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WEATHER INFORMATION FOR SMART GRIDS

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ABSTRACT

Smart Grids are electric grids which intelligently respond to the behavior and actions of producers and consumers of electric power. Weather information is critical to several aspects of Smart Grids. For instance, energy consumption may be high on a hot summer afternoon, but drop off dramatically if thunderstorm outflow cools the region. Knowledge of the current state of the atmosphere and accurate predictions on the time scales of days, hours, and minutes can enable energy producers to optimally schedule their generation resources. In Smart Grids, weather information is coupled with GIS-based asset management systems to precisely estimate customer demand and generation needs. Additionally, it allows grid operators to assess the areas of weather anticipation, energy supply and consumption monitoring, and outage management.

1. SMART GRIDS

Smart Grids are electric grids which intelligently respond to the behavior and actions of producers and consumers of electric power. They are intended to make electricity more reliable, less expensive, and to enhance the use of renewable resources. GE Energy and Weather Decision Technologies, Inc. (WDT), are working to mitigate weather impacts on Smart Grids.

We have identified a number of ways in which weather can impact electric grids. First, unanticipated weather can affect the scheduling of power resources. As an example, an afternoon thunderstorm may cool down temperatures over a metropolitan area. If the event is not foreseen, a utility may overschedule resources, at increased cost to it and its customers. Other examples include changes in cloud cover (affects temperature and solar energy production), wind ramps (affects wind energy production), and excessive heat (limits capacity of transmission lines). In the same vein, accurate forecasts allow optimum use of renewable resources.

Second, infrastructure can be damaged by extreme weather. Transmission lines are typically affected by ice accumulations, high winds, and tornadoes. Lightning strikes can damage transformers and substations. Even bird droppings can accumulate to the point where arcing occurs in high relative humidity. On the other hand, adequate notice of favorable weather allows for maintenance to be scheduled with minimal impact to the grid.

Weather information is used by Smart Grids in two principal ways. First, gridded current and future weather information can be coupled with GIS-based asset management systems to precisely estimate customer demand and generation needs. Second, operator control is needed in the areas of weather anticipation, energy supply and consumption monitoring, and outage management.

2. WEATHER DATA AND PRODUCTS

Utilizing a “forecast funnel” approach, we list weather events in order of lead time, from a few days in advance to the hours and minutes leading up to the event. Damage assessment and response occurs following the event.

2.1. *Average Recurrence Interval (ARI)*

Extreme rainfall can result in flooding and the necessity to release water from hydroelectric dams. Such events can be placed into a historical context using the concept of Average Recurrence Interval (ARI). Also called a “return period,” ARI represents a current precipitation event (amount per unit time) as the average number of years (climatologically) between equivalent events for a specific location. An ARI of 100 years is the same as a 1% probability of an event occurring in any given year (“100-year event”).

Rainfall frequencies have been calculated in terms of amount and period (e.g., the probability or ARI of 10 inches of rain in 24 hours). These frequencies are provided in NOAA Atlas 14, which is currently undergoing revision at the NWS Hydrometeorological Design Studies Center (HDSC).

Metstat and WDT have extended this technology to produce gridded and forecast ARIs in real-time for operational applications. The analyses use radar-derived rainfall estimates that are adjusted using previous correlations

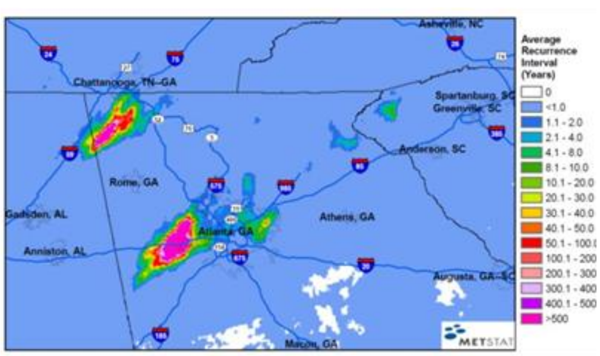

Figure 1. Average Recurrence Interval (ARI, years) for 24-hour rainfall ending 1200 UTC 21 September 2009, computed based on radar data and adjusted with rain gauge measurements.

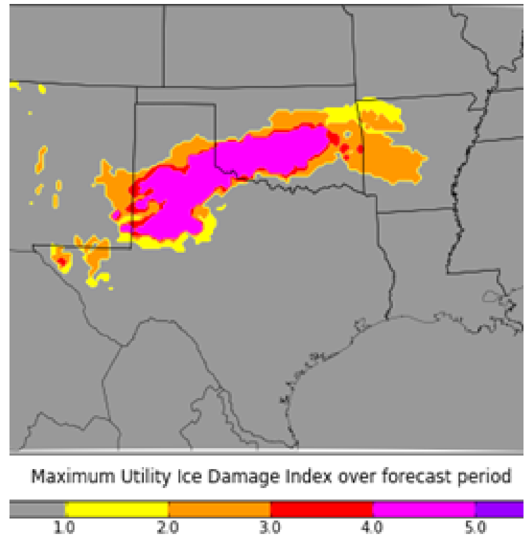

Figure 2. Maximum Utility Ice Damage Index over the 36-hour forecast period ending 0000 UTC 29 January 2010.

with rain gauge data (Parzybok et al., 2011; Fig. 1). Forecast ARIs are computed using Weather Research and Forecasting Model (WRF) rainfall predictions (Parzybok and Shaw, 2012).

2.2. *Utility Ice Damage Index*

During an ice storm, the combination of ice accumulation due to freezing rain, coupled with wind, can lead to downed power lines resulting in widespread power outages. The Tulsa NWS Forecast Office has created an Ice Damage Index based on National Digital Forecast Database (NDFD) grids of ice accumulation and maximum wind speed (McManus et al., 2008). We have extended this algorithm to work with gridded mesoscale and global forecast model output, and are currently running it based on WDT’s operational WRF model runs (Fig. 2).

2.3. *Avian Drop Zone Index*

In the southern U.S., roosting buzzards can lead to the buildup of feces on high-voltage power lines. If not periodically cleaned via heavy rain or manual washing, arcing can occur in certain weather scenarios such as fog, light mist, or high relative humidity, leading to widespread

Figure 3. Avian Drop Zone Index over a portion of north Texas on 8 December 2011. The scale is 0 to 15+ (red), nominally representing the number of days since transmission lines have been cleaned via heavy rain.

outages. WDT has combined its state-of-the science gridded precipitation estimates (using radar and rain gauge information) with its mesoscale NWP output to characterize the threat of buildup. By tracking how long it has been since heavy precipitation has occurred at any location, areas expecting weather conditions favorable for arcing can be highlighted. The grid operator can then decide whether to manually wash threatened line segments (Fig. 3).

2.4. Wind and Solar Forecasting

Renewable energy components such as wind and solar present an additional challenge in that both the power demand and the generating capacity depend on the weather. For instance, a cold front may dramatically affect wind farm output while concurrently affecting demand due to changes in temperature and cloud cover.

Wind and solar forecast systems are generally built on mesoscale forecast models such as WRF. The output of these models is tuned based on the validation of previous forecasts. Wind forecasts are often "downscaled" to match the terrain of the wind farm. Solar forecasts are improved by knowledge of aerosols and pollutants.

2.5. Severe Weather Nowcasting and Alerting

WDT's comprehensive asset monitoring and alerting system uses GIS techniques to determine if monitored assets (custom locations specified by the user, such a power substations, operations centers, wind farm locations, etc.) are within a weather watch, warning or advisory issued by the NWS. Additionally, WDT provides custom alerts not provided by the NWS, such as lightning, hail (including multiple size thresholds), and heavy rain, to include estimated time of arrival and departure. These alerts can be fed directly into operations center decision support tools as well as sent directly to individuals via email and text messaging.

Methods of pure time extrapolation using a series of observed precipitation measurements or radar mosaics generally produce much more accurate forecasts in the 0-3 hour time frame, with skill dropping to that of NWP models near the 6 hour forecast. One such scheme for precipitation nowcasting is the McGill Algorithm for Precipitation nowcasting by Lagrangian Extrapolation (MAPLE), developed at McGill University. This algorithm has been used operationally by WDT since 2003 to drive nowcasting product generation.

WDT uses real-time, high-precision lightning strike information to provide time-critical alerts of lightning hazards via its Lightning Decision Support System (LDSS™), which is used extensively within power grid operations centers as a stand-alone display and alerting

Figure 4. WDT iMapPro display of lightning strikes, 1-hour LightningPredictor™ projections (orange shading), and radar mosaic.

system. The lighting data consisting of time, location, and strength information can be readily integrated into Smart Grid technologies.

In addition, WDT's LightningPredictor™ is able to project the lightning threat up to one hour into the future by combining observed lightning density with motion vectors from MAPLE (Fig. 4). Beyond one hour, WDT produces NWP-based lightning potential, and all of these outlook products can be integrated as shapes or grids within Smart Grid software solutions.

2.6. Tornadic Circulation Track

Mesocyclones (rotating supercell thunderstorms) are associated with severe downburst winds and tornadoes. They can be readily identified in radar data by their rotation signature. By examining a series of radar data, a tornadic circulation (or mesocyclone) track can be determined. WDT's product examines the mean wind shear in the lowest 3 km of the atmosphere. Results from multiple radars are mosaicked onto a 500-m CONUS grid which is updated every 2 minutes (Baranowski et al., 2012; Fig. 5). The algorithm is being enhanced using data from dual-polarimetric radars as those data become available (Porter et al., 2012). The product thus serves as an automated, real-time "damage survey." In contrast, spotter and public reports of tornadoes and damaging winds are sparse and often contain location errors.

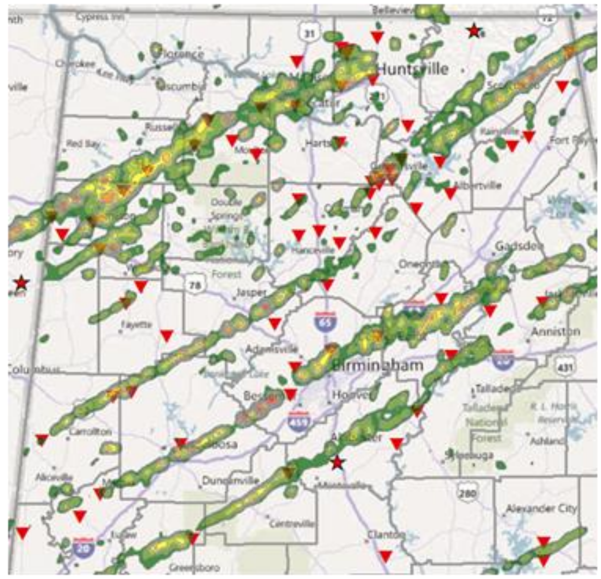

Figure 5. Tornadic Circulation Track and storm reports in northern Alabama on 27 April 2011.

3. SMART GRID INTEGRATION

GE Energy and WDT are exploring ways to mitigate weather impacts on Smart Grids. Weather information is presently utilized by utility operators in the form of current-day and day-ahead forecasts, which include load forecasts and renewable generation forecasts for up to 24 hours (Ruzic et al., 2003). Because actual weather can vary significantly at a local level, the integration of radar data, lightning strike locations, and very-short-term weather predictions (up to one or two hours ahead) into Smart Grid control systems helps utilities anticipate electrical outages and equipment failures within a well-defined geographical region.

3.1. Algorithmic Input

By combining weather predictions and historical patterns with the geographical locations of power lines, consumers, outages, and wind and solar farms, new predictions become available to electric utilities in terms of outages, reliability, and operational effectiveness.

Combining local weather predictions with electric power equipment management is possible because many utilities track power lines, distribution transformers, circuit breakers, and so on, using GIS-based asset management systems. The shared information is the location of assets and weather events. Also, unlike power transmission which connects regions together, power distribution is typically bound to a limited geographical area. By recording over time the effects of similar weather events on energy consumption and supply, heuristics can be established to quantify the impact of a decrease in wind speed or a rise in temperature on the power grid. Short-term weather forecasts enable utilities to anticipate weather impacts to the grid and improve responsiveness.

Figure 6. Timeline for weather products (top) and operator response (bottom).

The input forecast grids are derived from forecasts based on the Advanced Research WRF (ARW) and other models. The WRF forecasts are initialized using a combination of the Local Analysis and Prediction System (LAPS) and Four-Dimensional Data Assimilation (FDDA).

3.2. Operator Control

Electric power distribution lines are organized into "feeders" that carry electric power supply from a transmission substation to arterial roads and neighborhoods. Distribution feeders normally do not affect each other and are thus operated independently of each other.

Weather predictions for individual feeders as related to renewable resource availability, local cloud cover and temperature, and storm path become a new decision factor for electric utility operators (Figure 6). Decisions assuming uniform weather forecasts are now framed within high-resolution predictions of storm paths, local wind gusts, microclimates, and bird activity. The availability of local predictions allows operators to tailor an effective response to meet the needs and weather exposure of individual distribution feeders.

1) Weather Anticipation

Anticipation of exceptional weather events such as winter storms is the first step in operator control. Weather event preparation has several implications :

- People adapt their activities and travel plans according to the weather (e.g., by staying at home when roads are icy).
- Business activity may change during weather events based on the availability of workers and supplies, and visitor activity.
- In certain areas, consumption may increase above typical levels as a result of people changing their activities and travel plans.

The loading conditions on the power grid are different during severe weather and may result in widespread outages. Utilities that are aware of possible widespread outages can dispatch crew and perform preparatory work in advance of the weather event and reduce the severity of the impact of weather.

2) Energy Supply and Consumption Monitoring

Supervisory control and data acquisition systems (SCADA) provide measurements informing operators of energized and de-energized neighborhoods in real-time. Overlaying weather information with real-time measurements allows operators to witness the effects of local weather events such as intermittent cloud cover and storm damage, as they relate to electricity supply and consumption. Weather impacts may be particularly significant in power grids with high solar and wind farm penetration.

Figure 7. Conceptual overlay of weather and electrical power system showing tornado track detections (shading), tornado reports (triangles), power outages (diamonds), generating facilities (G), substations (sub), and main transmission lines (black and red dotted).

3) Outage Management

Finally, Outage Management Systems (OMS) centralize outage decisions and dispatch repair crews. Weather data offer formal evidence to determine whether outages are caused by weather events or by other reasons. With this insight, operators can dispatch crews according to outage causes (Figure 7).

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