Uncertainty Visualization for Crisis Management in Smart Grid Environments

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Abstract. Visual analytics systems are in place within smart grid environments to alleviate crisis situations by allowing decision makers to perceive and understand the severity of a crisis situation. However, errors in measurements that are propagated due to various reasons (such as data transformations, errors in measurement devices etc.) can make the decision makers less confident in deriving information. Therefore, analysis and visualization of uncertainty within such data has become important. In this paper we utilize two uncertainty propagation techniques: sampling and Monte Carlo simulation, to propagate uncertainties inherent in power data within our smart grid environment, and compare their performance to best fit our use-case. We found that the Monte Carlo simulation method is most suitable for measuring uncertainty in our application domain. Further, we identified most effective visual metaphors to communicate uncertainty to the crisis managers.

Keywords: uncertainty visualization, decision making, smart grids

1 Introduction

Electric power grids are the backbone of our society, since failures in the electricity supply has a strong impact on the fundamental societal structures such as life/health, environment, and economy, among others. The rise of renewable energy of small energy producers such as photo-voltaic increases the system's complexity. To integrate these producers and to transfer their energy to other regions communication infrastructures and energy infrastructures are tightly coupled, which increases the effectiveness, however, also increases the vulnerability since failures in one infrastructure can cascade into the other. Visualization systems are needed that abstract the complex information of both infrastructures in case of a crisis to enable crisis response by decision makers. In [5] and [6] the authors abstract the incoming data from each infrastructure element and apply a set of rules to map this information to a color encoded scale that highlights which elements are in normal, danger or alarm mode. This mapping is consistent over all infrastructures and thus, allow interdisciplinary teams to "perceive" and "understand" a crisis situation. Further, the system predicts based on the past data, the currents status, and the users' actions, a possible future subsequent development of the situation and of all infrastructure elements. This allows the evaluation of alternative actions and therefore supports the crisis managers in the decision making process. The decider will draw a decision based on the visualization of the current and future state (alarm level) of infrastructures and the detail information of elements of interest based on the propagated subsequent development of alternative actions. However, such analysis systems are error prone. Errors propagated by the measurement modules or the discrepancy between simulation models and reality reduce the confidence of decision makers for such systems in general. Her/his trust into measurements and predictions is of major importance and thus, such systems must highlight how uncertain or certain some predictions or measurements are. In this paper, we will present our work in

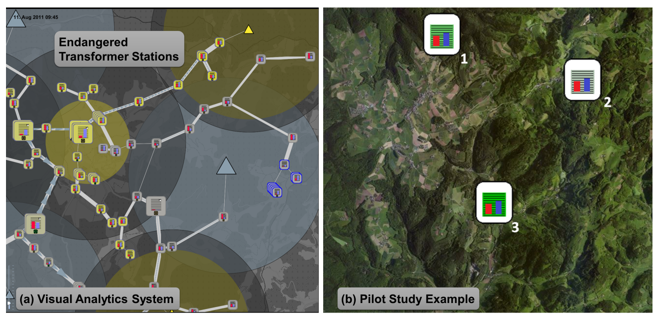

Fig. 1. (a) Transformer stations (rectangles) are connected via power lines and are also connected to the communication infrastructure (triangles), which transfers the information to the central control room. The transmission range of the mobile stations is visualized as concentric circles. While gray indicates normal operation mode, the yellow elements on the screen reveal a severe situation. High deviations in voltage cascaded from the energy grid into the mobile grid due to failures of the power supply. (b) An example of the intuitiveness test in the pilot study. The low to high uncertainty in modular power data is depicted through low to high Green color saturation. Here, the correct low, medium, high ordering of the uncertainty visualization is therefore 2, 1, 3

progress that utilizes robust statistical methods such as Monte Carlo simulation to measure uncertainties of single measurands and aggregated uncertainties for alarm levels. We currently evaluate these methods and present a comparison of Monte Carlo simulation and sampling methods, and choose the most suitable method for propagating uncertainties within Smart Grid monitoring. Further, we present our selection of uncertainty visualization methods as adapted from [3] to visualize the quantified power data uncertainties, and test the effectiveness of these visualization designs within a pilot study environment.

Therefore our two fold contribution is 1) comparison results of the two uncertainty propagation techniques within our dataset, 2) visual design candidates for multidimensional uncertainties, and tentative evaluations of these uncertainty visualization candidates for their *effectiveness*.

2 Related Work

Statistical propagation and visualization of uncertainty in spatio-temporal data has long been studied in various settings [9], [11], and these visualizations have been evaluated in previous works such as [4], [8]. Uncertainty can be defined as *a parameter associated with the result of a measurement that characterizes the dispersion of the values that could reasonably be attributed to the measurand* [10], and the quantification and visualization of these uncertainties is important for thorough data analysis, information derivation and decision making.

Lee & Chen [2] examined several widely used uncertainty propagation techniques in order to understand the characteristics and limitation of these methods, and further compare heir performances. We chose the sampling and the Monte Carlo simulation techniques to propagate the uncertainties within the power dataset, and compare their performance within the dataset.

Bertin's work on visual variables [1] was extended by, for example, Morrison [7] and MacEachren [3]. Furthermore, MacEachren manipulated the focus variable in to four metaphors; (i) Contour crispness, (ii) Fill clarity, (iii) Fog, and (iv) Resolution. We adapt these semiotics to visualize the aggregated power uncertainty as well as the modular power uncertainty, and tested their *effectiveness* in a pilot study environment.

3 Monte Carlo Simulation and Sampling Methods for Uncertainty Propagation of Power Data in Smart Grids

Sampling typically takes the distribution of a selected subset of the data and estimates the characteristics of the whole dataset. Within our power dataset we incorporated this method and further constructed a 95% confidence interval with which we demonstrate the inherent uncertainty in the modular power data.

Monte Carlo technique models the statistical errors in the data by the use of ordinary statistics and random variables, assuming that the errors have a Gaussian probability distribution function. Continuous repetition of the simulation removes the variations in the probability distribution function. The uncertainty in the data is therefore propagated by the mean error and the standard deviation for each data point. Once again with a 95% confidence interval we demonstrate the inherent uncertainty in the modular power data. An example is shown in Figure 2. We carried out the above two methods for two random weeks of the data that are available for three transformer stations within the smart grid network. For the comparison of the two methods we counted how many data points are within and outside of the 95% confidence interval. The method that shows more data points within the 95% confidence interval is considered more appropriate for our dataset. Figure 2 (a) shows the comparison results for the three transformer stations, and (b) for a selected transformer station in Helgenreute. This comparison shows us that the Monte Carlo simulation method works better within our dataset.

The aggregated uncertainty for the alarm levels is estimated by the classifier that maps the incoming field information, the detected anomalies and expected behavior of an element to discrete alarm levels. The distance to the decision bounder indicates how sure the classifier is in the assignment (e.g., the element was assigned to “danger” class but it was also close to the bounder to “normal” and thus, the classifier is more uncertain).

(a)

Week	Sampling	MCS	Transformer station
1st week	in:514 out158	in: 566 out: 106	Helgenreute
	in:413 out: 259	in:505 out: 167	Rathaus
	in: 492 out: 180	in: 643 out: 29	Eckle
2nd week	in: 1230 out: 786	in: 1513 out: 503	All the transformer tations

(b)

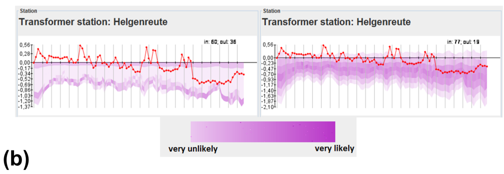

Fig. 2. (a) Comparison results of Sampling and Monte Carlo Simulation (MCS) methods for the three transformer stations. (b) Sampling method (left) and MCS method (right) to propagate power uncertainty at the Helgenreute transformer station. Low to high Purple color saturation indicates the high and low uncertainties

4 Uncertainty Visualization Candidates

We picked 7 visual metaphors to visualize the modular power uncertainty and the aggregated power uncertainty. These are filling, color transparency, color saturation, noise lines, fuzzy borders, border color hue, and icons. In order to stay consistent with the existing visualization infrastructure (Figure 1 a), we designed appropriate candidates to visualize the aggregated uncertainty and the modular uncertainty of power data. These visualizations are shown in Figure 3. Considering the smart grid monitoring requirements and with a goal of reducing the solution space, we picked the most effective visualizations through conducting a pilot study with 6 users (all 6 with a visualization background and aware of the smart grid environment). As a first step in the pilot study we showed a randomized order (1, 2, 3) of low, medium and high uncertainty depictions of chosen visualizations. Then we asked the users to give the correct order of the uncertainty visualizations from low, medium to high (Figure 1 b). At the next step we conducted qualitative interviews to rank the visualizations (based on preference, understanding). This allow us to assess the intuitiveness of the different visualizations. The first three visualizations with significant differences in high rating were selected as an outcome. Therefore for modular power uncertainty visualization we selected transparency, color saturation and icons. For aggregated power uncertainty we selected fuzzy borders, transparency and noise lines.

5 Conclusion

In our work in progress, we have compared two uncertainty propagation techniques,sampling and Monte Carlo simulation to propagate the uncertainties

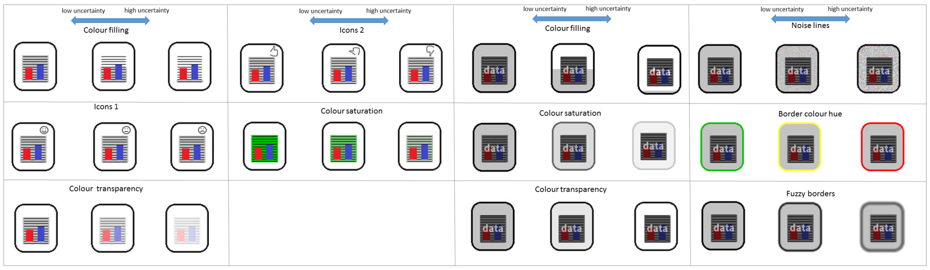

Fig. 3. Candidates for modular power uncertainty visualization (left, inner rectangles) and aggregated power uncertainty visualization (right, border of the rectangle)

inherent in a power dataset within a smart grid network, and found that the Monte Carlo simulation method works better within our smart grid scenario. Further, we have conducted a pilot study to select the most effective uncertainty visualization methods for modular and aggregated power uncertainty respectively. With high rating from the users, we have selected transparency, color saturation and icons to visualize the modular power uncertainty, and fuzzy borders, transparency and noise lines to visualize the aggregated power uncertainty within our smart grid network. In future work, we will use the selected uncertainty visualization methods to design combinations of modular and aggregated power uncertainty in one depiction, and further evaluate their effectiveness in a larger study.

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