An Advanced Framework for Improving Situational Awareness in Electric Power Grid Operation

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Abstract: With the deployment of new smart grid technologies and the penetration of renewable energy in power systems, significant uncertainty and variability is being introduced into power grid operation. Traditionally, the Energy Management System (EMS) operates the power grid in a deterministic mode, and thus will not be sufficient for the future control center in a stochastic environment with faster dynamics. One of the main challenges is to improve situational awareness. This paper reviews the current status of power grid operation and presents a vision of improving wide-area situational awareness for a future control center. An advanced framework, consisting of parallel state estimation, state prediction, parallel contingency selection, parallel contingency analysis, and advanced visual analytics, is proposed to provide capabilities needed for better decision support by utilizing high performance computing (HPC) techniques and advanced visual analytic techniques. Research results are presented to support the proposed vision and framework.

Keywords: Energy Management Systems (EMS), Situational Awareness, High Performance Computing, State Estimation, State Prediction, Contingency Selection, Contingency Analysis, Visual Analytics

1. INTRODUCTION

With the deployment of new smart grid technologies and the penetration of renewable energy in power systems, the traditional Energy Management System (EMS) functions operating in a deterministic mode will not be adequate for the future control center. There are new challenges, such as stochastic modelling, uncertainty quantification, computational speed, and advanced situational awareness that need to be overcome to upgrade today’s EMS functions to make them suitable for smart grid operation.

There are several publications about future control centers. For example, Wu et.al. (2005) discussed their view of a future grid service-based control center: an ultimate distributed control center, focused on information and communication technologies. In (Li et al. 2009), the authors provided their vision on the next generation monitoring, assessment and control functions in a future control center. Cheung et al. (2010) proposed their vision of smart dispatch in the context of a control center in the smart grid environment. This paper focuses on the challenge of advanced situational awareness, and also describes some ongoing related research conducted by the authors.

Inadequate situational awareness and ineffective visualization of power system conditions have been identified as two of the main reasons for the Northeast blackout of 2003 in North America (DOE 2004). The main issues related to situational awareness in today’s control center are:

(1) Low computational speed for key situational awareness related EMS functions, such as state estimation, contingency selection, and contingency analysis. In today’s practice, for state estimation, there is significant potential for reducing the computational time by applying high performance techniques and advanced mathematic algorithms. For contingency analysis, normally a small number of predefined cases are selected. This could result in an incomplete system status, and it is not suitable for the future “N-x” contingency analysis (i.e., failures of multiple components). In addition, with the increase of system demand, as well as the penetration of renewable energy (Smith and Parsons 2007), the system operating points can change rapidly in a short time period. Thus, there is a great need to improve computational speed for these functions to allow operators see a complete picture of real-time system status.

(2) Significant increase of variation and uncertainty (DeMeo et al. 2005). This increase is mainly caused by the fast growth of variable renewable generation. To operate grid more reliable, the predictive capability of knowing future system status is desired.

(3) Lack of an advanced visual and analytic tool. Contingency analysis and other large power system analysis techniques produce large amounts of data. Presently, most of the current commercial tools use tabular data to represent system status, which is not easy to interpret within a short timeframe when the system is stressed. Advanced visualization techniques are therefore needed to provide improved visualization capabilities over a wide geographic area and help operators to make timely decisions.

To solve the three issues mentioned above and provide more decision-support to operators in future control centers, an advanced framework (Fig. 1) is proposed below. Parallel state estimation is required to provide estimated system states...
based on field measurements and a system model. The estimated system states are the basis for contingency analysis and visualization to gain situational awareness for current system. They are also the inputs for state prediction to predict future system states and future situational awareness with different uncertainty levels. The blocks of parallel state estimation, parallel contingency selection, and parallel contingency analysis focus on improving computational speed by utilizing HPC techniques and advanced algorithms as an enabling force in the integrated real-time platform (Huang et al. 2008a). The block of state prediction is to provide predictive capability for grid operation, and the block of advanced visualization is focused on post-processing selected contingency analysis output data. Overall, the framework provides following capabilities:

- Real-time computational application capability
- N-x contingency analysis/selection capability
- Predictive capability
- Probabilistic analysis capability
- Large-scale visualization with analytic and probabilistic capabilities

Fig. 1 The framework for improving situational awareness

This paper is organized as follows: Section 2 describes state estimation and state prediction, followed by Section 3 on contingency selection. Parallel contingency analysis will be discussed in Section 4, and advanced visualization will be covered in Section 5. Finally, Section 6 presents an overall vision and concluding remarks.

2. STATE ESTIMATION AND PREDICTION

2.1 Background

As shown in the Fig. 2, a state estimator is an essential tool for power grid operation, which estimates the states (i.e., bus voltage magnitudes and angles) of a power system by fitting the power system model to a set of real-time measurements. A state estimator receives field measurement data (e.g., line power flow, bus voltage magnitude) from remote terminal units (RTUs) through the Supervisory Control and Data Acquisition (SCADA) system. With this data, it performs least square estimation of power system states, and then derives the other essential variables (e.g., the power generated by a generator, the electric current passing through transmission lines). The resulting states are an optimal fit with improved accuracy compared with the raw measurement. They are used by many other essential power grid operation applications, such as contingency analysis, automatic generation control, optimal and power flow to improve operational efficiency and reliability of a power system (Abur 2004).

Fig. 2 State Estimation in Power System

2.2 Parallel State Estimation

Obtaining system status in near real-time becomes more and more important with high penetration of variable generation sources. High performance computing techniques and advanced mathematic algorithms play critical roles here.

Parallel state estimation techniques have been investigated for many years. There are numerous publications in this area. The following are a few examples. Wallach et al. (1981), Habiballah and Irving (1995), and Seidu and Mukai (1985) developed their algorithms based on multipartitioning techniques. Falcao et al. (1995) applied coupling constraints optimization techniques. Nordman and Lehtonen (2005) proposed an agent-based distributed state estimation concept. Dag and Alvarado (1997a, b) discussed applying preconditioned conjugate gradient (PCG) method to solve state estimation problem.

The authors conducted research recently to study parallel state estimation. A PCG algorithm has been implemented in a cluster machine. Different preconditioners have been tested. An Euclidian preconditioner has been identified as an efficient one to solve the state estimation problem. Compared with a Jacobi preconditioner, the number of iterations using the Euclidian preconditioner can be reduced by 40 times and the computational speed is 10 times faster. A case study with the Western Electricity Coordinating Council (WECC) 2005 HS2A base case, including about 14,000 buses (WECC 2005) showed that the state estimation can be solved at around 5 seconds with 8 CPU cores. This computational speed is much faster than that in today’s industrial practice (1-2 minutes for WECC). This significant improvement allows the operators to obtain system status in real time, and thus they have more time to recognize and respond system problems. The performance analysis of parallel state estimation can be found in Fig. 3.
2.3 State Prediction

With the parallel state estimation technique, operators are able to obtain the system states in real time. As mentioned in Section 1, with the increase of variation and uncertainty introduced by the renewable energy sources, to improve the reliability and efficiency of power system operation, it is desirable to estimate future states of a power system. The leading time of predicted states allows operators to take proactive remedial reactions when potential security violation is impending. In particular, an estimate of the power system future states is helpful in managing the variability and uncertainty of renewable generation sources. compares the concepts of state estimation and state prediction. The state estimation provides the point estimation of power system states, while the state prediction forecasts the future states with confidence intervals.

Fig. 4. The comparison between state estimation and state prediction

There are two key elements in the power system state prediction methodology, i.e., the prediction method and the prediction error quantification method. The prediction method forecasts the values of states in the next time instant. The prediction error quantification method gives the confidence interval of the forecast. Note that the forecasted value is a point estimation, which only contains partial information. A confidence interval should accompany the forecasted value to show the accuracy of the prediction.

2.3.1 The state prediction method

A naïve approach of predicting power system states is to use the current value as the prediction. It assumes that these variables are the same and will remain the same as when the measurements were last taken. With this naïve approach, the state prediction result is the same as the state estimation results because variation and uncertainty are overlooked.

Ignoring these changes and uncertainties can bring in significant errors in the state prediction. The high penetration level of renewable energy sources brings in more variation and uncertainty, which will exacerbate the problem of prediction errors with this naïve approach.

To improve prediction accuracy, a dynamic model needs to be built. For the prediction in the time horizon of minutes, many low frequency dynamics mechanisms (e.g., load changes, load following control, optimal power flow control) have to be taken into consideration. There is not yet a clearly structured physical model to effectively describe the combined lower frequency responses. Various methods and schemes are proposed to predict power system states (Jain and Shivakumar 2009). The state prediction method proposed by Sinha and Mondal (1999), Mallieu et al. (1987), and Rousseaux et al. (1987) uses Artificial Neural Network (ANN) to forecast bus load, and then uses the forecast load as explanatory variables to predict states. This method appears to be realistic and promising in that it captures the load as major driving factors in the power grid. Also, Ferryman et al. (2011) have obtained promising results on the predictability of real power flow using a univariate multiple linear regression method based on phasor measurement unit (PMU) data. Yet, for a practical application, a more extensive study is needed to improve the prediction accuracy and robustness by comprehensively taking into consideration other underlying driving mechanisms (e.g., market, weather, smart appliances).

2.3.2 The prediction error quantification method

Because of unknown mechanisms and inputs, there are always uncertainties associated with any predicted values of power grid variables. There are two sources for uncertainty in the power system state estimation (Al-Othman and Irving 2006): measurement uncertainty and parameter uncertainty. The measurement uncertainty is from measurement noise. The parameter uncertainty is from power system modelling errors (e.g., time skew of the measurement, approximation of the p-equivalent model, approximation of the resistance and reactance). When the uncertainty level is low (e.g. the traditional state estimation), it is a common practice to present estimation results in a deterministic framework. When the uncertainty levels are high, a predicted value presented within a statistical framework can reveal the full picture, and provides helpful guidance to grid operations. For example, a prediction of 1000-MW power flow with ±10-MW error bars (95% confidence interval) carries more information than a simple point prediction of 1000-MW. Furthermore, a prediction of 1000MW±10MW is more accurate than a prediction of 1000MW±500MW.

Quantification of the prediction errors is closely associated with the prediction method. Many prediction methods attempt to build dynamic models, which minimize the difference between the predicted values and measurements for historical data sets. The unknown mechanisms and inputs are modelled as noises. The methods for quantifying prediction errors depend on how the noise sources are modelled in the dynamic model. In (Kyriakides and Heydt 2006), a linear model and Gaussian (normal) noise are
assumed, and analytical approaches are used to quantify state prediction errors. Note that the linearity and Gaussian noise assumptions reduce the computation intensity by providing analytical solutions, but limit the applicability of the method because of reduced accuracy from linear approximation and a limited noise model. For a more general noise distribution and non-linear model, there is no general analytical solution to quantify prediction errors, and numerical approaches (e.g., Monte Carlo methods) are usually used to circumvent the difficulty. The Monte-Carlo method calculates the prediction errors by repeatedly sampling the original error distribution (Wikipedia 2009). The Monte-Carlo method is widely used for studying the statistical problems because of its simplicity. However, the number of samples required by the Monte-Carlo method is very large and increases with the dimension of the problem. Current western North American power system has over 14,000 buses (i.e., 28,000 states) and the number of Monte-Carlo samples is prohibitively large, which makes the problem becomes computationally infeasible.

One of the key elements in building a prediction methodology for power grid states is the effective leading time. The effective leading time is the time difference between the instant that the prediction is finished and the targeted prediction time (Fig. 5). To effectively guide power grid operations, it is desirable that the time delay caused by communication and computation be reduced. This ensures that the prediction can be finished within the limited time to obtain an effective leading time. The prediction errors normally increase with increasing leading time of prediction algorithms. The delay from communication and computation should be shorter than the leading time of the prediction algorithm to be an “actual prediction”. To achieve the same effective leading time with higher accuracy, it is desirable to shorten the time delay from computation and communication.

Fig. 5. Leading time and effective leading time of prediction algorithms

To overcome the computational problem brought in by the Monte-Carlo method, a collocation method (Lucor et al. 2004) was applied by Lin et al. (2011) on the power grid state prediction to reduce the number of samples, while maintaining the estimation accuracy. The collocation method uses a smaller number of samples than the Monte-Carlo method to represent the error distribution. Case study results using an IEEE 14-bus system (Power online) show that the Monte-Carlo method requires 1000 samples, while the collocation method only requires 101 samples to reach the same level of estimation accuracy in quantifying the prediction errors. In addition, both the Monte-Carlo method and the collocation method are scalable. Thus, parallel computation methods can be applied to further shorten the computation time.

2.4 Discussion

Currently, a power system is operated using past states obtained from state estimation. With the state predictor added, a power system will be operated based on the best information from the past, current, and future states. Thus, with more complete and accurate information, it is expected that power systems can be operated with improved reliability and efficiency.

State prediction can be categorized into short-term prediction (seconds to minutes), mid-term prediction (hours), and long-term prediction (days). Different state prediction intervals have different applications and impacts. For the short-term prediction interval (seconds to minutes), the prediction results can be used to provide the guideline for the load following and regulation control applications.

3. CONTINGENCY SELECTION

Contingency selection is a technique for identifying the most credible contingencies from a large candidate set of possibilities, and hence reduce the computational time in contingency analysis. In today’s practice, a small number of contingency cases are predefined for detailed contingency analysis, which can potentially miss some critical contingency cases, resulting in an incomplete system status. This scenario will get worse when considering the large amount of “N-x” contingency analysis cases. Therefore, to meet the requirements in reliability standards (NERC online) and prevent cascading failures, there is a great need for “N-x” contingency selection.

In the past several decades, significant research has been conducted in the area of contingency selection. The following are a few examples. Ejebe and Wollenberg (1979) proposed the basis of the system performance indices (PI) approach for contingency ranking. Ejebe et al. (1988), Mikolimm and Wollenberg (1981), Chen and Bose (1989), and Hadjsaid et al. (1993) discussed a PI voltage violation related method based on approximate power flow solutions. Zaborszky et al. (1980) discussed contingency evaluation using concentric relaxation methods. Meliopoulos and Cheng (1990) proposed a hybrid contingency selection method. Kang and Meliopoulos (2002) proposed a quadratized power flow sensitivity analysis algorithm. Pandit et al. (2003) proposed a fuzzy neural network method. These existing methods are of differing accuracies in identifying the credible set of contingency cases. From the computational point of view, many of these methods still involve some kind of simplified analysis of all contingency cases. The methods may be suitable for “N-1” (i.e., failures of any one component) contingency analysis. However, for “N-x” analysis, because of the sheer number of contingency cases, it is impractical for using these methods even with simplified computation. To perform smart contingency selection for “N-x” contingency analysis, more efficient contingency selection methods are required.
Graph theory has been applied to power grid topology for identifying severe multiple contingencies. Donde et al. (2008) proposed an approach assisted by a minimum cut concept and partitioning algorithm to identify a few line outages that results in a severe system failure. Ababei and Kavasseri (2010) implemented an extreme event screening algorithm based on constrained and unbalanced partitioning with two objectives: minimization of the size of cut and maximization of the power-imbalance between partitions.

The authors also have conducted “N-x” contingency selection by applying graph-theory-based betweenness centrality algorithms to power grid topology. All the betweenness centrality algorithms are related to the computation of shortest paths, which involve Brande’s Algorithm (Brande 2001). The complexity of Brande’s Algorithm is \(O(nm\log n + n^3\log n)\), denoted as \(T(BA)\), where \(n\) is the number of nodes (buses) in the graph and \(m\) is the number of edges (transmission lines) in the graph. The idea is to convert power grid topology to a weighted graph, then apply a betweenness centrality-based algorithm (Freeman 1977) to the weighted graph. Then, compute the betweenness score and identify the edges that are mostly frequently located at a shortest path. The higher the edge betweenness score (the most “travelled” edge), the more important the transmission line is. Based on this idea, the authors implemented the parallel edge betweenness algorithm on a Cray XMT machine to utilize the unique feature of the massively hardware-based multithreaded platform with globally shared memory (CASS-MT online). Case studies show that it took 13 seconds to compute the edge betweenness scores for the 14,000-node WECC case with 64 processors. Superior scalability has been achieved on the Cray XMT machine, which indicates that the implementation is very suitable for larger power grid graphs. Some early research outcomes can be found in Chen et al. (2009) and Jin et al. (2009).

The goal of “N-x” contingency selection is to identify groups of \(x\) edges where failure would have maximal impact on a power system network. To identify the important groups of \(x\) edges, the concept of group betweenness centrality Everett and Borgatti (1999) has been implemented, improved, and applied to power grid topology to perform “N-x” contingency selection by the authors.

Group betweenness is defined as the ratio of shortest paths that pass through any member of the group to all shortest paths between all pairs of vertices in a graph. The importance of a group of \(x\) edges in a power grid is measured as the influence on the connectivity in the graph. However, the complexity of original group betweenness algorithm is \(O(m^2T(BA)) - O(m^2(n\log n))\), which is not efficient. The authors incorporated a path betweenness algorithm (Puzis et al. 2007) to reduce the computational complexity to \(O(m^2)\), a reduction at the order of \(n\log n\). The improved group betweenness algorithm has been implemented on the Cray XMT machine and, as expected, superior scalability was obtained. Fig. 6 shows the performance analysis result for the betweenness algorithm on the Cray XMT in log scale.

The group betweenness centrality algorithm has been applied to the IEEE 14-bus system. Table 1 shows the N-I contingency selection based on betweenness scores and PI scores, and Table 2 shows the N-2 contingency selection based on group betweenness scores and PI scores. The PI score is computed according to (1):

\[
P_I = \sum_{i=1}^{n} \left( \frac{P_i}{P_{\text{max}}} \right)^2
\]

where \(P_i\) and \(P_{\text{max}}\) are the power flow and the capacity limit on the \(i^{th}\) branch, respectively; \(m\) is the number of branches; \(n\) is an integer. \(n\) is assigned as 2 in this study in order to invoke more weight on the branches that have higher overload rates.

### Table 1: N-I contingency selection based on betweenness score and PI score for IEEE 14-bus system

<table>
<thead>
<tr>
<th>branch</th>
<th>PI-ranking</th>
<th>Betweenness Ranking</th>
<th>Betweenness score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-2</td>
<td>1-unstable</td>
<td>1</td>
<td>13</td>
</tr>
<tr>
<td>2-3</td>
<td>2</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>2-4</td>
<td>3</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td>1-5</td>
<td>4</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>5-6</td>
<td>5</td>
<td>3</td>
<td>10</td>
</tr>
</tbody>
</table>

### Table 2: N-2 contingency selection based on group betweenness (GB) score and PI score for IEEE 14-bus system

<table>
<thead>
<tr>
<th>branches</th>
<th>PI-ranking</th>
<th>GB ranking</th>
<th>GB score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-2 2-3</td>
<td>1</td>
<td>9</td>
<td>25</td>
</tr>
<tr>
<td>1-5 2-3</td>
<td>2</td>
<td>15</td>
<td>22</td>
</tr>
<tr>
<td>1-2 2-4</td>
<td>3</td>
<td>3</td>
<td>30</td>
</tr>
<tr>
<td>1-5 2-4</td>
<td>4</td>
<td>2</td>
<td>31</td>
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<tr>
<td>2-3 2-4</td>
<td>5</td>
<td>10</td>
<td>24</td>
</tr>
<tr>
<td>1-2 1-5</td>
<td>6</td>
<td>13</td>
<td>23</td>
</tr>
<tr>
<td>1-2 5-6</td>
<td>7</td>
<td>5</td>
<td>27</td>
</tr>
<tr>
<td>1-5 5-6</td>
<td>8</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>2-3 5-6</td>
<td>9</td>
<td>11</td>
<td>24</td>
</tr>
<tr>
<td>2-4 5-6</td>
<td>10</td>
<td>1</td>
<td>32</td>
</tr>
</tbody>
</table>
From Table 1, notice that the betweenness ranking is able to identify the 5 most severe "N-1" contingencies in the top 5 branches with highest betweenness score. From Table 2, the top 10 most severe "N-2" contingencies can be caught in the top 20 branches with highest group betweenness score.

These promising results show the potential capability of the graph centrality-based algorithm for the emerging need of "N-x" contingency selection.

4. CONTINGENCY ANALYSIS

Contingency analysis is a key EMS function to assess the ability of the power grid to sustain various combinations of power grid component failures. As mentioned in previous section, today’s contingency analysis can be updated only every few minutes. Furthermore, if only computes a pre-selected set of "N-1" contingency cases and a few "N-2" cases, which cannot meet the emerging needs of "N-x" contingency analysis. Because of the exponential increase in the combinatorial number of contingency cases as "x" becomes larger, high performance computing techniques have to be involved to handle the substantial computational burden.

The authors have conducted extensive research on parallel contingency analysis (Huang et al. 2009). A counter-based dynamic load balancing scheme, shown in Fig. 7, has been proposed to obtain optimal computational time among all processors. With this balancing scheme, the contingency tasks are allocated to processors based on the availability of a processor. Therefore, the tasks are more evenly distributed in terms of execution time by significantly reducing processor idle time.

Proc 0:
(1) Distribute base case Y0 matrix
(2) Perform dynamic load balancing
(3) Distribute case information to other processors
(4) Perform contingency analysis

Other Proc's:
(1) Update Y matrix based on case information: Y = Y0 + ΔY
(2) Perform contingency analysis

With the help of this scheme, 512 processors took only 31 seconds to perform full "N-1" contingency analysis for the WECC system (~20,000 cases) and 448 seconds for 300,000 N-2 contingency cases. A speedup of 507 with 512 processors was achieved for the latter case (Huang et al. 2009). The authors later proposed a multi-counter based dynamic load balancing scheme to further increase speed-up and evaluate the performance of this scheme with different computing environments (Chen et al. 2010a). This counter-based dynamic load balancing scheme is also applicable for probabilistic analysis, and is compatible with the state prediction technique described in Section 2.3.

5. ADVANCED VISUAL ANALYTICS

With newly developed technologies and hardware, some EMS tools have been enhanced and are able to generate more accurate and useful data. However, to make the data useful to operators, advanced visualization techniques are needed to present data in a meaningful way. Otherwise, no matter how good the data is, operators may not be able to digest the data and respond in a short timeframe, especially when they operate a large system with a complicated situation. This section focuses on the visualization of power system contingency analysis as an example. Contingency analysis identifies operation violations if one or more elements fail. A violation is a situation where an operation limit, such as transmission line load capacity or substation voltage threshold, is exceeded. Operators rely on the violation results to gain situational awareness and make decisions on mitigation actions if necessary. The burden of decision-making falls on the shoulders of the operators.

In today’s control center, tabular display or raw data representation is dominant for contingency analysis output data. An example is shown in Fig. 8. In Fig. 8, each row represents a violation of contingency analysis, without showing the geographical location of the violation and the contingency causing this violation. The severity level among all violations and contingencies is also absent. This tabular display may be adequate when the number of violations is small. However, when there are significantly more contingencies with violations, it is then impractical to require an operator to sift through all the data to understand the system situation within several seconds or minutes. There is a gap between a large amount of data and actionable information to operators.

![Tabular representation of violation data](image)

Fig. 8. Tabular representation of violation data in a state-of-the-art power grid operation tool

Because of the above-mentioned challenges in processing large volumes of data from the contingency analysis process, there is a need for an advanced decision support tool to analyze the data, extract useful and necessary information, and provide decision support for power grid operators to find the best solution.

There is some research already conducted in the area of developing visualization techniques for contingency analysis.
data. For instance, Bacher et al. (1995) discussed a toolset based on image visualization. Sun and Overbye (2003, 2004), and Overbey et al. (2005) describe both 2D and 3D visualization techniques to display contingency analysis results. Human factor testing is also discussed in (Overbey 2005). These publications are mainly focused on visualization techniques, and lack of analytic functions for decision support.

To provide better decision support to operators, the authors developed an advanced decision-support tool based on contingency analysis for power grid operations (Huang et al. 2008b) (Chen et al. 2010a). This tool has the features of:

1) Improve situational awareness by visualizing and analyzing the change of risk levels in violations
2) Identify system trends by performing trending analysis based on analyzing the system risk level
3) Predict the consequences of potential problems by analyzing the pattern of impact
4) Assess the effect of operator actions via interactive risk analysis to help an operator identify the best action.

All these features, shown in Fig. 9, have been tested with the WECC system.

Fig. 9: The features of the developed decision-support tool

In order to further test the decision-support tool considering the effect of human factor, the decision support tool has been enhanced and transplanted to an advanced graphical contingency analysis (GCA) tool (GCA online). The advantages of the tool are: (1) provides intuitive graphical representation, allowing faster and more accurate identification of potential operational problems; (2) ranks contingencies to focus the operator’s attention on the most severe ones and to prioritize preventative actions; and (3) interactively assess operator actions in terms of what to expect if an action is taken, providing more-informed decision-making in an actual event. Two user studies have been successfully conducted using this tool. The first user study can be found at (Gretzer et al. 2009); the second user study was embedded into a WECC operator training course held in the Electrical Infrastructure Operation Center (EIOC online) at the Pacific Northwest National Laboratory (PNNL). Preliminary analysis of results of experimental studies indicates that the GCA tool is effective in addressing the complexity of the contingency analysis problem. The tool facilitates proactive, rather than reactive, strategies, and reduces the number of “steps” that operators must examine in arriving at effective solutions.

Overall, all the features of the advanced visual analytics tool are in an operator-friendly manner to meet real-time requirements in the smart grid environment.

6. CONCLUSIONS

An advanced framework for improving situational awareness in power grid operation has been proposed. The framework has the features of (1) high performance computing technology to enable real-time applications, including state estimation, N-x contingency analysis, and N-x contingency selection; (2) predictive capability; (3) probabilistic analysis capability to quantify the uncertainties introduced by penetration of intermittent renewable energy; and (4) large-scale visual analytical capabilities. Research outcomes obtained by the authors were presented to support the vision.

This is a fairly complex framework, involving multi-disciplinary expertise in the domains such as high performance computing, statistics and visual analytics, in addition to power engineering. Though significant work remains to be done to complete all the elements in this framework, the power industry has seen the tremendous value from these tools. With further penetration of smart grid technologies, the power grid operation is transitioning from today’s deterministic environment to a future control center in a stochastic environment with faster dynamics. The proposed framework is expected to help the transition and bring higher efficiency and reliability to power grid operation.

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