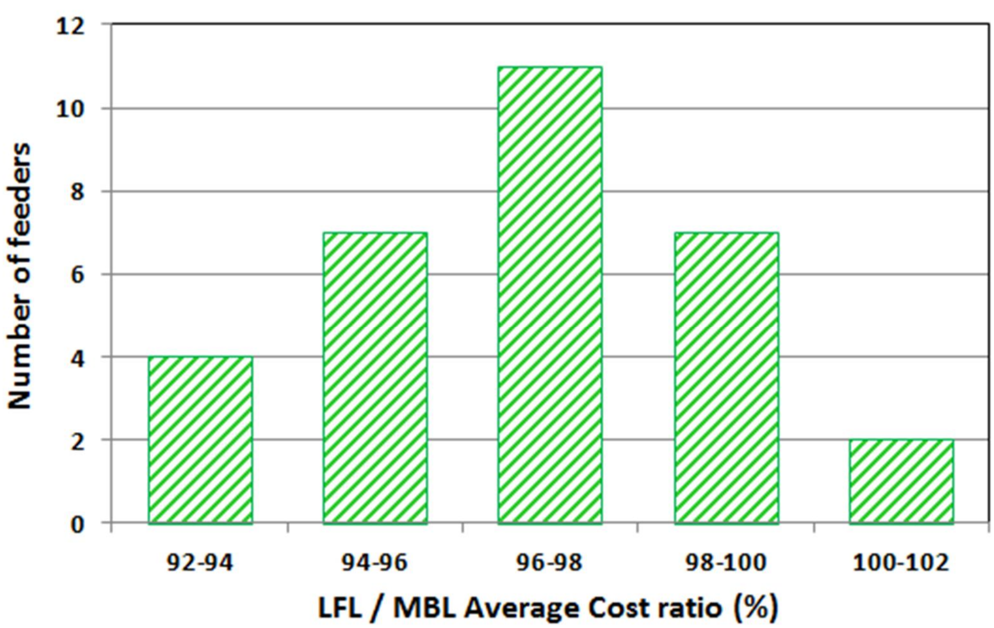


Figure 2-6. Histogram to show average cost of LFL/MBL ratio occurrence percentage

2.4.3. Improved overall accuracy

Having investigated the high accuracy of the loss calculation and cost calculation somewhat independently, the two factors are considered together, in evaluating the total cost of losses on each feeder. Once again, a comparison for each feeder is charted in Figure 2-5, and a histogram is developed in Figure 2-7 to show how frequently the total costs are underestimated by various amounts.

Comparing Figure 2-3 with Figure 2-7 shows that, when the inaccuracy of using the average price is combined with the inaccuracy of calculating losses based only on a peak load flow and a load factor, the underestimation grows worse. Assuming the Measurement Based Loss (MBL) calculation to be the most accurate, almost half of the feeders were underestimated by 60-80% with the Loss Factor Loss (LFL) method.

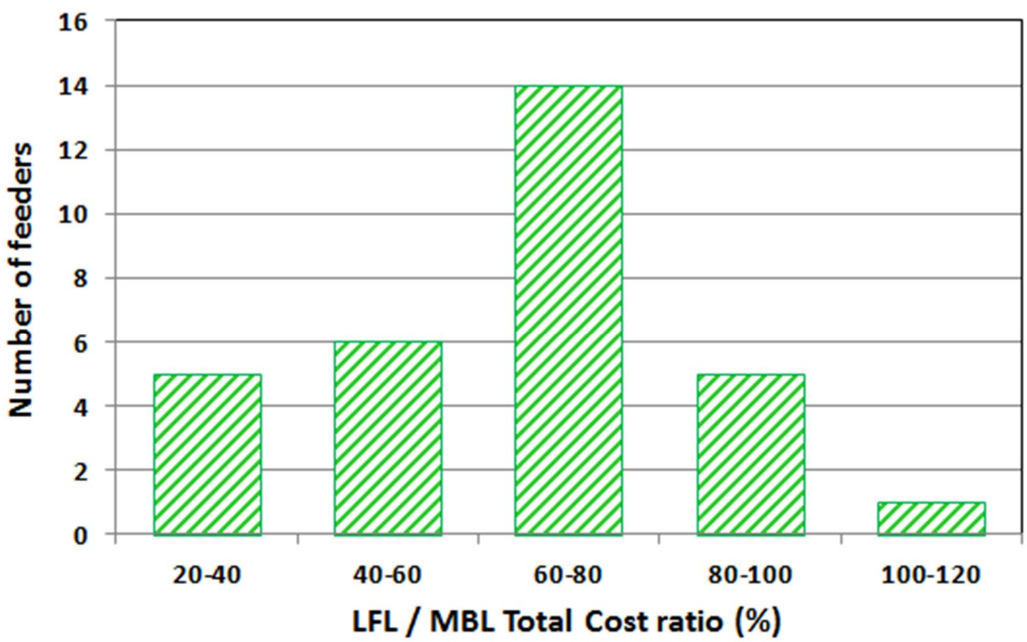


Figure 2-7. Histogram to show total cost of LFL/MBL ratio occurrence

2.5. An investigation of the impact of cost calculation accuracy on electric power distribution system planning decisions

It is worth considering now the importance of an accurate cost calculation in the planning process. A number of factors drive the planning process, including feeder capacity (both preventing overloads and ensuring acceptable customer voltage levels), reliability (both frequency and duration of outages), and the cost of the project. Part of the cost of the project that must be calculated for optimal power system planning includes the relative cost of losses of the various designs under consideration.

For this investigation, a phase balancing option is considered [17]. Utilities may want to reduce the phase imbalance to prevent an overload on one of the phases without having to re-conductor. Alternatively, they may want to reduce the phase imbalance to reduce voltage drop that is leaving customers on one phase with worse voltage than the other phases. In other cases, they may simply be interested in reducing losses on the feeder, and, since the losses are proportional to the square of the current, balancing the current on the three phases will result in lower total losses over the three phases.

When phase moves are evaluated, the same customer and feeder load information may be used that was described in section 2.2.1. Obviously, the feeder currents will no longer match the feeder measurements after phase balancing, but the customer scaling factors calculated from the as-is model may be applied when running power flow on the planned model.

A feeder was chosen from the set of feeders analyzed above that had a considerable phase imbalance. Table 2-3 summarizes the results of the two calculation methods.

Table 2-3. Comparison of methods for phase balancing

		Annual Energy Losses (kWh)	Annual Loss Cost ($)
Load Factor Loss	Unbalanced	266944	12340
	Balanced	263480	12180
	Difference	3464	160
Measured Based Loss	Unbalanced	499488	24231
	Balanced	492343	23833
	Difference	7145	397

Here, we see that, if the LFL method is used to calculate losses, the utility will expect to save only $160 per year through the reduction in losses. Using a more accurate calculation, however, shows that the utility will likely save more than twice that figure. The resulting difference in payback period can significantly affect the utility's decision to accept or reject the proposed phase move. Thus, if the utility were using only the peak analysis and load factor to calculate losses, they might reject a plan that would otherwise prove benefits to them.

2.6. Conclusion

Two methods for calculating total annual feeder losses were presented. The first, using only peak analysis and an annual load factor, has been widely used throughout the electric power industry. The second, using hourly feeder and customer load data, has only more recently become feasible to utilities as the cost of gathering such data has decreased. In addition to comparing these loss calculation methods, two different approaches to calculating the cost of these losses were discussed. Since many utilities pay a time-varying cost for the energy they serve to their customers, calculating the total cost of losses based on an average cost of energy can noticeably underestimate the cost of losses.

These differences were quantified using feeder and customer load data for a system of 31 feeders. Histograms were presented which demonstrate the frequency with which the load factor and average cost methods underestimated the actual losses and costs by different levels.

The wide range of accuracy with which the peak analysis and load factor method estimated losses provides a system level perspective on the two methods: improving the accuracy of the feeder loss calculation is essential for identifying feeders with opportunities for cost-effective efficiency upgrades.

After presenting this system-level assessment, a feeder-level assessment was performed, wherein the cost savings of a phase balancing operation was evaluated. The difference in accuracy between the two methods showed that, with a more accurate method of calculating feeder losses, the electric power system planning engineer can make wiser choices as to which designs to implement in improving the performance of the distribution system.

Chapter 3 Centralized Control of Volt-VAR Devices for CVR and Efficiency

3.1. Introduction

Most of the electric power distribution feeders in operation today were constructed with technology that is now decades old. As new customers are connected and existing loads change, utilities face the need to upgrade systems to prevent overloads and low voltages. Even when the loads are not changing, utilities may face incentives from regulatory agencies to improve reliability. Recent technological advancements have given utilities new ways of resolving overloads and low voltages and improving reliability. Some technological improvements involve retrofitting older equipment with new control and communication devices. Such technologies can be more cost-efficient than the traditional solution of building new substations and lines.

One example of equipment which may often be cost-effectively retrofitted is the shunt capacitor. A capacitor may have been installed with no more control than a manually-operated, ganged, three-phase switch. In many such cases, the capacitor must be manually switched off during low-load seasons. Leaving the capacitor on during the low load seasons would cause unacceptably high voltages or leading power factors [12, 18]. The cost of sending a crew to switch a capacitor manually varies depending on the utility's labor costs and the location of the capacitor, but in some cases, switching a capacitor on and off once per year can cost $400 per year [12]. Because of the switching cost, manually operated capacitors are switched infrequently, and may operate inefficiently for much of the year.

A common upgrade to the manually-switched capacitor would be a local controller that either switches based on time-clock settings (to switch off during hours of lower expected load) or based on a local voltage measurement (to switch off when the voltage exceeds a certain threshold and switch back on when the voltage falls below another threshold).

Local controllers make decisions with very limited data (historical loading data for time-controlled capacitors or a local voltage measurement for voltage-controlled capacitors). The switching implemented with local controllers may be far from optimal. With communications technology, decisions could be made at a centralized controller where a detailed model and many real-time measurements are taken into account to determine set-points for local controllers. For example, if a local controller for a switched capacitor uses voltage set points which specify a range for control, the centralized controller could update the voltage set-points.

The set points determined by the centralized controller would coordinate the capacitor banks operation with other controllable devices on the feeder. The set points to the switched capacitor may change due to a number of conditions, including: 1-changes in loading level; 2-reconfiguration of the feeder; 3-a change in the operational strategy, such as a voltage conservation reduction strategy or operating the feeder to supply the maximum load. Not only switched capacitors would be considered by the centralized controller, but set points would also be specified for voltage regulators, substation transformer load tap changers (LTC), and other devices such as Distributed Energy Resources.

Many papers have been written which explain the effects of capacitor control on system performance. Reference [19] describes an algorithm for optimal capacitor placement based on determining nodes whose voltages affect losses in the system the most. Reference [20] presents a dynamic programming based algorithm for determining the optimum number, location, and size of capacitors. Reference [21] uses dynamic programming to determine optimal controller switching to reduce feeder losses. Reference [22] explores the use of computer software to find solutions to the problem of optimum location and size based on the calculation of kVAR-miles, feeder losses, and power factor. In [23] the authors discuss volt-var control of capacitors, and optimum capacitor bank installation with advanced distribution automation. In [24], author proposed a coordinated control algorithm to achieve better voltage and reactive power compensation and operation times of LTC and switched capacitors, but did not consider load-voltage dependency. Reference [25] explores a voltage control method based on voltage violations when distributed generators are installed. Reference [26] explores a voltage issues by injecting new distributed resources, and provides coordinated voltage regulation method to get rid of voltage rise problems. Reference [27] investigates the centralized control by transformer tap changing without considering other control devices.

The work here focuses on the economic benefit of coordinated, model-based control. That is, the actions of all of the automated control devices are coordinated through the centralized-model calculations. Such coordination includes: 1-coordination with devices that are still operating using local controls that cannot be affected by the centralized-model control calculations (i.e., no communications); 2-coordination of control devices when reconfigurations occur, and a feeder either gains or loses automated control devices; 3-coordination when the control objective for the feeder changes, such as changing from most efficient feeder operations (i.e., minimizing losses of the feeder itself) to conservation voltage reduction.

The operating strategy for a coordinated, model-based control may be changed in real-time [28]. One operating strategy that may be used is reduction of feeder losses. Another operating strategy is conservation voltage reduction, where the energy delivered to customer loads is reduced by operating the loads at lower but acceptable voltage levels. The reduction in energy results in a lower feeder demand and also lower electric bills to customers. Yet another strategy that may be employed by the coordinated, model-based control is to maximize the amount of load that may be served by the feeder. This strategy typically results in the feeder being operated at higher but acceptable voltage levels, where overloads and/or low voltages are being avoided.

This chapter is organized as follows: The distribution system model under study is described in section 3.2. Time varying load estimation and coordinated control are introduced in sections 3.3 and 3.4, respectively. Case studies and a discussion of the results are provided in section 3.5. Finally, conclusions of chapter 3 are given in section 3.6.

3.2. System Model for Coordinated Control

This study evaluates a model containing 17437 components, or objects, in eleven feeders supplied by seven different substation transformers. The geographic topology of the feeders is shown in Figure 3-1.

Figure 3-1. Eleven feeder system used in study

The load on the system consists of residential and small commercial customers, totaling 21991 customers served by 3472 distribution transformers. The system has 16 fixed shunt capacitors, 12 switched shunt capacitors and 1 voltage regulator.

All twelve switchable capacitors have gang-operated controllers. Besides the seven substation transformers, each with an LTC, there is also one voltage regulator in the system that regulates all three phases independently. Table 3-1 presents additional details for these control devices.

Table 3-1. System device information

Control Device Type	Rating/Classification	#	Controller Type
Switched Capacitor (SC1)	13.2 kV @ 400 kVar / phase	10	Gang
Switched Capacitor (SC2)	13.2 kV @ 200 kVar / phase	1	Gang
Switched Capacitor (SC3)	13.2 kV @ 300 kVar / phase	1	Gang
Fixed Capacitor 1	13.2 kV @ 200 kVar / phase	8	N/A
Fixed Capacitor 2	13.2 kV @ 400 kVar / phase	8	N/A
Voltage Regulator (VR)	250kVA / 328Amp 32 Step, 10% Regulator @ 13.2kV	1	By-Phase Control
Load Tab Changer (LTC)	16 Step LTC w/5% Reg	7	By-Phase Control

3.3. Time Varying Load and Cost of Energy

In this work, customers are grouped into classes to perform customer class based load estimation. The customer kWhr consumption billing data is used to formulate the estimates of loads, including class-based diversity factors, and kWhr-to-Peak-kW conversion factors [13].

Hourly load data for different types of customers which are aggregated at each service location are used in the load flow study [29]. Figure 3-2 and Figure 3-3 illustrate two diversified load curves, one for small commercial and the other for small residential customers, in June.

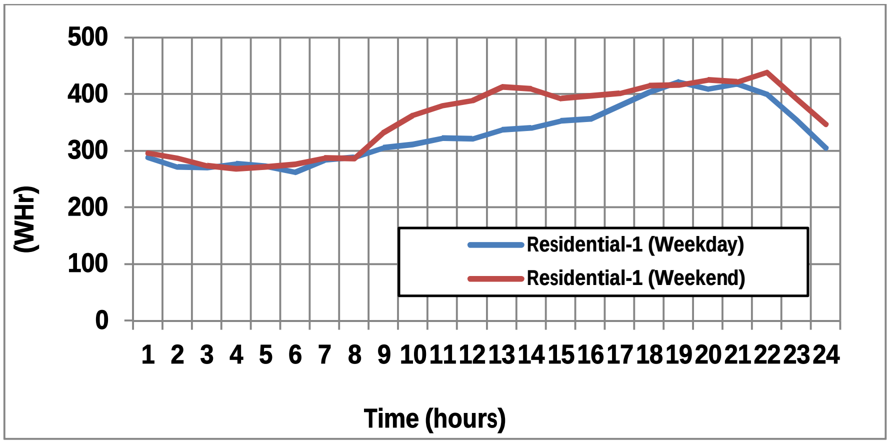


Figure 3-2. Small residential customer diversified load curves for June

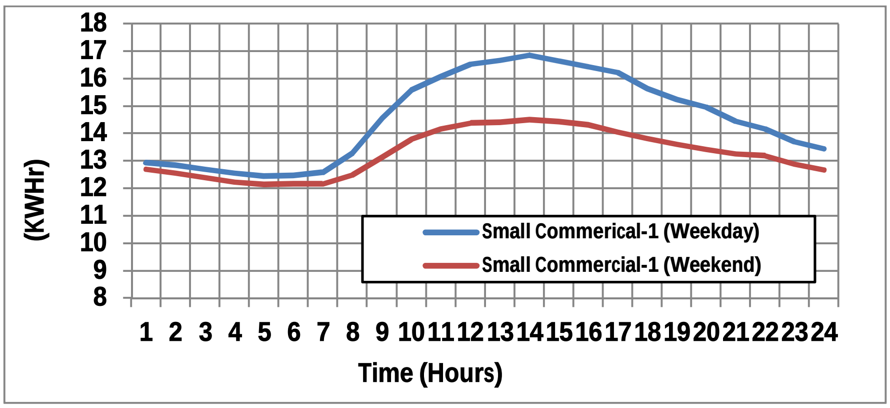


Figure 3-3. Small commercial customer diversified load curves for June

An accurate assessment of the cost savings available from loss reduction depends not only upon calculating the consumption and losses at different times of the day and year, but also upon calculating the cost of energy accurately at the corresponding times of day and year. Utilities operating in regions with competitive electric energy markets pay different prices for energy at different times of day. These prices vary by location (primarily due to congestion in the transmission system), and are called Locational Marginal Prices (LMPs). Since the power system model used in this study comes from the state of New York, corresponding LMP data from the New York Independent System Operator was used in calculating the cost of losses at each hour [16].

3.4. Coordinated Control Algorithm

Local control approach is far from being an optimal approach. With local control settings for controllable devices are based on very limited data such as data that does not change with changing conditions of the circuit, such as time, or circuit measurements at only a single point in the circuit.

The coordinated control approach used in this work is based on [25]. The coordinated control system operates using an Integrated System Model (ISM) as described in [22].

The coordinated control algorithm is used here with two control strategy objectives. The first is minimizing the overall feeder loss. The other is conservation voltage reduction, which aims to minimize the overall customer voltage while maintaining the voltage throughout the system such that every customer is served within a specified voltage range [30]. The control algorithm is described below:

Step 1: The control algorithm first discovers all the controllable devices in the model, which, in this study includes switched shunt capacitors, voltage regulators, and substation transformers with load tap changers. In the discussion below, capacitors are single-step devices, since here they only have two control states—on and off. Voltage regulators and transformer LTCs are multi-step devices, since there is a range of valid control states. In addition to discovering the devices, the control algorithm also discovers the existing set points of these devices. Since the algorithm is designed to be run in real-time, multi-step devices are only allowed to move within a user-specified number of steps from their current position. Also, no two capacitors on a single feeder may be switched at the same time. This is to prevent unacceptable voltage flicker.

Step 2: For each loop, customer voltages and system losses are calculated.

Step 3: The system is first analyzed for overloads and/or voltage limit violations, and the controllers are adjusted first to reduce loading on overloaded components and/or to eliminate low voltages if possible. Once overloads or low voltages are addressed, the algorithm then considers the selected control strategy, which in this case is either conservation voltage reduction or minimizing feeder losses.

Step 4: The solution found is saved and serves as the starting state for coordinated control analysis at the next time point.

Step 5: When the algorithm has finished, it provides the list of control devices that minimizes the selected control strategy objective function.

In the work here the coordinated control process is automatically run for every hour within a year, or 8760 time points are analyzed. The economic benefits may then be computed using the system losses, the energy consumption, and the worth of the energy using the hourly LMP data.

3.5. Simulations and Results

The study consists of two parts. In Part I, system losses and energy delivered will be analyzed. Part II addresses the value of coordinated control in eliminating low voltage problems.

Part I: The simulation results will be grouped by feeder and by substation transformer. Table 3-2 shows the number and types of controllable devices for each feeder and which transformer the feeder is associated with, where the abbreviation “Xfrm” is used for transformer.

Table 3-2. Device information

	Feeder #	# Devices	Device Types
Xfrm 1	**1**	1	LTC
	2	3	(2) SC1,LTC
	3	2	SC1,LTC
	4	1	LTC
Xfrm 2	**5**	3	SC1,VR, LTC
Xfrm 3	**6**	3	SC1, SC2, LTC
	7	2	SC1, LTC
Xfrm 4	**8**	3	(2) SC1, LTC
Xfrm 5	**9**	3	SC1,SC3, LTC
Xfrm 6	**10**	2	SC1, LTC
Xfrm 7	**11**	1	LTC

Figure 3-4 presents a comparison of the losses with and without the coordinated control. The "existing" system uses local voltage control for all device types. The coordinated control algorithm is permitted to operate the regulating transformers in the substation, the voltage regulator, and the switchable capacitors. As discussed in Section 3.2, the hourly calculated losses are aligned with LMP cost data in calculating the worth of the losses.

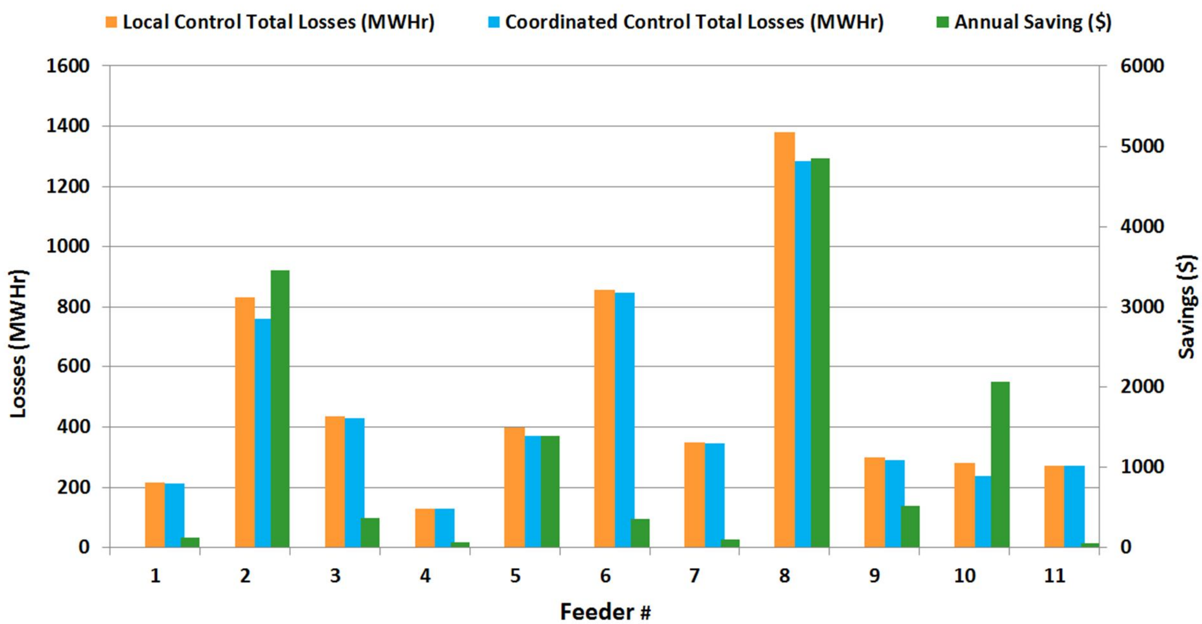
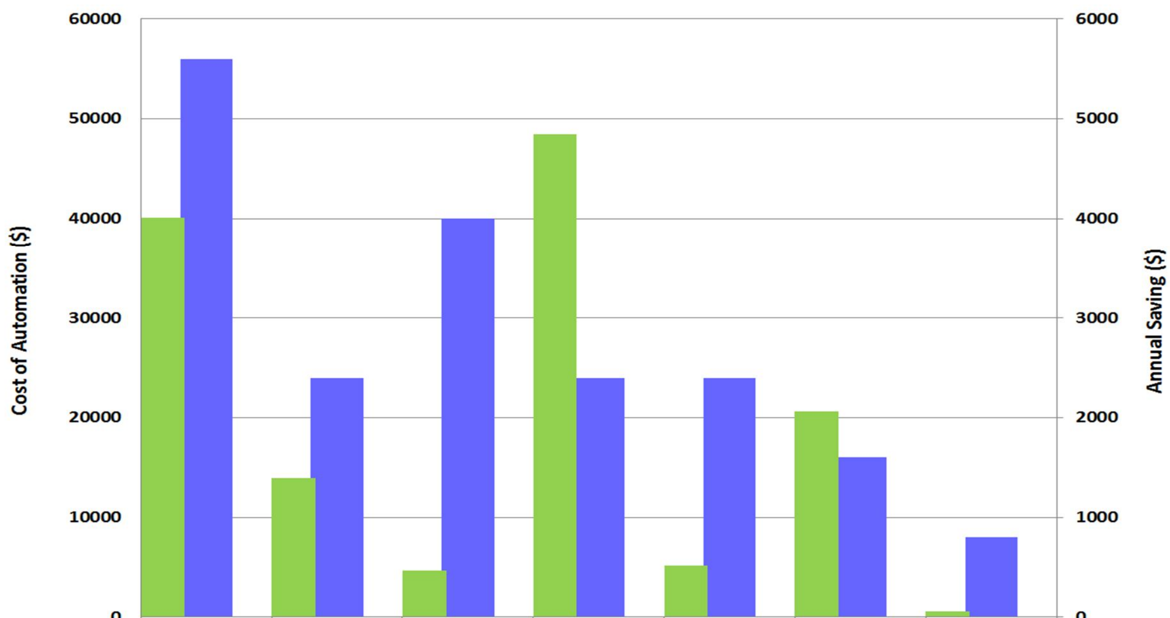


Figure 3-4. Comparison of losses and savings

The loss savings realized on each feeder varies based on the number of controllable devices and the relative difference in control states as determined by the local controller versus the coordinated controller. Since different devices will provide different savings to the utility, it is helpful to compare the cost of implementing the coordinated control with the savings due to reduction in losses. The estimated costs of upgrading each individual device (All switched capacitor types, voltage regulators, and load tap changers) with the remote communication and control equipment needed for coordinated control are $8000. This cost is based upon having radio communications in place, and does not take into account the cost of the communication infrastructure.

In addition to the cost of upgrading the individual devices, the utility faces additional costs of implementing the communication and control infrastructure. Approximate costs have been provided in Figure 3-5 for each substation, so that the cost savings from the loss reduction may be compared to the installation costs to calculate a payback period.

Using the data from Figure 3-5, the utility can identify feeders for which coordinated control is cost-effective. As mentioned in section 3.4, the algorithm may be run to either minimize feeder losses or minimize the average voltage. When the voltage is reduced, constant-impedance loads, like incandescent lighting, are also reduced.



Substation Transformer ->	1	2	3	4	5	6	7
Cost of Automation	56000	24000	40000	24000	24000	16000	8000
Annual Savings	4010	1391	465	4845	517	2065	53
Payback Period(years)	13.96	17.25	86.02	4.95	46.42	7.74	150.94

Figure 3-5. Annual saving and payback period

Next using coordinated control to implement conservation voltage reduction will be considered. Table 3-3 shows the reduction in energy consumption, where all loads is modeled as constant current. Calculation of the worth of energy is based on an estimated flat rate of $0.10 per KWhr. In Table 3-3, the abbreviation "Coord" is used for Coordinated.

Table 3-3. Savings for customer side

	Feeder #	Local Control Energy Delivered (Mwhr)	Coord Control Energy Delivered (Mwhr)	Reduced Energy (%)	Worth ($k)
Xfrm 1	**1**	24805.46	24386.53	1.69%	41.89
	2	39347.39	38304.41	2.65%	104.30
	3	40939.62	40273.43	1.63%	66.62
	4	19495.82	19152.65	1.76%	34.32
Xfrm 2	**5**	39551.63	39188.71	0.92%	36.29
Xfrm 3	**6**	57675.62	58363.69	-1.19%	-68.81
	7	39742.50	39547.24	0.49%	19.53
Xfrm 4	**8**	21038.63	20374.83	3.16%	66.38
Xfrm 5	**9**	26594.37	26280.67	1.18%	31.37
Xfrm 6	**10**	22611.45	22453.09	0.70%	15.84
Xfrm 7	**11**	44296.78	44915.01	-1.40%	-61.82

Table 3-3 shows that for most feeders the coordinated control with conservation voltage reduction results in reduction in energy consumption and savings to the utility customer. There are two feeders for which the coordinated control does not reduce the energy consumption below that of the local control, feeders 6 and 11. This is because in these feeders low voltage violations exist that are not taken into account by the local controllers, but are corrected by the coordinated control. Next, in Part II, coordinated control correction of low voltages will be considered.

Part II: In this part the simulation is performed for the year 2017 where the load growth has resulted in a number of low voltage problems (below 114V on the secondary side of the distribution transformers). Table 3-4 compares the performance of Coordinated Control with local control.

Table 3-4. Comparison of number of locations with voltage less than 114 between local control and coordinated control

	Feeder #	Local control count of low voltages	Low Voltages with local control as (%) of time varying loads	Coord control count of low voltages	Low Voltages with coord control as (%) of time varying loads
Xfrm 1	1	598	0.0252%	0	0.0000%
	2	4370	0.1327%	70	0.0021%
	3	46	0.0023%	0	0.0000%
	4	547	0.0484%	41	0.0036%
Xfrm2	5	3596	0.1425%	1225	0.0486%
Xfrm 3	6	5311	0.2743%	936	0.0483%
	7	5122	0.2670%	553	0.0288%
Xfrm 4	8	0	0.0000%	0	0.0000%
Xfrm5	9	1677	0.0674%	4	0.0002%
Xfrm6	10	10576	0.5889%	1242	0.0692%
Xfrm7	11	185	0.0218%	0	0.0000%

There are 2486 load points in the model, and the analysis is performed for 8760 different time or loading points. This results in 2,1777,360 evaluations of load points at which low voltages could exist. Table 3-4 shows the count and also percentage of low voltage points for the local control strategy and also for the coordinated control strategy. Overall the local control has a total of 1.5706% low voltages, whereas the coordinated control reduces this number to 0.2008%. The utility will need to spend money to correct the low voltage problems. With the local control, all feeders in the system have low voltage problems. However, with the coordinated control, four of the feeders have no low voltage problems, and the low voltage problems in all feeders are significantly reduced with the coordinated control.

3.6. Conclusion of Coordinated Control

Model based coordinated control is compared with local control on a system consisting of 11 feeders which have very different combinations of controllers. Three comparisons are considered.

In the first comparison the feeder losses with local control are compared with coordinated control for minimizing feeder losses. In this comparison payback periods of coordinated control investments are calculated based on the loss savings. Some of the payback periods, such as 5 years, would justify the investment in coordinated control without any other considerations. However, some of the payback periods, such as 150 years, are too long to justify the investment.

In the second comparison local control is compared with coordinated control for conservation voltage reduction. In nine of the feeders there is considerable savings due to the reduction in energy consumption, and these savings could also be used to justify investments in coordinated control.

In the third comparison, local control is compared with coordinated control for eliminating low voltage problems. There are significantly more low voltage problems with the local control, and with local control all feeders have low voltage problems. However, with the coordinated control four of the feeders do not have low voltage problems, and the low voltage problems that need correction are significantly less with the coordinated control, which will result in a saving to the utility.

Across the three comparisons – minimizing feeder losses, minimizing energy consumption, and eliminating low voltages – the coordinated control shows significant advantages over the local control.

Chapter 4 Centralized Switching and Reconfiguration for Restoration

4.1. Introduction

Storms are a concern for the electric grid due to the damage to the power system, the cost of restoration, and the deterioration in system reliability from interruption of customers [31]. A major storm in Canada and the north- eastern USA in 1998 resulted in millions of households suffering in darkness and cold for several weeks [32] .

Besides the property damage, the economic impact of storms on utilities, customers, and society can be substantial. The eventual recovery costs are usually paid by all customers of the utility, including those customers who suffered the interruption costs, by surcharges or increased rates over a period of time. Sometimes the utility has to absorb the costs. In some cases there may be bleed-over into municipal taxes. The restoration data from 14 utilities shows that the average cost is $48.7 million per major storm [33]. For some utilities, the restoration costs may be as great as their net operating income, or even exceed it in a few cases [33]. The costs of storms are expected to increase along with increases in population.

The cost of storms involves equipment repairs, logistics, and generally very large labor efforts [34-36]. When a major storm hits, utilities have to rely on their support network of contractors and often borrowed crews from other utilities. Insufficient outside resources or inefficient crew dispatching can lead to a much larger price tag, which is usually ultimately paid by customers, and has a negative impact on the reputation of the utility management.

The emergence of smart grid technology provides utilities with an approach to lowering the costs of storm response while at the same time improving storm response [37-39]. Traditionally, when a fault occurs during a storm, the utility sends crews to identify the location, to manually operate switches to isolate the fault to a smaller area and restore power to some customers, to perform repairs, and finally to restore power to all customers. It can take hours to days for crews to complete the tasks, depending on the coverage size of the de-energized area, the number of devices that need to be operated, the mobilized resources available, the severity of the weather and its impact on road conditions.

With automation technology of the smart grid, automated switching devices can be added into the system. Tasks of fault isolation and network reconfigurations can be performed in seconds with computerized remote control. This not only significantly reduces the storm cost from resource logistics and crew hours spent operating switches, but also improves the system reliability and customer service quality by reducing the overall customer outage time [40].

In this paper we evaluate the reliability and economic benefits that utilities can gain for storm restoration if manual switches are replaced with automatic ones. For investor-owned utilities, this reliability and cost benefit analysis provides estimated impacts that can be used in cost-effective planning of the deployment of automated devices. There is little work that has been reported in this area. [33] describes a way to quantitatively evaluate the impact of automatic switches on system reliability. But [33] is not aimed at storm evaluations, and the system considered contains only three feeders. To determine the value of automated switches a larger system of feeders is needed, where load can be rolled among many feeders in order to achieve a restoration.

Analytical modeling and Monte Carlo simulation are the two fundamental approaches for power system reliability analysis. In previous work, an analytical storm outage model was proposed to predict the number of outages during the storm [41]. This helps utilities to plan crews in advance. However, for the purpose of restoration analysis, the behavior of the distribution system needs to be analyzed, including the system reconfiguration procedures. Therefore, simulation of system states is a must.

Events during storms are naturally stochastic [42, 43]. When assessing the system reliability, there are many works that use only two weather state representations, a normal-weather stage and an adverse-weather stage. Constant failure rates and restoration times are assumed for each weather stage [44-46] .

However, this approach does not fit storm simulation scenarios because during storms the failure rates of electric equipment vary hour-by-hour and storm-by-storm [41, 47]. In modeling failures, probability distribution functions are selected, such as the exponential distribution, which can approximate the physical system behavior only to a certain degree.

The study here provides a flexible approach to modeling storm events that mimics actual storm statistics closely using data that is available at utilities. The storms are classified into types. For each type of equipment in the system, the number of failures at each hour of a type of storm is extracted from utility historical records, which vary hour by hour. The equipment storm failure events are mimicked by using Monte Carlo simulation to randomly pick the given number of components to fail during each hour of the storm. As failures progress, the system is continually reconfigured for power restoration. At each hour the customers without power service are counted. The total customer outage duration is compared with and without automated switching devices. Hard dollar benefits from the reduction in storm response man hours spent operating switches are estimated, and the cost of the automated switches is taken into account.

A major question that the work here addresses involves whether or not the reliability can be maintained as well by just operating a small number of rapidly operated switches versus operating with a large number of manually operated switches. This paper is organized as follows: Modeling of the system under study is described in section 4.2. Historical outage data analysis for storm categorizing and reliability parameter extraction is introduced in section 4.3. Monte Carlo simulation and the calculation of storm failure events and system reconfiguration for restoration are described in section 4.4. Case studies and a discussion of the results are provided in section 4.5. Finally, conclusions are given in section 4.6.

4.2. System Used for Storm Restoration

Figure 4-1 illustrates the system model used in the study. The model has seven substations, 14 feeders, and 17437 modeled components or individual pieces of equipment. The type of components and their corresponding numbers are shown in Table 4-1. SCADA operable recloses are used as automated switches. Gang operated air break switches, disconnect switches, and fused cutouts are used as manually operated switches.

All customers receiving service from the power system are modeled, with the total number of customers being 21199. The system contains 3472 load points, where each load point may have different numbers of customers. In this work, customers are grouped into classes to perform customer class based load estimation. Table 4-2 provides a summary of the customer types modeled in the system.

The reliability calculations performed here are in terms of customer hours of interruption, and reliability parameters are a function of storm type. These will be discussed further in the next section. Thus, the change in reliability by using automated devices is reflected by counting the changes in customer-hours of interruption.

Figure 4-1. Seven substations, fourteen feeder model

Table 4-1. Component types and numbers for storm simulation

Component Type	Numbers
Primary Overhead Line	6027
Overhead Line Cutout	828
Overhead Distribution Transformer	2148
Overhead Step Transformer	14
Voltage Regulator	1
Recloser	78
Capacitor	31
GOAB	45
Disconnect Switches	286
Underground Primary Cable	2917
Underground Distribution Transformer	1292
Underground switches	32
Busses (transmission/distribution)	8
Transformer (transmission/distribution)	15
Breaker/ switch (transmission/distribution)	8

Table 4-2. Customer types and numbers for storm simulation

Class Name	Customer Numbers
Residential-1	19196
Residential -2	18
Residential -3	13
Small Commercial Type 1	2079
Small Commercial Type H	81
Large Commercial Type 1	506
Traffic Light- 100W	4
Single Large Load Type 1	86
Single Large Load Type 2	8
Total Number of Customer	21991

4.3. Storm Modeling

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 two weather stations located in the 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 [41]. Table 4-3 presents the storm classifications. Note that the lowest and highest temperatures and the highest wind speed that occurred during the storm are used to classify the storms.

Table 4-3. Storm classification

Storm Type	Description	T Range (^oF)	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			

Depending on the type of storm, equipment repair times and failure rates change. Figure 4-2 shows the average hourly numbers of failures of low temperature storms with high speed wind (LS) and high temperature storms with high speed wind (HS), during the first twenty storm hours. From the figure it may be seen that the number of failures fluctuates along with the hour of the storm. We can also see that the failure numbers not only different hour by hour, but also have different patterns for different types of storms.

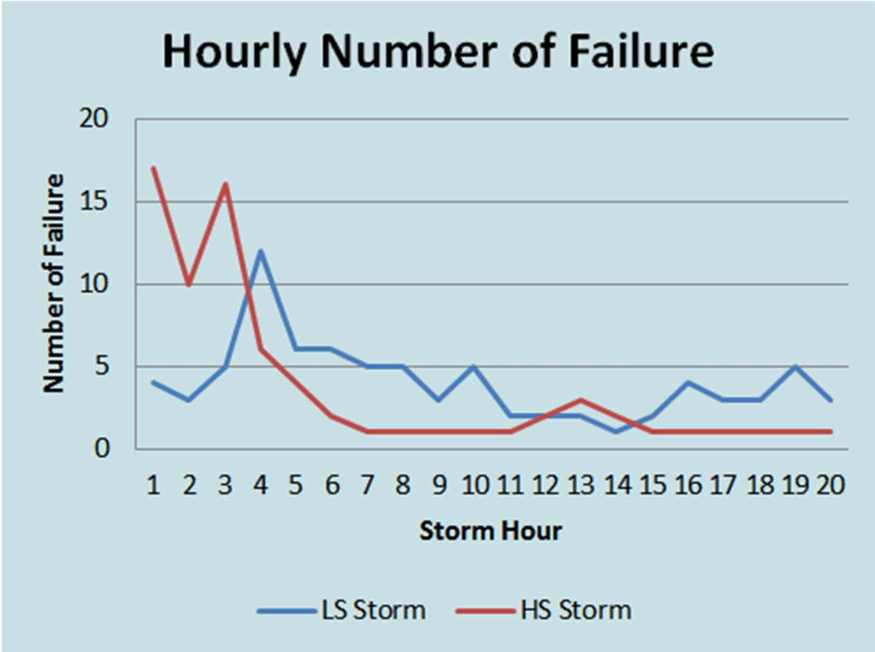


Figure 4-2. Average hourly number of failures for low temperature, storm wind (LS) and high temperature, strong wind (HS) type storms

In Table 4-4 there are fifteen types of equipment listed along with their associated storm dependent repair times. In Table 4-4 na means there was no record of this type of equipment failing during this type of storm. Thus, equipment with na for a certain storm type are not failed in the simulation during that storm type.

Table 4-4. Component repair time by storm types

Category	Component Type	Average Repair Time (Hr)					
		M	L	H	MS	HS	LS
Over-Head Primary	Line(Primary)	4	6	9	10	15	27
	Cutcout	3	9	9	9	9	11
	DistTransformer	3	7	7	13	14	22
	StepTransformer	3	na	na	9	13	18
	VoltageRegulator	na	na	na	na	na	na
	Recloser	2	na	na	2	2	16
	Capacitor	na	na	na	na	na	na
	GOAB	na	na	na	na	12	4
	Switch	5	na	1	27	1	14
Under-Ground Primary	Cable(Primary)	8	0	21	7	9	23
	DistTransformer	18	na	8	15	8	7
	Switch	12	na	na	na	5	1
Trans-mission /Sub-station	Buss	1	2	na	na	18	na
	Transformer	na	na	7	na	5	34
	Breaker/Switch	2	na	1	1	na	na

4.4. Storm Events and Restoration Simulation

The simulation procedure consists of two main parts: 1) A Monte Carlo simulation randomly picks components to fail based on the historical storm statistical data. 2) A reconfiguration algorithm isolates failures and restores services if possible. This section explains these two procedures, and how they are integrated with the “model centric” analysis for fast calculation.

4.4.1. Storm Events Simulation

Simulating weather-related component failure events and their consequences are central to the system reliability evaluation. Many literatures on reliability consider component failure rates to be constant during adverse weather conditions. As presented in the introduction and also shown in Figure 4-2, during extreme weather conditions, it is unrealistic to use a fixed value to represent the failure rates of components. By utilizing available data from the utility's database of historical outages, the study here provides a simulation that mimics what is happening during each type of storm. The ultimate objective is to examine the relative effectiveness of using automated switching devices versus manual switching operations.

Monte Carlo simulations are used to determine outcomes for uncertain situations. 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 [43]. Figure 4-3 illustrates the process flow of the storm event and restoration simulation.

Given a storm type, for each hour during the storm the average number of failed pieces of equipment, NF_i, for each type of equipment, T, and their average repair time are extracted from the historical outage database. The Monte Carlo module then randomly picks N components of type T among all components in the system of type T. The destructive impact of the storm failure events are then alleviated by performing reconfiguration for restoration, using either automated or manual switching operations, depending upon the model. The final storm events are checked by performing a load flow calculation on the reconfigured system, and information is collected on the customers that have lost power.

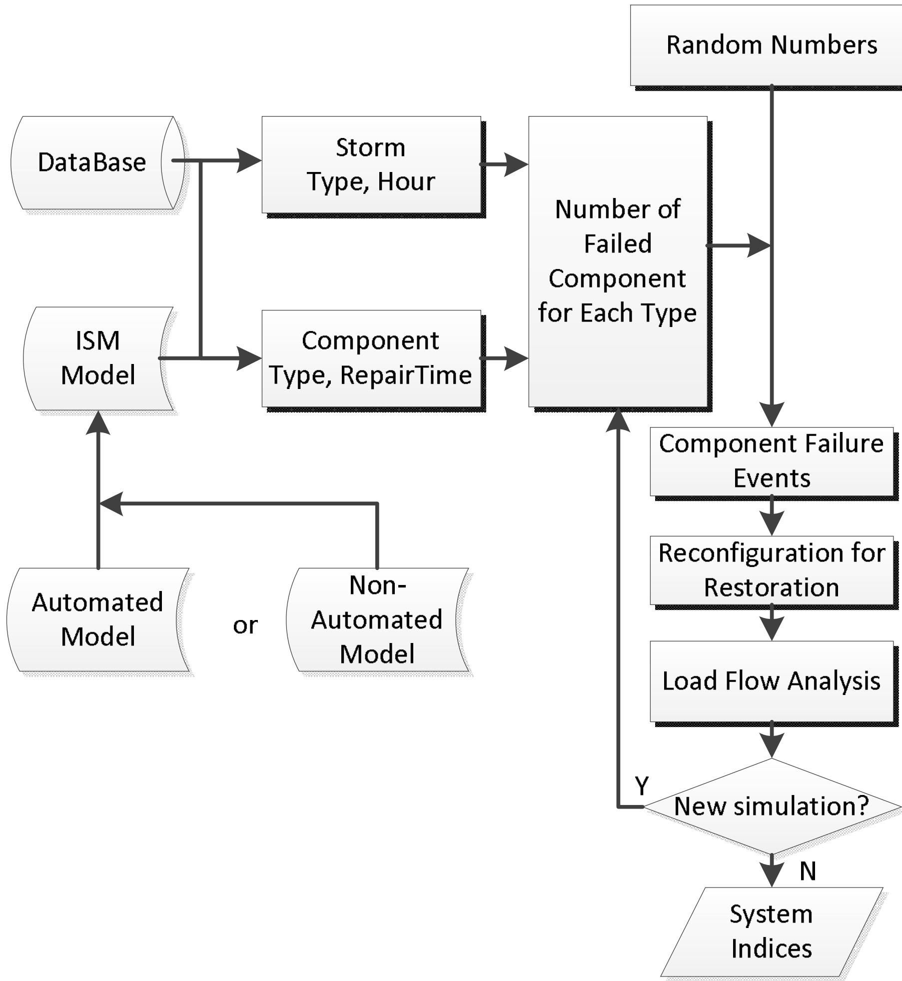


Figure 4-3. Data flow of storm simulation

4.4.2. Reconfiguration for Restoration

The objective of reconfiguration is to operate sectionalizing devices to restore power. Because of the complexity of the reconfiguration problem [48, 49] and the simulation speed requirement for storm analysis, the reconfiguration method used here is a fast, greedy algorithm which seeks a “good enough” solution rather than a true optimum.

Figure 4-4 illustrates the reconfiguration for restoration algorithm flow. Reconfiguration starts by isolating the failure, which is done by finding the closest devices surrounding the failure (the isolating devices) and opening them so that no power can reach the failure. In the automated model only automated switches are used as isolating devices. Once the failure is isolated, reconfiguration goes through the area downstream of the failure which has lost power (the outage area) and opens devices it finds there. This is done in order to allow for partial restoration of the failed area, in the event no switch operation(s) can restore power to the entire outage area. These devices are tracked by the reconfiguration algorithm so that it can undo any unnecessary operations later.

Once devices have been opened in this way, the reconfiguration algorithm starts to close devices to restore service to the outage area. The algorithm collects a list of all open devices bordering the outage area which are not among those isolating the failure. It then picks a device and closes it. If closing the device causes a constraint violation in the system (i.e., overcurrent or under-voltage), reconfiguration re-opens the device and removes it from the list. If no constraint violation is found, power has successfully been restored to part of the outages area. The list of devices bordering the outage area is then updated, and reconfiguration selects a new device to close. 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 without violating system constraints. Lastly, reconfiguration re-closes any devices it opened in the outage area which can be closed without providing power to any new segments of the system.

The final list of devices reported by the reconfiguration algorithm includes the isolating devices, and the list of boundary devices that can be closed along the way without system constraint violations.

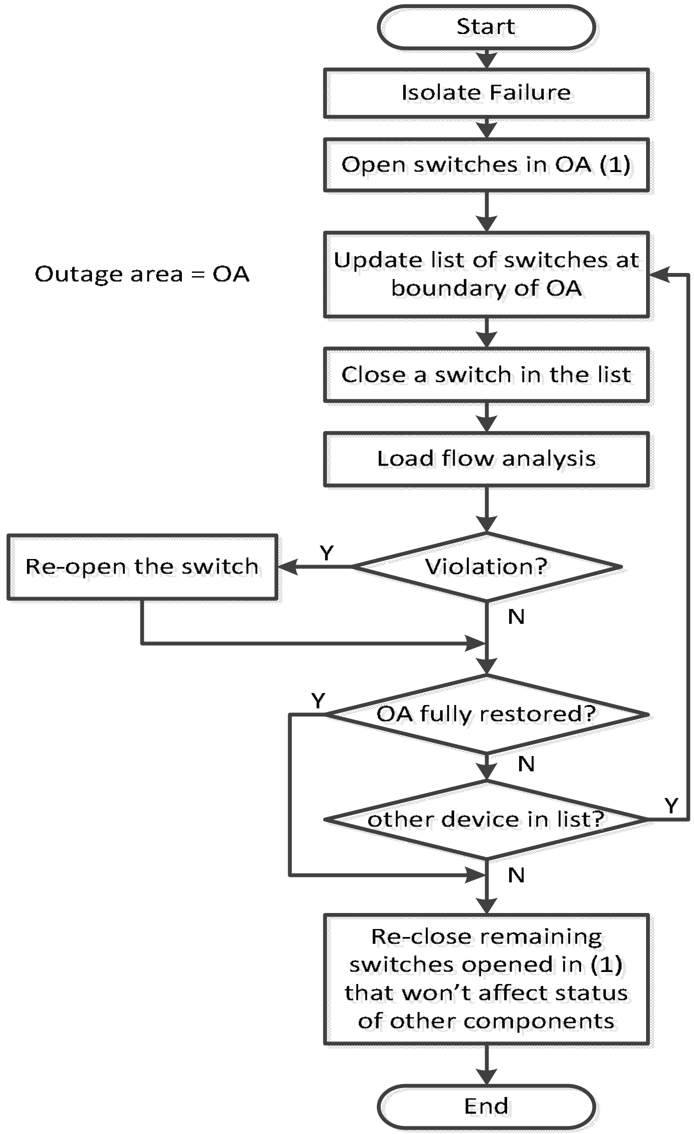


Figure 4-4. Reconfiguration for restoration algorithm

4.4.3. Storm Restoration Calculation

Simulation involving power flow studies, weather related failure events, and reconfiguration for restoration is challenging. The model described in section 4.2 is a single model that contains all data needed to perform the power flow analysis, reconfiguration studies, and customer outage calculations, which is referred to as Integrated System Model (ISM) [50]. All calculations are based on **G**raph **T**race

Analysis [51] 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.

4.5. Results and Discussions

Utilities want to determine if an investment in distribution automation is economically attractive. An investment in automated switches can perhaps help delay investments in new substations because of the reconfiguration ability to rapidly access existing system capacity. An investment in automated switches can also reduce the number of hours field crews spend in accomplishing tasks. The effect that automated switches can have on allowing crews to more rapidly restore power during storms is investigated here.

The investigation is performed in the system described in section 4.2. Two simulations are performed here, one in which all sectionalizing devices except protective devices are manually operated, and another where a portion of the switches have been automated, which are referred as the manual system and the automated system in the following discussions. In the automated system only automated switches are operated. In the automated system, there are about nine automated devices for every two feeders, with each automated switch covering about 250 customers. On average, there are 76 manual switches per feeder for the manual model. A concern is whether or not the reliability of the system can be maintained by operating only a small number of automated switches.

The purpose of the simulation is to compare the relative effectiveness of using automated switching devices over manual operations under different storm conditions. The number of switching operations associated with each failure may involve one or more switching devices. In the simulation it is assumed that the operation of an automatic switch takes 0 hours. For manual switching operations associated with a given failure, we assume that it takes one hour for the field crew to locate and operate the first device, and then it takes fifteen minutes for each of the remaining switches to be operated. These operation times were derived from the utility operating experience.

Table 4-5 shows results from the Monte Carlo storm simulations. For manual system operations under a certain storm condition the estimated number of manual device operations per storm and the estimated manual switching hours needed for reconfiguration are reported. The interruption hours for the customers due to manually operated switches is collected. After reconfiguration, if there are still some areas where the power cannot be restored, it will rely on the repair time of equipment to calculate interruption hours. This amount of customer interruption time is reported as customer interruption time due to the repair event. The total customer interruption time is the sum of the interruption hours due to switching and the interruption hours due to the repair event.

For the automated model under a certain storm condition, the simulation reports the estimated number of automated device operations. With the assumption that it takes no crew time for automated switch operations, the overall customer interruption time only needs to account for customer interruption after reconfiguration due to the repair event. The reliability improvement ratio shown in Table 4-5 is calculated as the ratio of total customer interruption time using manual switching to the total customer interruption time using automated switching.

Consider an example from Table 4-5 for the low temperature, strong wind storms (LS storm). It may be seen that on average there are 460 automated switch operations with the automated system and 1069 manual switch operations with the manual system, requiring 403 hours of crew time. The interruption hours for the customers are divided into hours associated with the switching events and hours associated with the repair. Note that the Automated Model has fewer hours of interruption.

In order to compare the length of the storm response and operation cost between the automated and manual systems, we take into account the number of crews working. Assumes automation of the 14 feeder system is representative of automation of entire system. Table 4-6 column 2, shows the average number of hours crews spend operating manual switches for each storm type as simulated with the manual model. The table also provides averages for the number of crews working each storm type, the cost per hour of the storm type, the number of storms of each type that occur in a 10 year period, and estimated savings of the automated model over the manual model during a 10 year period.

We can see that the overall storm response is shorter on average with the automated model due to the manual switching time. The money that can be saved ranges from 0.3 million to 3 million depending on the storm types. For instance, in the low temperature, strong wind storm, crews are going to spend on average 2.4 hours operating manual switches, where this does not occur in the automated model. Thus, the low temperature, strong wind storm response is on average shortened by 2.4 hours. Low temperature, strong wind storms cost on average $120k per storm hour. Thus, shortening the storm response by 2.4 hours saves on average $283k per low temperature, strong wind storm. Over the ten year period, the automated model has a non-discounted savings of $9592k in storm restoration over the manual model.

Table 4-5. Results of 14 feeder systems

	H_Storm		HS_Storm		M_Storm	
	Manual Circuit	Auto Circuit	Manual Circuit	Auto Circuit	Manual Circuit	Auto Circuit
#Auto Device Operation	0	47	0	250	0	70
#Manual Device Operation	105	0	564	0	159	0
Switching Hour	40	0	213	0	60	0
Customer Interrupt Time due to Switching Event	27,987	0	162,754	0	43,800	0
Customer Interrupt Time due to Repair Event	85,687	95,859	711,563	745,988	59,862	60,925
Total Customer Interrupt Time	**113,674**	**95,859**	**874,317**	**745,988**	**103,662**	**60,925**
Reliability Improvement Ratio		1.19		1.17		1.70
	MS_Storm		**L_Storm**		**LS_Storm**	
	Manual Circuit	**Auto Circuit**	**Manual Circuit**	**Auto Circuit**	**Manual Circuit**	**Auto Circuit**
#Auto Device Operation	0	194	0	147	0	460
#Manual Device Operation	448	0	339	0	1,069	0
Switching Hour	168	0	127	0	403	0
Customer Interrupt Time due to Switching Event	120,416	0	101,146	0	337,736	0
Customer Interrupt Time due to Repair Event	410,643	431,580	189,675	196,880	2,474,736	2,623,756
Total Customer Interrupt Time	**531,059**	**431,580**	**290,821**	**196,880**	**2,812,471**	**2,623,756**
Reliability Improvement Ratio		1.23		1.48		1.07

Table 4-6. Economic benefit by utilizing automated switching

Storm Type	Manual Model Switching Hours per Storm	Number of Crews Working Storm	Storm Cost Per Hour ($k)	Savings Per Storm ($k)	Number of Storms in 10 Year Period	Savings in 10 Years ($k)
H	40	100	70	28	13	364
M	60			42	12	504
HS	213	142	100	150	17	2,550
MS	168			118	23	2,721
L	127	171	120	89	7	624
LS	403			283	10	2,828

4.6. Storm Restoration Conclusion

After storms cause damage and service interruptions, faster system restoration can be achieved by deploying automated restoration procedures. In this work, a method that relies upon using commonly existing utility data to perform storm simulations that mimic real storms is presented. The purpose of the storm simulation is to examine reliability and cost benefits from automated switching for storm response.

The simulation results give estimated numbers of manual or automated switching operations for each type of storm. Estimated customer interruption times due to the switching operations or the final equipment repair events are also provided. Given a system topology and a device automation design plan, the simulation approach presented is able to evaluate benefits of grid automation, including effects on customer reliability and reduced storm response time. The approach presented in this work has focused on storm response, but the same simulation approach could be applied to blue-sky day evaluations. The study shows that deploying automated restoration procedures can bring the system back faster with significant economic benefits.

Chapter 5 Smart Grid Design with Distribution Automation

5.1. Introduction

Distribution automation (DA) that uses existing system capacity more effectively, that results in improved system efficiency, and that maintains system reliability along with requiring less financial investment is desirable. To these ends two types of automation are considered, automated switches [48] and coordinated control [52].

Design for the DA and the control calculations that run as part of the DA all use the same root model, with the goal that this root model may be used to solve all analysis problems. Here this is referred to as a model-centric approach to DA. With the model-centric approach the same root model is used across all functions – planning, design, training, real-time analysis, and real-time control. The model is built and maintained from many sources of data, including the geographical information system, customer information system, load research statistics, outage management system, weather data, SCADA historian, and SCADA interfaces.

Many experts throughout the organization contribute to the same model, and as the model is used more and more the integrity of the data associated with the model improves. The model here represents a 14-feeder system with 7 substation transformers. The base year model contains 2148 distribution transformers and 21991 customers, where all load measurements of each individual customer are included in the analysis. The 14-feeder system represents approximately 5% of the utility's entire system and is representative of the entire system. It is felt that a pilot system of this size is necessary to evaluate the true effectiveness of the automated switches.

For both design and control calculations, the calculations that run on the model make use of a year's worth of customer load data, where load estimates for a given hour and day-of-the-year rely on load research statistics [13, 29]. The control calculations also make use of SCADA measurements, including start-of-feeder measurements, automated switch and control device measurements, fault indicator measurements, and fault current measurements.

Advanced algorithms with analysis automation are helpful to evaluating DA designs. Algorithms used here include hourly load analysis for a ten-year period involving customer load growth assumptions, reconfiguration for restoration with either manual or automated switches, and Monte Carlo simulation [53] analysis of the system under storm conditions. The overall analysis involves millions of power flow runs, and automation of the analysis process is a must.

To better prepare the 14-feeder system for the DA, phase balancing and capacitor design are performed [54]. Both designs were performed for and evaluated against the time varying load. The phase balancing is performed in order to provide a more balanced capacity across the phases for use by the automated switching. The capacitor design is performed in order to provide a more controllable system for use by the coordinated control. As will be shown, both of these design efforts resulted in a more efficient system that provides increased capacity and controllability, where the capacity increases help reliability due to rapid reconfiguration.

Design against the time varying load [55] is very important to the results presented. Design for just peak load results in a less efficient and less controllable system that provides less balanced capacity and less total capacity.

SCADA data was used to validate the phase balanced and capacitor design changes, where field measurements were gathered prior to the implementation of the designs, and again field measurements were collected following the field implementation. Comparing the field measurements before and after the implementation of the designs validates the value of the time varying designs and also helps to validate the model used for the control calculations involving reconfiguration and coordinated control.

Sixty-three automated SCADA switches were installed in the 14-feeder system and placed under model-based control. The intelligence for the automated switches comes from the model-centric calculations. Because of this it is possible to use inexpensive automated switches that do not require field programming. Substation contingency analysis that makes use of a real-time reconfiguration for restoration algorithm shows that building a new substation can be delayed if the automated switches are installed. That is, with the forecasted load growth the required reliability criteria could be met either with automated switches or with a new substation.

Analysis of ten years' worth of storm data revealed that storms that affect the system could be categorized into six storm types [41]. Monte Carlo simulations that analyze the system under these six types of storm conditions and which make use of a real-time reconfiguration for restoration algorithm are used in evaluating the automated switches. For a selected storm type, the Monte Carlo simulations considered up to 6000 individual storm simulations, where storm response is compared with and without the automated switches. Results from this analysis shows that with automated switches the storm response could be shortened for all six types of storms. Thus, customer power is restored quicker and at the same time the storm response costs less.

With the model-centric approach the coordinated control calculations use the same model as the automated switching analysis. The coordinated control has three modes of control which are: 1-Conservation Voltage Reduction (CVR); 2-Optimum Feeder Efficiency; and 3-Maximum Feeder Capacity.

This chapter is organized as follows: The system studied is described in section 5.2. The effects of the DA on efficiency, reliability, and capacity are discussed in section 5.3. Results of the studies, along with field validations, are presented in section 5.4. Finally conclusions of chapter 5 are presented in 5.5.

5.2. System Used in Evaluations

The system used for the evaluations is shown in Figure 5-1. This system consists of 14-feeders supplied by seven different substation transformers. The location of the substation of interest for contingency evaluations is shown in Figure 5-1.

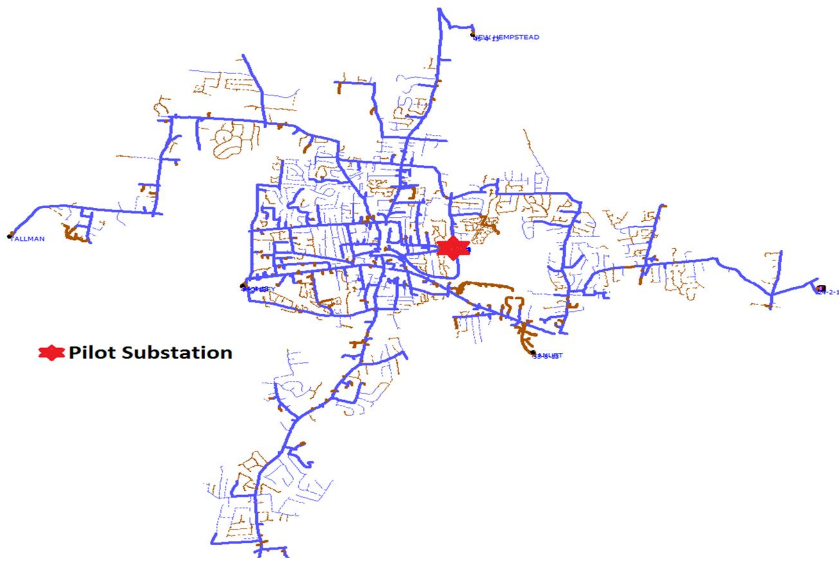


Figure 5-1. Fourteen feeder systems with substation of interest highlighted

The system has 7 load tap changers, 16 fixed shunt capacitors, 12 switched shunt capacitors, and 1 voltage regulator. The voltage regulator has individual phase controls. Table 4-1 presents information related to substations, feeders, and components in the system, including control devices.

The load on the system consists of residential, industrial and small commercial customers, totaling 21991 customers served by 2148 overhead distribution transformers. Each customer and their load measurements are modeled.

5.3. DA and System efficiency, reliability and capacity: Design and Analysis

This section investigates how the DA preparatory actions and the DA itself affect efficiency, reliability, and capacity. Analyses used in the evaluations are described. Results from the analysis will be described in the next section.

5.3.1. Efficiency

System efficiency is affected by phase balancing, capacitor redesign, and coordinated control.

a) *Phase balancing* here involves moving a lateral from one phase to another, in effect moving load around among the phases and balancing phase current flows [17]. Phase balancing over the time varying load is considered as preparatory to the DA. Balanced loading across the phases provides an evenly distributed capacity for the reconfiguration to work with. Furthermore, the balancing reduces losses and improves system efficiency, releasing even more capacity that may be used to meet reliability requirements during contingencies.

The phase balancing algorithm used here prioritizes the phase moves, with the highest priority phase move providing the greatest reduction in losses over the time varying load, the next highest priority phase move providing the next greatest reduction in losses, and so forth. Typically, even with feeders that have over 200 single phase laterals, three phase moves are sufficient to get more than 90% of the loss reduction that is possible.

b) *Capacitor redesign* is also considered as preparatory to the DA. The term “redesign” is used because the existing system already had capacitors installed, but the existing capacitors had been designed for peak load conditions [56]. Figure 5-2 shows a feeder power factor plotted against hour-of-the-year where the capacitors were designed for the summer peak load condition. Note that the feeder operates much of the time close to unity power factor during summer hours. However, much of the time the power factor goes leading, resulting in inefficient operation. Designing against summer, winter, fall, and summer conditions can result in overall improved operations. Note that the phase balancing is performed before the capacitor redesign since the phase balancing often affects the capacitor redesign.

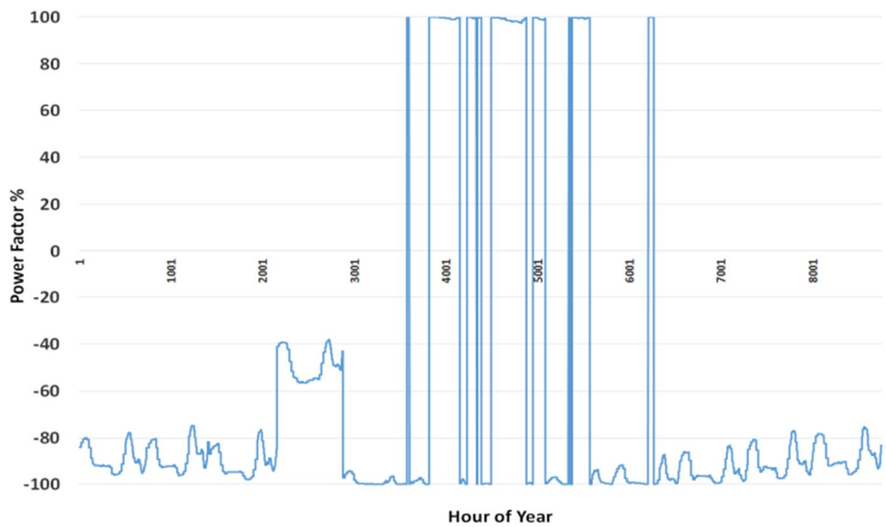


Figure 5-2. Feeder power factor resulting from summer peak design, where a negative percentage indicates a leading power factor.

Coordinated control of load tap changing transformers, switched capacitors, and voltage regulators can improve feeder efficiency [25]. Here the model-centric control algorithms run in a hierarchical control architecture illustrated in Figure 5-3, where some of the local controllers have communications and run under coordinated control, and some of the local controllers operate relying only on local measurements. In the architecture the model-centric control calculations are performed at the higher hierarchical level, where measurements from throughout the system are used in performing the calculations. The model-centric control layer updates local controller set points throughout the day to improve performance. If there is no communications to a local controller, the model-centric calculations will simulate the expected actions of the local controller in calculating what the other controllers should do. If communications is lost, then all local controllers continue to work with the last received setpoint as long as no system constraint violations occur. However, as long as the communications are working, the coordinated control can make better decisions than local controllers operating independently with limited knowledge of the system [52].

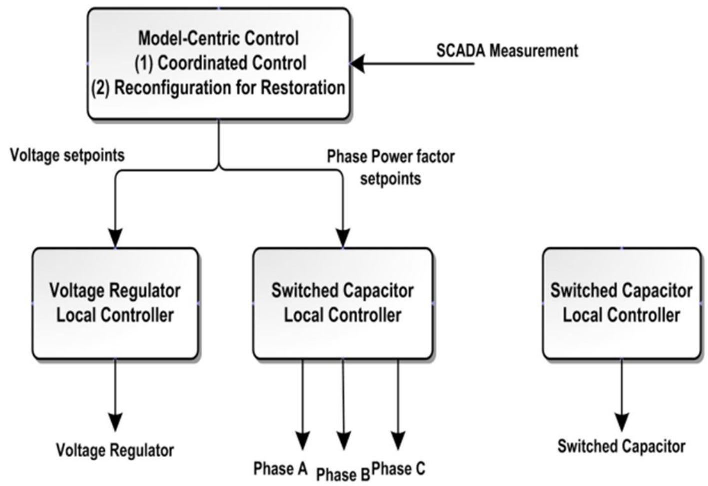


Figure 5-3. Hierarchical control architecture, where some local controllers run under coordinated control and some local controllers run with just local measurements.

A major benefit of model-based, coordinated control is the ability to switch control objectives. That is, the coordinated control can be used to achieve minimum losses on the distribution feeder, or it can be used to implement conservation voltage reduction, or it can be used to achieve maximum capacity under heavily loaded conditions [57]. Another benefit of coordinated control is a reduction of controller motion over local control [58]. Furthermore, as new challenges emerge, the hierarchical, model-based control provides flexibility to deal with emerging challenges in a cost effective manner.

5.3.2. Reliability

There are 63 automated SCADA switches installed in the fourteen feeder system. Figure 5-4 illustrates the automated switch design for two of the feeders, where each feeder has a midpoint recloser and three SCADA or automated switches. There is a tie recloser between the two feeders. The midpoint recloser, automated switches, and tie recloser are under the control of the model-based reconfiguration for restoration algorithm. Thus, for the two feeder system shown, there are nine sectionalizing devices under model-centric control. As will be shown, this automation can have a significant effect on the reliability of the system during both storms and contingencies.

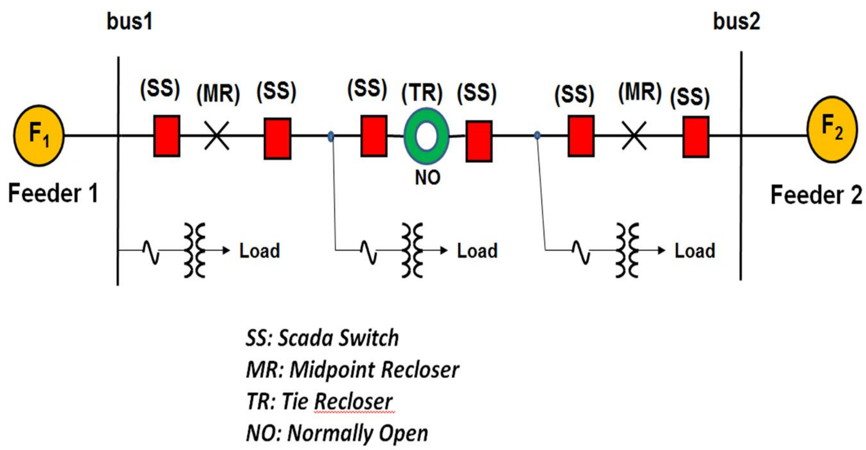


Figure 5-4. Representative automated switches design for two feeders.

a) *Storm Restoration*

A Monte Carlo simulation is used to evaluate reliability benefits available from automated switching during storm restoration. The storm simulation consists of two basic parts that are iterated as the storm simulation progresses. In the first part, the Monte Carlo simulation fails and repairs components (i.e., based upon component type storm failure and repair rates) as the storm progresses [43, 50]. In the second part of the storm simulation, failures that have just occurred are isolated, and switching operations are used to restore power as much as possible prior to completing the repairs [59]. In one storm simulation automated switches are not included in the model and only manual switching is used [49]. In a second storm simulation automated switches are included in the model and only automated switches are used in the restoration of power. Comparisons of the performance of the manually operated system versus the automated system are then performed.

Table 4-3 shows the different storm types used in the storm simulations [41]. For each storm type shown in Table 4-3, two Monte Carlo simulations are performed, one with just manual switching operations, and one where automatic switches have been added to the system and are used in the storm response.

b) *Substation Transformer Contingencies*

Automated switches do not increase the inherent capacity of the system, but they do provide more rapid access to existing capacity, which can help maintain reliability requirements with load growth.

The substation of interest is indicated by the star shown in Figure 5-1. Fourteen feeder systems with substation of interest highlighted, and details of the substation are shown in Figure 5-5. The substation has eight feeders. Within the substation there are two transformer banks, banks 1 and 2. The normal rating for each bank is 42 MVA.

Access to the existing capacity of the system shown in Figure 5-1 can be improved with automated switches, which can help with meeting reliability requirements associated with contingencies. Contingencies considered here are failures of substation transformers. For substation transformer failures there is a limit of 60,000 hours of customer downtime during the first 24 hours of interruption. When a substation transformer fails and this 60,000 hour limit is exceeded, then the system must be upgraded to bring the hours of downtime below 60,000 [60]. Because each individual customer in the 14-feeder system is modeled, hours of downtime can be calculated by the Monte Carlo simulation by counting the number of customers without power during each hour of the storm simulation.

When the substation transformer failure downtime limit is exceeded, the classical solution is to invest in adding a new substation. However, adding automated switches provides more rapid access to existing capacity by moving the load around among feeders, and this provides an alternative to the classical solution for meeting reliability requirements with load growth.

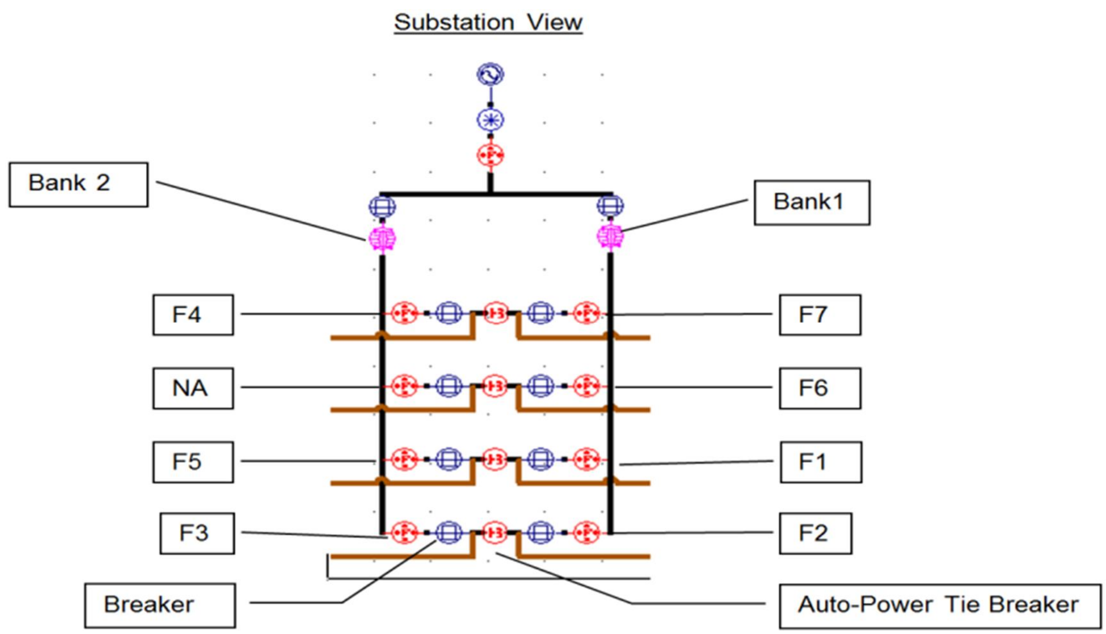


Figure 5-5. Substation considered in substation deferral study, where location of substation is indicated as pilot substation in Figure 5-1.

5.3.3. Capacity Evaluation

Similar to system efficiency, system capacity is affected by phase balancing, capacitor redesign, and coordinated control. Three-phase capacity is limited by the highest loaded phase. Phase balancing helps to increase the usability of the three phase capacity of the system, presenting a more balanced three-phase system for use by reconfiguration for restoration. Better capacitor redesign also helps to increase system capacity. It is important that the capacity increases be maintained over the time-varying load since the reconfiguration needs as much capacity as possible for picking up load at all points in time.

The coordinated control considered here has a maximum capacity mode [25]. Coordinated control makes better use of system capacity than local control, especially during reconfiguration of the system. This is because the coordinated control immediately responds to system reconfigurations by re-calculating local controller set points. It should be noted that updates to local setpoints are not only needed because of loads being switched from one feeder to another, but are especially needed when a controller itself is switched from one feeder to another.

Quasi-steady state power flow analysis is used to evaluate capacity increases in the next section.

5.4. DA Evaluation and Validation Results

5.4.1. Efficiency Evaluation Results

a) Phase balancing that takes into account time varying loads was performed on the 14-feeders of Figure 5-1. Then, a series of 8760 quasi-steady state power flow runs (i.e., one for each hour of the year) was made on the test system of Figure 5-1 prior to phase balancing, and then a series of 8760 power flow runs was made on the phase balanced system.

Figure 5-6 compares the system power factor that results from the two quasi-steady state power flow runs, where it may be noted that the phase balancing design has a slightly higher efficiency across all time points than the base case. It should be noted that the feeders considered here are very short, being around 5 miles long. Much longer feeders would typically result in larger efficiency improvements from phase balancing.

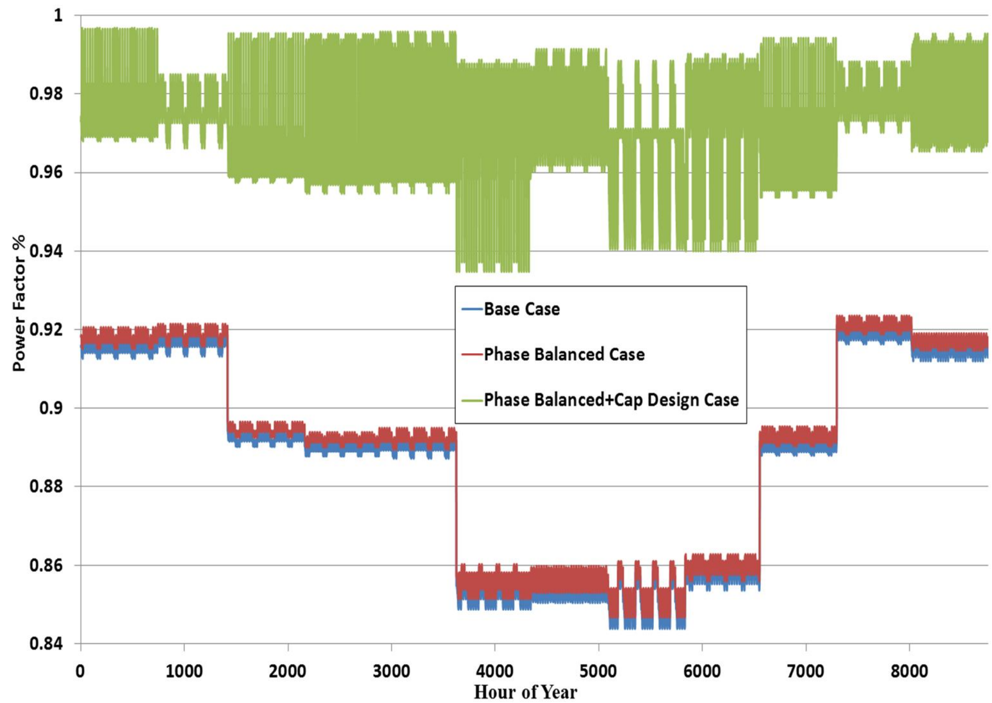


Figure 5-6. Overall 14 feeder power factor for base case, phase balanced case and capacitor design case across 8760 hours in year.

Figure 5-7 shows a field validation of the phase balancing operations. Start-of-feeder phase current measurements were recorded by a SCADA historian and the current measurements are compared prior to and after the phase balancing operation. The plot covers several days of operation and shows how the phase balancing operation affects the phase current flows. From the plot it may be seen that phase A current (red curve in Figure 5-7) is getting back together with other phase currents at the time when the phase balancing occurred.

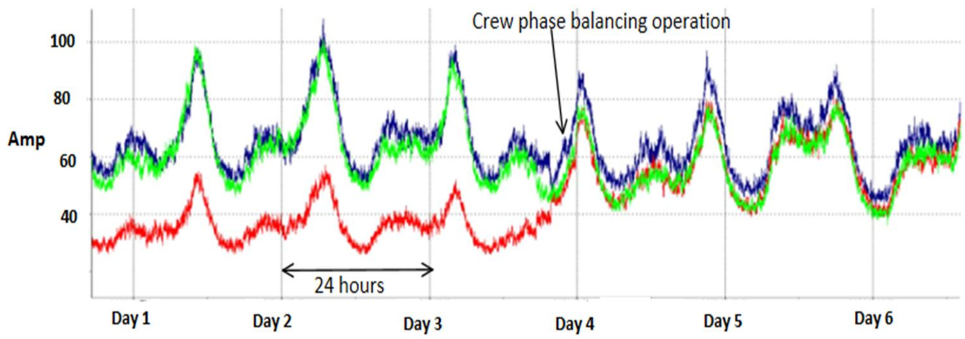


Figure 5-7. Representative phase A(red), B(blue), and C(green) current measurements at start of feeder for phase balancing validation, where time of phase balancing occurred late on day 3

b) Capacitor design is often performed for a single time point, the peak. This can result in inefficient operation of the feeder over much of the year as illustrated in Figure 5-2.

Figure 5-8 shows how capacitor design performed for the time-varying load can provide excellent efficiency throughout the year. From comparing Figure 5-2 and Figure 5-8 it may be seen that there are significant efficiency improvements from the time-varying design versus peak load only design.

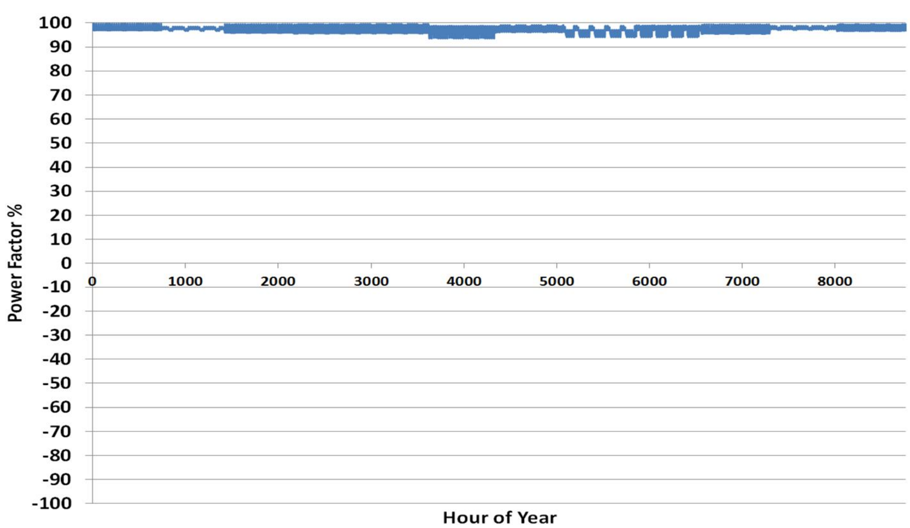


Figure 5-8. Feeder power factor with time-varying capacitor design

Figure 5-6 shows the time variation of the 14-feeder system power factor following the capacitor redesign. It may be seen that there is a significant improvement in the system power factor following the capacitor redesign.

Substation power factor measurements were made prior to the capacitor redesign, and again following the field implementation of the capacitor redesign. Table 5-1 shows three such measurements. From the measurements it may be seen that the power factor measured at the transformer banks in the substations shown increased following the redesign.

Table 5-1. Validation of capacitor design

Substation	Transformer Bank	Power Factor Before Design	Power Factor After Design
Substation A	1	0.9620	0.9702
Substation A	2	0.9347	0.9950
Substation B	3	0.9759	0.9865

c) The coordinated control solution for minimum system losses (efficiency mode) of the 14-feeder system is compared with the coordinated control for Conservation Voltage Reduction (CVR) mode solution, and results are shown in Table 5-2. When the coordinated control works to minimize the system losses, the system voltages run higher (to minimize losses in power transmission) than when the coordinated control works to minimize the operating voltage (while still maintaining the voltage above the lower limit of 114 volts) in order to reduce the energy drawn by the loads.

The results shown in Table 5-2 are based upon using a 1% load-voltage dependency factor where a 1% reduction in voltage results in 1% reduction in current. An interesting observation from Table 5-2 is that the CVR mode results in a greater transmission loss reduction, even though the feeder is running at a lower voltage. This transmission loss reduction is attributed to the smaller loads being supplied in the CVR mode. Thus, raising the voltage, and decreasing the current flow, results in reducing transmission system losses with a constant power load, but not necessarily with a voltage dependent load.

Table 5-2. Comparison of coordinated control modes

		CVR Mode	Efficiency Mode
Manual Model	**MWHr supplied**	376,099.30	376,099.30
	Total Losses (MWH)	5449.795	5449.796
Automated Model	**MWHr Supplied**	365,177.04	373,240.30
	Total Losses (MWH)	5,134.95	5,182.38
Comparison	**Energy Supplied Reduction (MWHr)**	10,922.26	2,859.00
	Loss Reduction (MWH)	314.85	267.42
	Energy Supplied Reduction (%)	2.90%	0.76%
	Loss Reduction (%)	5.78%	4.91%

5.4.2. Reliability Evaluation Results

a) Storm Restoration Evaluation Case

In the Monte Carlo simulation it is assumed that automated switches can be operated instantaneously. For manual switch operations and for a given failure it is assumed that it takes 1 hour to operate the first manual switch and each additional manual switch operation associated with the failure is assumed to take 15 minutes. These manual switch operation times were obtained from utility operating experience and statistics.

Table 5-3 compares the results of the Automated System (i.e., system with 63 SCADA switches) with the system with just manually operated switches for each of the storm types. In Table 5-3 the number of hours that crews spend operating manual switches for each storm type is shown for the Manual System. The crews do not spend any time operating switches in the Automated System.

Table 5-3. Customer outages times and SAIDI improvements for different types of storms

		Manually Switched System		Automatic-ally Switched System	SAIDI Improve-ment
Type of Storm	Average Number of Failures per Storm	Device Switching Hours	Total Customer Outage Hours	Total Customer Outage Hours	%
H	18	40	113,674	95,859	0.4051
HS	96	213	874,317	745,988	2.9178
M	27	60	103,662	60,925	0.9717
MS	74	168	531,059	431,580	2.2618
L	55	132	301,707	197,353	2.3727
LS	173	403	2,812,471	2,623,756	4.2907

Table 5-3 also shows the total customer outage hours for both systems for each type of storm. From the last column in Table 5-3 it may be noted that the automated system provides significant improvements in SAIDI over the manually operated system.

b) Contingency Evaluation Case

A comparison of customer downtimes that result from transformer bank failures is now considered. For the projected load growth, the customer downtime for the system with manually operated switches will be compared to the system with automated switches, where the automated switch design is illustrated in Figure 5-4. Figure 5-9 and Figure 5-10 illustrate the results of the comparison for banks 1 and 2, respectively, where the transformer banks of interest are shown in Figure 5-5.

The red line in Figure 5-9 and Figure 5-10 indicated the limit of 60,000 hours of customer downtime. The green lines in Figure 5-9 and Figure 5-10 represent the hours of customer downtime as a function of year for the manually switched system, where load growth causes the customer downtime to increase from one year to the next. The blue line is for the system with automated switches. As may be seen from the figures, with the manually operated system the reliability criteria is violated in year 2021 for both transformer failures, whereas for the system with automated switches the reliability criteria is not violated until year 2028. Also from Figure 5-9 and Figure 5-10 it may be noted that between years 2014-2017 the automated system results in approximately 10,000 fewer hours of customer downtime than the manually operated system. It may also be noted from Figure 5-9 that the automated system results in 100% backup for Bank 1 from 2014-2017.

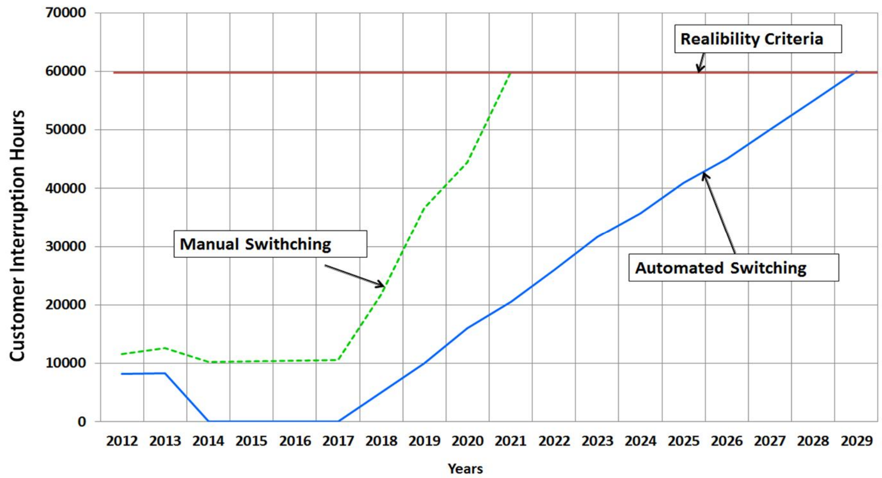


Figure 5-9. Reliability criteria comparison between manual and automated switching performance for failure of existing substation transformer bank 1

Thus, the building of a new substation needed for meeting the reliability criteria can be delayed approximately 7 years with the automated system. Or, in other words, the smart grid automation can be considered as an alternative to starting the construction of and investment in a new substation.

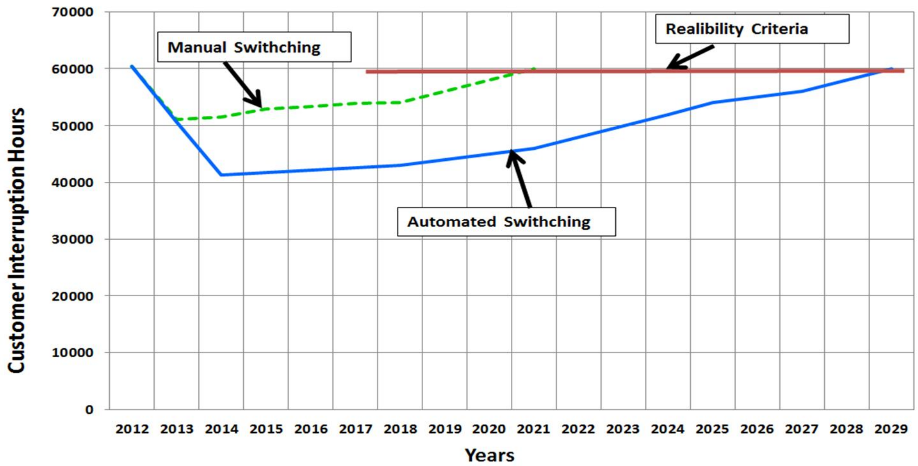


Figure 5-10. Reliability criteria comparison between manual and automated switching performance for failure of existing substation transformer bank 2

5.4.3. Capacity Evaluation Results

Figure 5-11 compares the system capacity for year 2017 before phase balancing and capacitor design were performed with the system capacity after phase balancing and capacitor design were performed, where system capacity is measured relative to the highest loaded phase on each feeder. This is the phase that would set the limit on the allowable size of new 3-phase loads.

The green curve in Figure 5-11 shows the difference in remaining capacity between the system that has been phase balanced with capacitor design and the system without phase balancing and capacitor design. From Figure 5-11 it is interesting to note that the increase in capacity is larger during the summer months (i.e., approximately hours 3600-5760), and since this is a summer peaking system, the larger increase in capacity is occurring when it is needed the most.

The summation of the increase in capacity over all 8760 hours is 1845 MVA. The average hourly increase in capacity for the system is 210 kW. This extra capacity can be used for providing power to neighboring feeders during contingencies.

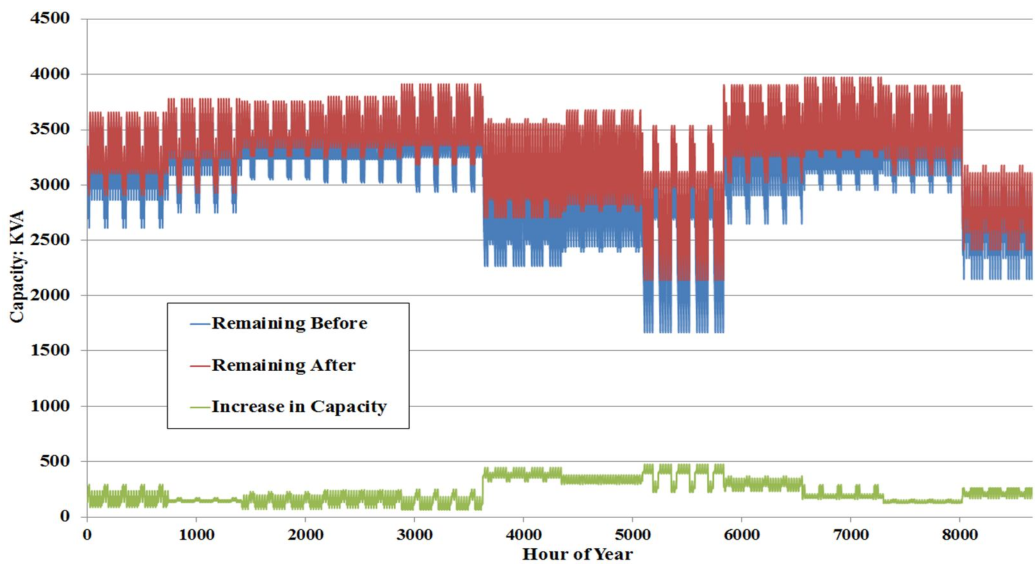


Figure 5-11. Remaining capacities and increase in capacity before and after design

5.5. Conclusion of DA

In the work here a detailed model of the system that includes every customer served by the system is used for both design and real-time analysis and control, leading to a model-centric distribution automation system. Here the model is used to evaluate the effects of investments made in distribution automation and their value measured in terms of system efficiency, reliability, and capacity.

In efficiency and capacity evaluations time varying phase balancing and capacitor designs are considered as part of the smart grid investments because they provide a more controllable system for coordinated control and they also provide greater three-phase capacity for automated switching operations. It is demonstrated that significant improvements in efficiency can be obtained with time varying designs versus peak designs.

It is also demonstrated that significant increases in capacity are also available from the time-varying phase balancing and capacitor designs. These capacity increases can provide greater opportunities to aid the automated switching operations and help improve reliability. An interesting observation from the analysis is that the capacity increases were greatest when the system load was the greatest, which is the desired result.

Coordinated control for maximum feeder efficiency is compared with coordinated control for Conservation Voltage Reduction (CVR) mode. An interesting result is that the CVR mode, with the lower average feeder voltage, actually results in less loss in the feeders themselves.

In reliability evaluations automated switches are considered from two perspectives – how they can aid in restoring power more rapidly for storm restoration and how they can aid in major contingencies by providing more rapid access to system capacity. In the storms considered here, with automated switches the field crews went directly to repairs and did not spend time operating switches. With this approach there were more customers without power while the crews were doing the repairs. This is because there were approximately 12x more manual switches in the system than automated switches. However, the crews were able to get the power restored quicker in the automated system, and this resulted in overall less downtime for the customers as compared to the manually switched system.

The reliability effects of automated switches were also considered on contingencies involving substation transformer failures. For the system considered here it was demonstrated that reliability criteria could be met for 7 years longer with the automated system. As a result the building of a new substation could be delayed.

For the 14-feeder system considered, the results show that distribution automation provides very positive benefits for system efficiency, reliability, and capacity. As has been experienced in other industries, investments in system automation can lead to increased production and performance.

Chapter 6 Smart Grid Economic Evaluation in Hard Dollars

6.1. Introduction

Smart grid automation investments that result in making better use of existing distribution system capacity, which improve efficiency, which maintain required reliability at lower cost than classical design approaches, and which reduce customer costs are investigated. Here smart grid investments are evaluated in terms of hard dollars. Benefits are quantified by comparing capital and operating costs of alternative designs. This stands in contrast to soft dollar benefits which, for example, attempt to estimate the value of improvements in reliability, which may be difficult to determine and/or justify. Here, a reduction in loss when the same load is supplied is counted as an energy savings and is included in the hard dollar evaluation.

The work here focuses on economic benefits, where the economic evaluations are based upon very detailed engineering analysis performed on a very detailed system model. The model used has a one-to-one correspondence with the geographical information system model of the system. The analysis is performed using hourly, time-varying loads and also hourly variations in the value of electric energy. Engineering analysis performed includes phase balancing, capacitor design, reconfiguration for restoration, Monte Carlo analysis, and coordinated control [52, 58].

The authors of [17] describe a phase balancing algorithm that reduces losses but do not present an economic evaluation. Similarly, the authors of [61] explain design considerations for capacitor design to reduce losses, but do not present an economic evaluation. In [57] the authors describe a model based distribution control scheme which is configurable and hierarchical, again without an economic evaluation. While [62] describes a way to evaluate the impact of partial automation on system reliability, it does not present an economic evaluation of shortened storm response. The authors of [47, 63] discuss the calculation of distribution system reliability indices using storm simulations but do not assess the economic value of improved storm response.

Hard dollar benefits from investments considered here arise from investing in automated switches, coordinated control of voltage regulators and capacitor banks, and preparatory actions of phase balancing and capacitor design. The preparatory actions are performed in order to get the most benefit from the automated switches and coordinated control, and they also result in efficiency improvements.

The analyses involves hourly power flow calculations over periods ranging from ten to 18 years, where hourly, time-varying loads are modeled and annual load growth factors by customer type are applied. Each individual customer is modeled along with the customers historical load measurements. Loads are modeled as voltage dependent, where a 1% load-voltage dependency is assumed. With this voltage dependency model, when the voltage decreases (increases) by 1%, then the current drawn by a load will decrease (increase) by 1%. Monte Carlo simulations [41] of switching operations during various types of storms are performed. The Monte Carlo storm simulations presented use statistical data derived from historical storms, and, for a specific type of storm, simulate up to 6000 hours of storm conditions to derive the results presented [50]. Algorithms used include reconfiguration for restoration [48], involving either manual or automated switches, and coordinated control involving two modes of control.

Electric energy prices are estimated on an hourly basis for the analysis periods. Using historical Locational Marginal Price (LMP) data, the historical LMP data is escalated based upon the U. S. Department of Energy's forecast for gas energy prices. Thus, the assumption is made that electric energy prices escalate as gas energy prices do. Hence, the time varying cost of electricity is modeled along with the time varying load on an hourly basis. Validations using field measurements are presented for the phase balancing and capacitor designs considered.

Cost benefits derive from: 1-Increased system efficiency; 2-Rapid access to existing system capacity; 3-Shortening the length of storm responses; and 4- Reduction in load energy. A soft benefit is improved customer reliability. Cost benefits among the investments are presented and compared.

This chapter is organized as follows: Evaluations to be performed are described in section 6.2. In sections 6.3-6.7 alternative ways of operating the system are compared, in each case using two different models. As the paper progresses from section 6.3 to 6.7, the comparisons build on one another from section to section, so that the incremental worth of an investment made on top of another investment can be assessed. Conclusions of chapter 6 are presented in section 6.8.

6.2. Descriptions of System Used and Design to be evaluated

The system used in the evaluations is shown in Figure 5-1. The system consists of 14 feeders supplied by seven different substations. Of particular interest is a substation that has 7 feeders. This substation, which is shown as a star in Figure 5-1, will be used in a substation deferral study associated with maintaining reliability. Feeders from other substations that interface with feeders from the substation of interest are modeled to create the system studied here.

Table 4-1 presents information related to substations, feeders, and components in the system, including controlled devices. The system has 16 fixed shunt capacitors, 12 switched shunt capacitors, and 1 voltage regulator. The capacitors listed in Table 4-1 are actually determined in the capacitor design study described below, but are listed here for completeness in describing the model.

Table 4-2 presents information about customers modeled in the system. The load on the system consists of residential, industrial and small commercial customers, totaling 21991 customers served by 2148 overhead distribution transformers. In the Monte Carlo reliability evaluations described below, when equipment failures cause customer interruptions, the customers without power are counted in the calculations to determine reliability. In the voltage violations described in the coordinated control evaluation, low voltages at the 2148 distribution transformers are considered.

6.2.1. Description of Design Cases and Method of Cost Comparison Evaluations

Prior to any design changes, the model shown in Figure 5-1 is referred to as the Base Case Model. Following phase balancing design, a Phase Balanced Model is created. Then, capacitor design is performed on the Phase Balanced Model, creating the Capacitor Design Model. Finally automated switches are placed in the Capacitor Design Model, and a coordinated control system is added to the Capacitor Design Model, creating the Automated Model. Thus, altogether there are four different models that are used in the economic evaluations.

Cost comparisons are made between the Base Case Model and the Phase Balanced Model, and again cost comparisons are made between the Capacitor Design Model and the Phase Balanced Model. Thus, the incremental worth of the investment in capacitors can be determined. Two types of automation are included in the Automated Model, automated switches and coordinated control. Two modes of coordinated control are used, Conservation Voltage Reduction (CVR) mode and a Voltage Violation mode override. Cost comparisons are made between the Capacitor Design Model and the Automated Model for the following: 1-Storm restorations; 2-Substation Deferral 3-Customer energy use and feeder losses.

The cost comparisons include worth of losses, energy costs, labor costs, and equipment costs, but do not include the cost of the backbone communication system and the cost of the control center. Thus, costs of phase balancing, switched capacitor banks, automated reclosers, automated switches, automation of capacitor banks and voltage regulators, equipment installation costs, and hourly costs of field crews during storms are considered in the comparisons.

Based upon using individual customer load measurements and load research statistics, the loads vary from hour to hour in the analysis [29]. The feeders are analyzed on an hourly basis over a ten year period, and the losses for each hour are calculated. Electric energy prices are estimated on an hourly basis. Using historical LMP data, historical LMP data is escalated based upon the U. S. Department of Energy's forecast for gas energy prices [64]. Thus, the losses at a given hour are multiplied by the forecasted LMP price for that hour to determine the dollar worth of the losses. Figure 6-1 shows a plot of the LMP versus month of year used in the analysis.

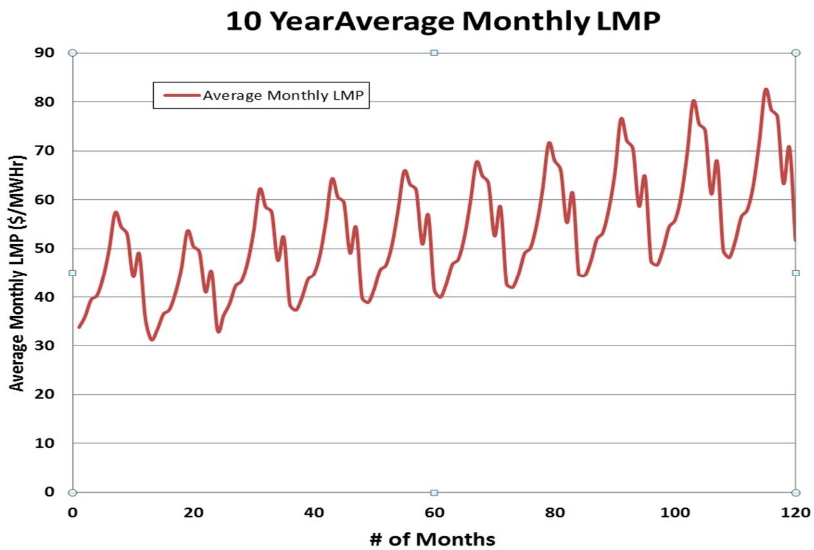


Figure 6-1. Average monthly LMP price used in analysis

Forecasted customer load growth is included in the analysis, and is especially important in the substation deferral evaluation between the Capacitor Design Model and the Automated Model.

6.3. Phase Balanced Model versus Base Case Model Evaluation

The Base Case model represents the system as initially configured prior to any design changes. Phase balancing and capacitor placement for time varying loads are considered as preparatory actions for smart grid investments. The "first step" for preparing for the smart grid automation is phase balancing. The phase balancing algorithm used in the analysis prioritizes the phase moves, with the highest priority phase move providing the greatest reduction in losses over the time-varying load, the next highest priority phase move providing the next greatest reduction in losses, and so forth [22]. Even with feeders that have over 100 single-phase laterals, phase moves for three laterals are often sufficient to achieve 95% or more of the loss reduction available.

Using start-of-circuit phase current measurements from a SCADA historian, the phase balancing design changes were validated. Figure 5-7 shows phases A, B, and C current flows obtained from the SCADA historian. During the approximately five day period shown in Figure 5-7 the feeder was phase balanced. The phase balancing operation occurred where the three current flows come close together.

Balancing over the time-varying load also balances, and for three-phase loads increases, the system capacity that is available to automated switches. Phase balancing should be performed before capacitor placement, since the phase balancing result affects phase loading and power factors that affect capacitor placement. Performing phase balancing prior to capacitor design can sometimes result in improved control with fewer capacitors and lower cost [54].

The cost of phase balancing the 14 feeders was $56k. Including the cost of the phase balancing, the Phase Balanced Model provided non-discounted efficiency savings of $134k over the Base Case Model for the 10 year period.

6.4. Capacitor Design Model versus Phase Balanced Model Evaluation

Capacitors can be used to reduce system losses [56] and control voltages. Following phase balancing, the next step in preparing for the smart grid automation was to perform and implement the capacitor design and then to validate the results with field measurements. The feeders considered here originally had existing capacitor banks, and so the study here may also be thought of as a capacitor redesign study. As a result of the capacitor design using the time-varying load, many of the existing capacitor banks were moved and/or changed out with new banks of different sizes. Capacitor design over the time varying load improves the ability of the coordinated control to manage voltage. Table 5-1 shows also capacitor replacement operation results from field measurement to validate results of capacitor design over power factor.

The economics of the Capacitor Design model was compared against the economics of the Phase Balanced model. The cost of purchasing and installing new capacitors is used in the evaluation. In the economic comparison the worth of the difference in losses between the Phase Balanced Model and the Capacitor Design Model is compared over the 10 year period. The cost of equipment and installation labor for the 12 switched capacitors and 16 fixed capacitors was $496k, where fixed capacitors cost $16k and switched capacitors cost $20k. The Capacitor Design Model provided non-discounted efficiency savings of $322k over the Phase Balanced Model for the 10 year period.

6.5. Automated Model versus Capacitor Design Model: Switch Automation and Storm Restoration

Recent storms impacted the utility with costs in the neighborhood of $25 to $35 million dollars [33, 41]. During a storm event the hourly costs of crews is high [41, 47, 65]. Switch automation allows crews to skip operating switches and go directly to repairs [42, 66]. However, there are approximately 16 manual switches for every automated switch in the design considered here. A concern is whether or not the reliability of the system can be maintained with so few automated switches relative to the manual switches.

Table 4-3 shows different storm type descriptions considered in the analysis, with the average length in hours of each storm type [41].

Figure 5-4 shows a representative schematic of the automated switch design, where just two feeders are considered. Each feeder has a midpoint recloser and there is a tie recloser between the feeders. Customer counts between the automated SCADA switches are limited to approximately 250 customers. Altogether 63 automated SCADA switches were installed in the 14 feeder system.

Monte Carlo simulations are performed for both the Capacitor Design Model, which just has manual switches, and the Automated Model, and then comparisons of the storm restoration between the two models are performed. The Monte Carlo simulation randomly selects and fails components based on the statistics of the storm type being simulated. In performing the storm restoration calculations, each time a component is failed, the Monte Carlo simulation employs a reconfiguration for restoration algorithm to operate switches, where in the Capacitor Design Model manual switches are operated, and in the Automated Model only automated switches are operated [49]. The simulation iterates through the hours of the storm, and then repeats a new storm simulation, until convergence of the Monte Carlo process occurs. In the simulation it is assumed that the operation of an automatic switch takes 0 hours. For a given failure, it is assumed that the operation of the first manual switch requires 1 hour, and the operation of each additional manual switch associated with the failure requires 15 minutes each. These operation times were derived from the utility operating experience.

It is assumed that it takes no crew time for automated switch operations. Table 6-1 shows results from the simulation for low temperature, strong wind storms. From Table 6-1 it may be seen that on average there are 460 automated switch operations with the Automated Model and 1069 manual switch operations with the Capacitor Design Model, requiring 403 hours of crew time. The interruption hours for the customers are divided into hours associated with the switching events and hours associated with the repair. Note that the Automated Model has fewer hours of interruption.

Table 6-1. Results of Monte Carlo simulations comparing capacitor design model with automated model for low temperature, strong wind storm

Model	Automatic Device Operations	Manual Device Operations	Hours Spent In Switching Operations	Interruption Hours due to Switching Event	Interruption Hours due to Repair Event	Total Hours of Interruption
Capacitor Design Model	0	1069	403	337736	2474736	2812471
Automated	460	0	0	0	2623756	2623756

Table 6-2, column 2, shows the average number of hours crews spend operating manual switches for each storm type as simulated with the Capacitor Design Model. Table 6-2 also provides averages for the number of crews working each storm type, the cost per hour of the storm type, the number of storms of each type that occur in a 10 year period, and non-discounted savings of the Automated Model over the Capacitor Design Model during the 10 year period.

When performing cost benefit analysis, we assume automation of the 14 feeder system is representative of automation of entire system. From Table 6-2 we can see that the overall storm response is shorter on average with the Automated Model due to the manual switching time of the Capacitor Design Model. For instance, in the low temperature, strong wind storm, crews are going to spend on average 2.4 hours operating manual switches, where this does not occur in the Automated Model. Thus, the low temperature, strong wind storm response is on average shortened by 2.4 hours. Low temperature, strong wind storms cost on average $120k per hour. Thus, shortening the storm response by 2.4 hours saves on average $283k per low temperature, strong wind storm. Over the ten year period, the Automated Model has a non-discounted savings of $9592k in storm restoration over the Capacitor Design Model, where this savings represents savings extrapolated to the whole system based upon the results of the 14 feeder simulation.

Table 6-2. Monte Carlo simulation results for capacitor design model and savings of automated model versus capacitor design model over a ten year period

Storm Type	Capacitor Design Model Switching Hours per Storm	Number of Crews Working Storm	Storm Cost per Hour ($k)	Number of Storms in 10 Year Period	Savings in 10 Years ($k)
High Temperature	40	100	70	13	364
Moderate Temp	60	100	70	12	504
High Temperature Strong Wind	213	142	100	17	2550
Moderate Temp Strong Wind	168	142	100	23	2721
Low Temperature	127	171	120	7	624
Low Temperature Strong Wind	403	171	120	10	2830

6.6. Automated Model versus Capacitor Design Model: Switch Automation and Substation Deferral

The substation that is the focal point in the 14 feeder system for this study is illustrated in Figure 5-5. It has seven feeders that interface to feeders from other substations in the system. The substation has two transformers. Reliability requirements specify that if either transformer fails, then 62% or more of the load must be picked up either using capacity from the remaining transformer in the substation or from neighboring substations through switching operations. 38% or less of the load must be picked up within 24-hours by using a portable substation. However, the total customer hours of interruption must be maintained below 60,000 [60]. In the simulations the substation transformers are allowed to operate for 4 hours on Long Term Emergency Ratings. Note that the substation is designed with an auto-power tie breaker as shown in Figure 5-5.

Using customer load growth projections for the feeders, as illustrated for a representative feeder in Figure 6-2, the load on the system is grown until the reliability requirement cannot be satisfied. This is done for both the Capacitor Design Model and the Automated Model. When the Capacitor Design Model can no longer meet the reliability requirement, the cost of building a new substation to meet the reliability requirement is evaluated. The cost of adding the automated switches to the Automated Model is also evaluated, and a comparison between the costs of the Capacitor Design Model and the Automated Model is performed.

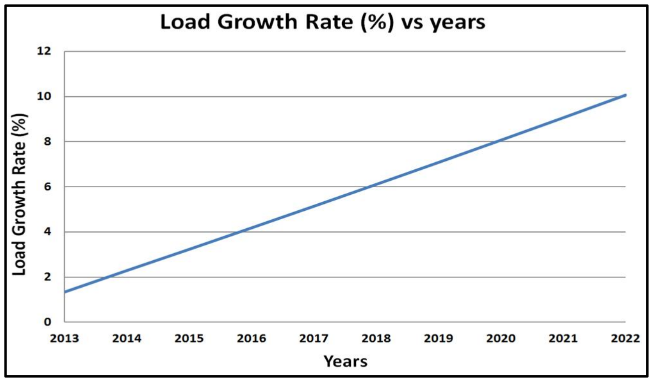


Figure 6-2. Sample feeder with percentage load growth rate used in study

Figure 5-10 shows the results from comparing the Capacitor Design Model with the Automated Model when transformer bank 2 of Figure 5-5 is failed. From Figure 5-10 it may be seen that the outage hours increase as a function of year, due to the annual load growth rates, for the bank failure.

The Capacitor Design Model, which has only manual switches, violates the reliability requirement of 60000 customer outage hours in 2021, whereas with the Automated Model the reliability requirement is not violated until year 2029. The cost of the new substation that is eventually going to be required is estimated to be $40000k in 2012 dollars. Thus, with the automated design, this capital investment is delayed for 8 years. In this comparison the Automated Model has a present worth savings of $7,380k over the Capacitor Design Model.

6.7. Automated Model versus Capacitor Design Model: Coordinated Control

The coordinated control runs in the control center and makes use of measurements from throughout the system to determine control settings that move the system toward optimum performance as the load varies. The coordinated control provides set points to local controllers. A major difference between the coordinated control and local control is the set points provided by the coordinated control are time varying. Here the coordinated control works with switched capacitors and voltage regulators.

The coordinated control considered has two modes: 1-Conservation Voltage Reduction (CVR) mode to reduce the energy drawn by loads; 2-Voltage override mode that overrides the CVR mode if voltage violations occur.

Table 6-3 compares energy between the Automated Model coordinated control CVR mode and the Capacitor Design Model, where a 1% load-voltage dependency is used. The feeder loss reduction achieved with the coordinated control is small because the Capacitor Design Model is already operating at a very high efficiency. The average feeder efficiency in the Capacitor Design Model is 0.9855, whereas the average feeder efficiency in the Automated Model is 0.9859, an increase of only 0.0004 in efficiency. However, due to CVR mode, over the 10 year period the non-discounted savings in energy of the Automated Model over the Capacitor Design Model was $2900k. The cost of automating the 12 switched capacitors and one voltage regulator in the 14 feeder system is $68k.

The voltage violations that occurred with the Automated Model were significantly less than those that occurred with the Capacitor Design Model. There were 2486 load points at which voltage violations were monitored over 8760 analysis points per year for 10 years, or 217,773,600 customer load voltage calculations. Over these load voltage calculations, 1.57% of the calculations in the Capacitor Design Model were low voltages and only 0.20% of the calculations in the Automated Model running the CVR mode were low voltage. In the Automated Model the control mode switches to voltage override when low voltages are encountered, so the Automated Model worked to eliminate low voltages [52].

Table 6-3. Comparison of automated model coordinated control CVR mode with capacitor design model for 10 year period

Model	Total Energy Supplied (MWHr)	Reduction in Energy (MWHr)
Capacitor Design Model	6853554.431	0
Automated Model coordinated control CVR mode	6802631.573	50922.858

6.8. Hard Dollar Calculation Conclusion

This chapter investigates the economics of smart grid automation investments in an incremental fashion by comparing the performance of different designs. Five economic comparisons are performed involving the worth of phase balancing, capacitor design, automated switches for providing rapid access to backup capacity with major transformer failures, the value of automated switches for storm restoration, and the value of coordinated control CVR mode. Validations of the phase balancing and capacitor design efforts are presented, and to some extend these validations provide confidence in the model that is used for the reconfiguration and coordinated control functions.

The investments in phase balancing and capacitor design for the time varying load provide efficiency improvements along with providing balanced capacity for automated switching (and increased three-phase load capacity), and capacitor device placement that is more optimal for coordinated control. The largest economic benefit is derived from the investments in automated switches that better utilize the existing system capacity, delaying much larger investments in new substations. The automated switches provide both economic and reliability benefits in substation deferral and also during storm conditions. A substation deferral study shows that reliability requirements with the automated system were satisfied for eight years longer than with the manually operated system. That is, the manually operated system required significant capital investment in a new substation eight years sooner than the automated system.

Furthermore, the automated switches provide significant cost benefits by helping to shorten the length of storm responses.

Finally, benefits of coordinated control are evaluated. If the controls were designed for the time varying load, then it is shown that the economic benefit from using coordinated control to minimize feeder losses can be small. However, if loads have sufficient voltage dependency, significant energy dollar savings can be realized by using coordinated control with CVR mode. Coordinated control, which evaluates voltages at all customer loads and creates time-varying setpoints that are provided to local controllers, results in significantly better voltage control than the use of local control that only uses a few voltage measurements and works with fixed setpoints.

The worth of the efficiency improvements and load energy reductions for the 14 feeder system over the 10 year period was $6,106k. The present value worth of the substation deferral was $7,380k. The automated switches also reduced storm response times, and an estimate of the worth of this savings for the whole system came to $9,592k. As has been shown in many other industries, investments in automation can improve performance while significantly reducing costs.

Chapter 7 Conclusion and Future Work

7.1. Conclusion

Evaluation of smart grid economy is not an easy process. This dissertation presents a series of analyses that show incremental cost-benefit ratios of a series of smart grid investments related to distribution automation. Each algorithm or stage provides its own benefit so that each stage can be quantified by its own, incremental cost benefit when compared with the previous stage. A contribution of this work is demonstrating how smart grid size data sets can be combined with engineering analysis and used in economic analysis. Included in the data sets are hourly time-varying load, the estimated hourly variation in the cost of energy for the next ten years, time-varying storm and outage data, time-varying SCADA measurements, and time varying load growth for 10 years into the future. It has been demonstrated that significant errors in calculations will occur when typical classical analysis is used where average assumptions are made. Using new technology for technology's sake will not satisfy industry leaders. However, monetizing smart grid technology into hard dollars can transform research into reality. To accomplish this more precise economic analysis, millions of system simulations are required with advanced engineering applications, including quasi-steady state power flow analysis, reconfiguration for restoration, Monte Carlo simulations that run for multiple days and coordinate control algorithms that implement conservation voltage reduction. Economic calculations are run on an hourly basis for up to a ten year period.

Coordinated Control of Volt/Var Devices, presented in Chapter 3, has the potential to both resolve overloads and reduces energy losses by more intelligently correcting power factor and by reducing the load served on the feeder. This work is important because it evaluates the benefits of a time varying control algorithm rather than just a seasonal or peak load control algorithm. In doing so, it avoids the under or overestimation of efficiency from the control algorithm based on peak load. Two comparisons were made between localized control and coordinated control. The first comparison evaluated the ability of centralized control to improve power factor and thereby minimize circuit losses. Since these losses cost the utility money, the investment is evaluated based on the loss savings. The second comparison focused on load-voltage dependency and the reduction of energy supplied when the voltage is reduced, and was therefore monetized based on reduced energy costs to customers. Since coordinated control makes use of a more sophisticated model in its decisions, it has the ability to reduce low voltage problems over the classical autonomous control used by utility control devices, and this work has shown this to be the case.

Volt/Var devices are not the only devices which may be automated. Utilities may also implement ***Coordinated Control of Switches for Storm Restoration***. This work is the first effort to simulate hourly time-varying storm restoration to calculate the effects of storms more precisely. In this work it is shown how utilities can use existing data that is very common to utilities and which may be used to estimate the labor cost of the storm with/without smart grid devices. Previous studies have focused on equipment failure rates that utilities do not typically have. In order to evaluate the effectiveness of automated switching during storms, the storms themselves must be modeled accurately. Chapter 4 illustrates how to use various storm models to evaluate the effectiveness of automated switching under different weather conditions, where the time-varying models are derived from existing utility outage data as a function of storm type and hour of the storm. In addition to historical storm data, historical repair and restoration data were used for further improvements in high accuracy. Use of utility data on the time to operate switches manually for different storm types for a given failure incident was used to perform more accurate analysis, where the time to operate the first switch always is significantly longer than the time to operate additional switches for a given failure incident.

Smart grid technologies were never intended to replace traditional power system planning such as phase balancing and capacitor placement. These design considerations should leverage the smart grid automation investments, affecting the available system capacity and the controllability of the system that the automation has to work with. A unique feature of this work is that the designs were performed for time varying load. It has been shown that good system design can provide greater returns on investments than some distribution automation investments, even though the distribution automation investments can provide significant returns on investment themselves. Furthermore, this is the first work that has used field measurements to validate the time-varying design investments over an entire system.

Chapter 5 presents a ***Distribution Automation for Smart Grid*** analysis approach, Utilities can use this approach to maximize the performance and cost-effectiveness of smart grid automation. The SCADA and related technologies that make automation possible also provide (together with more detailed models) the data needed to perform much more accurate power system analysis. In this section, detailed time-varying data is used to make both traditional and smart grid planning more accurate, both in terms of electrical performance evaluation (from voltage control to reliability improvements), and economic cost evaluation (from capital equipment purchase deferral to energy loss savings).

While most attention in academic literature has been devoted to the electrical performance of smart grid systems, only general conclusions have been drawn regarding ***Hard Dollar savings*** from smart grid investments. This is largely due to a lack of the detail modeling and load data described in Chapter 5. Chapter 6 builds upon the design sequence and modeling considerations of Chapter 5 by investigating more precise calculations of the economic benefits of smart grid investments on real-world distribution and transmission systems. The detailed load data enables more accurate calculations for energy loss savings and energy delivery reductions, for coordinated control, and for blue-sky and storm failure restorations.

While phase balancing and capacitor placement provide smaller cost savings, their lower implementation costs make their cost-benefit ratios remarkable. They also provide extra capacity and controllability for automating switching and automated Volt/Var control. The largest economic benefit derived from delaying capital investments in new substations, where following failures automated switches were used to rapidly access excess power system capacity, maintaining required reliability operating requirements. It has also been shown that distribution automation can lead to millions of dollars in utility labor savings that are also quite significant.

Field validation by an independent, third party has been performed on the basic design results presented here. The results of this study are being reported in different journals, and the reports are being used to justify building out distribution automation for the entire system.

7.2. Future Work

The following list provides considerations for further investigation of smart grid economic evaluation.

- The coordinated control study in Chapter 3 performs conservation voltage reduction under the assumption of constant voltage dependency throughout the year. Additional data regarding variations in voltage dependency throughout the year could provide more accurate results.

- Storm restoration in Chapter 4 provides rapid restoration methodologies with automated switches for six different types of storms. Additional types of storms could provide more interesting result, as could the consideration of failure of automated switches.

- The distribution system smart grid design sequence of Chapter 5 replaces locally controlled capacitors and manual switches with centrally controlled capacitors and switches without changing their locations. With centralized control, however, these devices may prove more beneficial at different locations.

- In addition to the hard dollar calculations performed in Chapter 6, soft dollar calculations including the value of reduced customer interruptions, reduced plant emissions, and more may be considered.

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