Stochastic Nodal Adequacy Platform: Spot Pricing of Adequacy

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Abstract

The modern power system is becoming significantly more reliant on weather-dependent generation technologies. Existing resource adequacy metrics are not adequate for systems with a high penetration of weather-dependent, stochastically behaving renewable resources. This paper provides an overview of the Stochastic Nodal Adequacy Platform (SNAP), a novel approach for evaluating the adequacy of a large-scale electrical grid at the nodal level while accounting for the stochastic nature of weather-dependent system components, the physical operation of the system, and the economics and market design governing unit commitment and dispatch. The output of a SNAP analysis is a set of metrics that quantify the adequacy of the system and the physical contribution and economic value that each individual system component contributes towards overall system adequacy. The latter metric – the SNAP value – is an hourly marginal resource adequacy price at every node in the system that can be integrated into existing power market design.

Keywords: Advanced Weather Science, Monte Carlo Methods, Nodal Resource Adequacy, Stochastic Analyses, Value of Lost Load.

1. Introduction

Ensuring resource adequacy of a bulk power system is one of the primary functions of system planning. Traditionally, system planners have studied resource adequacy using such probabilistic criteria as Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), or Loss of Load Hours (LOLH), which then lead to the determination of planning reserve margin requirements.[1] Maintaining an amount of installed capacity equal to the planning reserve margin requirement ensures the desired probabilistically measured level of resource adequacy. The economic justification behind this approach can be traced to the well-known relationship between the LOLH criteria, the Value of Lost Load (VOLL), and the annualized marginal cost of generation capacity (MCC) [14]:

$$LOLH \times VOLL = MCC. \quad \textbf{(1)}$$

The economic principle underlying this formula is well understood; generation capacity should continue to be built while the per unit annualized cost of adding capacity remains lower than the cost associated with the loss of load. When the incremental damage equates to the cost of adding capacity, as shown in Equation (1), the optimal level of resource adequacy is achieved. The annualized cost of capacity reflects the ratio of the generator's annual revenue requirement over its unforced capacity. The revenue requirement (positive or negative) equals the difference between the avoidable fixed costs of a generator and the revenues it receives in the market from sales of energy and ancillary services, as well as any additional revenue earned under regulatory rules in place (e.g., the production tax credit for qualifying technologies). The unforced capacity of a generator reflects its availability to meet system load at the time of need. Using these annualized capacity costs, a capacity merit order is formed. The last generator in the merit order needed to satisfy Equation (1) is the marginal generator and determines the value of MCC. In practice, the value of MCC is often approximated by the cost of new entry (CONE), i.e., the annualized cost of a peaking generator with a relatively low capital cost but high heat rate. Under this assumption, CONE is simply equal to the sum of the annualized capital costs and fixed O&M costs, while revenues from the energy and other markets are either ignored as insignificant or estimated based on the historical performance of similar generators in the market. Given that approximation, for systems that are short on capacity, Equation (1) is often restated in the following form:

[1] LOLP typically refers to the probability of load curtailment under predefined extreme conditions (e.g., peak hours). LOLE is generally defined in terms of the expected number of days in which load curtailments occur; under different conditions, loss of load in a given day may take place over a different number of hours, but that would still count as a single loss of load event for purposes of the LOLE calculation. LOLH is probably the most informative metric and accounts for not only the frequency of interruptions but also for their durations.

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$$LOLH \times VOLL = CONE. \quad \textbf{(2)}$$

Equation (1) leads to the following optimal level of LOLH:

$$LOLH^O = \frac{MCC}{VOLL}. \quad \textbf{(3)}$$

Using the CONE approximation, the optimal LOLH level is determined as

$$LOLH^O = \frac{CONE}{VOLL}. \quad \textbf{(4)}$$

Thus, the values of VOLL and MCC dictate the optimal value of the LOLH criterion, which in turn leads to the optimal level of planning reserve margin. The corresponding level of reserve margin is typically determined by running a series of probabilistic "loss of load studies" in which reserve margins vary until the benchmark level of LOLE or LOLH is achieved with required precision. See, for example, New York State Reliability Council [8]. The reserve margin is then used as a surrogate planning criteria applied in Integrated Resource Planning or in capacity market design.

This approach to resource adequacy emerged in the middle of the past century and was intended for relatively self-sufficient, concentrated territories served by vertically integrated utility companies. It is, however, inapplicable to large regional entities such as power pools and regional transmission organizations and independent system operators (RTO/ISOs) exposed to significant transmission constraints. See Rudkevich et al. [10, 11] and Rudkevich [12] for a more detailed discussion of the shortcomings of traditional adequacy criteria in transmission constrained systems and the need to address the resource adequacy problem at the nodal level.

Moreover, with the increasing penetration of weather-dependent, stochastically behaving renewable generation technologies such as wind- and solar-powered generation, system planning is facing a number of additional challenges rendering the traditional reserve margin criteria obsolete and largely misleading [3]. For example, the probabilistic nature of modern electrical systems has become significantly more complicated. Whereas, in years past, it consisted of relatively infrequent and largely independent outages of otherwise predictable central station generating units, it now involves a much larger number of stochastic objects exhibiting significant temporal and spatial correlation in their availabilities, load conditions, grid system characteristics, and outages, all of which depend on weather.

Furthermore, in response to these challenges, the planning and control system becomes more complex. System operators presently seek better ways to understand these uncertainties, improve system forecasting and visibility, and design more sophisticated methods of control and classes of ancillary services (see, for example, [16], [5], [6], [1], and [4]). As a result, the assessment of system adequacy cannot be properly accomplished without including these controls into analytical models addressing the adequacy problem.

A need exists for a new approach to assessing system adequacy that incorporates more frequent, closer to real-time analysis and produces more granular results. This paper provides a summary description of the Stochastic Nodal Adequacy Platform (SNAP), a modeling platform and approach designed to evaluate the adequacy of a large-scale electrical grid at the nodal level. SNAP accounts for the probabilistic dependency of the system on weather, detailed modeling of the physics of the system, its economics and market design, and explicit modeling of system controls, represented in the model as decision cycles.

Rooted in the fundamental theory of the spot pricing of electricity [13], SNAP extends and applies the nodal mathematics of power network economics to the valuation of system adequacy. The objective of SNAP is not to provide a new system planning rule but rather to serve as a process for assessing: (1) the adequacy of the system and (2) the physical contribution and economic value that each individual system component (e.g., generating unit or transmission line) contributes towards overall system adequacy. In other words, SNAP can be thought of as a mechanism underlying a spot market for adequacy.

It is important to note that, despite the increased complexity of the system, this approach to resource adequacy relies on the same economic principle of equating the marginal cost of additional capacity to the marginal damages associated with probable inability to serve consumers' demand. At the nodal level, Equation (1) takes the following form:

$$\mathbf{E}[MCC_n] = VOLL \times \sum_{t=1}^{T} \frac{\partial}{\partial L_n} \mathbf{E}[\theta_n(t,\omega)U(t,\omega)], \quad \textbf{(5)}$$

where $\mathbf{E}[MCC_n]$ is the expected value of the annualized marginal cost of adding a resource at node n of the electrical system, $\theta_n(t,\omega)$ is a random capacity factor for that marginal resource at time interval t under stochastic scenario ω, and $U(t,\omega)$ is the unserved energy in the entire system during time interval t under stochastic scenario ω. The derivative is taken with respect to electricity demand, L, at the location of the marginal resource. As the right-hand side of Equation (5) indicates, what is equated to the marginal cost of adding a resource is the incremental damage of unserved load valued at VOLL and apportioned to the capacity factor of the resource at the time of scarcity, if and when the latter occurs. Considering that $VOLL \times \frac{\partial U(t,\omega)}{\partial L_n}$ is the component of the locational marginal price (LMP) at node n caused by shedding system load, it follows that the compensation of the marginal resource in excess of revenues accrued in markets for energy and ancillary services at each point in time is determined by the nodal component of the price that is set by load shedding in the system. However, that price depends on the location of the resource, which determines its ability to relieve load shedding. Furthermore, the compensation depends on the resource availability at the time of scarcity. Equation (5) effectively establishes the compensation rule for any resource in the system for its contribution to system adequacy and is applicable to nodal networks and to systems with variable resources with weather dependency.

The remainder of this paper unfolds as follows. Section 2 introduces the various nodal metrics that form the output of a SNAP analysis and the computational approach to calculating them. Section 3 discusses the advanced weather science underlying SNAP. An overview of the SNAP modeling platform is presented in Section 4, and the results of a 24-hour case analysis are presented in Section 5.

2. SNAP nodal metrics

The structure of SNAP is designed to provide an efficient, general Monte Carlo-based computational process for assessing the contribution to system adequacy of each resource at every node of the electrical system and over time.

2.1. Description of metrics

As introduced in the previous section, Equation (5) is the basis for calculating the compensation owed to various types of components of the power grid for their contribution to the reliability of the system. The various nodal metrics calculated by SNAP are shown in Table 1.

Table 1. SNAP adequacy metrics.

Load	Generation and Storage	Transmission
Adequacy Payment	Adequacy Payment	Adequacy Payment to/from Supporting/Supported Neighbor
Conditional Load at Risk (CLaR)	ELCCd	Adequacy Rent
Expected Unserved Energy		

Let us define the hourly and locational value of the right-hand side of Equation (5) to be $SNAP_n(t,\omega)$, the stochastic nodal adequacy price of location (node) n at time t and stochastic scenario ω:

$$SNAP_n(t,\omega) = VOLL \times \frac{\partial}{\partial L_n} U(t,\omega), \qquad \textbf{(6)}$$

and $SNAP_n(t) = VOLL \times \frac{\partial}{\partial L_n} \mathbf{E}[U(t,\omega)]$ to be the adequacy price at location n and time t. At each nodal location in the system, $SNAP_n(t)$ represents the value of injecting or reducing an additional unit of MW at location n for adequacy of the entire system. If there is no load shed event, $SNAP_n(t)$ is equal to zero. Efficient calculation methods for the key component of $SNAP_n(t)$, expected marginal unserved energy, $\frac{\partial}{\partial L_n} \mathbf{E}[U(t,\omega)]$, are discussed in a later section.

In the event of scarcity, load participants at location n are assumed to be paying for the net load consumption (demand minus shed load):

$$AP_n^{Load}(t) = \mathbf{E}[L_n(t) - U_n(t,\omega)] \times SNAP_n(t,\omega). \quad \textbf{(7)}$$

Similarly, generating units and storage resources are compensated for their contribution to adequacy according to:

$$AP_i^{Gen}(t) = \mathbf{E}[P_{i|i\ in\ I^n}(t,\omega) \times SNAP_n(t,\omega), \qquad \textbf{(8)}$$

where I^n is the set of generating and storage units at location n. If, during a scarcity condition, a generating unit does not dispatch power, it is not compensated for contribution to system adequacy. In fact, effective load carrying capability on demand, ELCCd, is a performance measure for each generating and storage unit, calculated as the conditional dispatch at the time of scarcity, that can be used to evaluate the contribution of different types of generating resources to system reliability. At time t, ELCCd of unit i is given by:

$$ELCCd_i(t) = \mathbf{E}[P_i(t,\omega) \mid \omega \in \omega^{S_t}], \qquad \textbf{(9)}$$

where $P_i(t,\omega)$ is the dispatch of unit i at time t and stochastic scenario ω, and ω^{St} is the set of scenarios with scarcity at time t.

Conditional load at risk, a parallel metric to conditional value at risk (CvaR) widely used as a risk-focused financial metric, measures the system's vulnerability specifically under tail events unlike more commonly used LOLE and LOLH:

$$CLaR_n(t) = \mathbf{E}[U_n(t,\omega) \mid \omega \in \omega^{St}. \quad \mathbf{(10)}$$

Given the scarcity conditions, $CLaR_n(t)$, measures the severity of system risk.

The nodal adequacy price, $SNAP_n(t)$, also allows measuring the economic adequacy contribution of transmission resources. Adequacy payment to supporting neighboring entities from area a can be calculated as:

$$AP_a^{Tx}(t) = \sum_{a' \in a^C} \mathbf{E}[I_{a',a}(t,\omega) \times \Delta SNAP_{a',a}(t,\omega) \quad \mathbf{(11)}$$

where a' is a neighboring entity, a^C is a set of neighbors of area a, and $I_{a',a}(t,\omega)$ is the total transfer from area a to neighboring entity a'. $\Delta SNAP_{a',a}(t,\omega)$ is the difference between area level $SNAP$ values between area a and neighboring entity a'. Area level metrics can be calculated as the weighted average of SNAP values at all nodal locations belonging to the area.

Similarly, adequacy revenue collected from a neighboring entity supported during a scarcity event is given as:

$$AR_a^{Tx}(t) = \sum_{a' \in a^C} \mathbf{E}[I_{a,a'}(t,\omega) \times \Delta SNAP_{a,a'}(t,\omega) \quad \mathbf{(12)}$$

where $I_{a,a'}(t,\omega)$ is the total transfer from neighboring entity a' to area a. Lastly, adequacy rent for a given branch b can be calculated as:

$$R_b^{Tx}(t) = \mathbf{E}[f_b(t,\omega) \times \Delta SNAP_b(t,\omega)] \quad \mathbf{(13)}$$

where $f_b(t,\omega)$ is the flow on branch b and $\Delta SNAP_b(t,\omega)$ is the difference in $SNAP$ values between the beginning node and the ending node of branch b.

2.2. Computational approach to metrics

Computational realization of the metrics represented above requires evaluating a statistically significant size of stochastic scenarios such as system outage conditions and weather. Depending on the type of stochastic scenarios, multiple layers of scenario and variance reduction techniques have been employed to balance computational requirements with statistical significance and operational model detail.

System outage conditions are evaluated through a multi-step integrated scenario reduction method where the initial filtering of critical outage conditions is based on an estimation of scarcity conditions on a simplified mathematical model of the system. Only those critical outage conditions are solved in full operational detail.

A stratified sampling approach has been adopted to allocate computational resources efficiently to stochastic weather scenarios and time periods based on the variance of the estimated scarcity rate.

These methods are discussed in detail in another work that is currently in preparation [9]. The development of the stochastic weather scenarios underlying SNAP is further discussed in the next section.

3. Application of advanced weather science

SNAP recognizes and is built upon the reality that the largest supply and demand uncertainties in today's electric power sector are weather driven. The stochastic availability of renewable resources in front of the meter (wind and solar), the impact of renewable and other technologies operating behind the meter (DERs), and the impact of extreme weather events resulting from climate change have made the forecasting of resource adequacy far more challenging.

SNAP utilizes the dramatic advances in weather science developed by IBM, The Weather Company [21]. The forecasts used in the stochastic weather scenarios are based on inputs from 87 different numerical weather prediction models and their ensemble members on a 4km-by-4km grid worldwide. An ensemble copula coupling quantile technique is used to derive 100 synthetic weather system scenarios wherein each of the 100 scenarios has the same probability of occurrence [18, 19, 20]. Within each forecast scenario, the variables are internally consistent in space and time. Figure 1 shows the underlying 2,000 METAR weather stations, wind and PV sites, and cities and towns with populations of 20,000 or more in the Midcontinent Independent System Operator (MISO) territory.

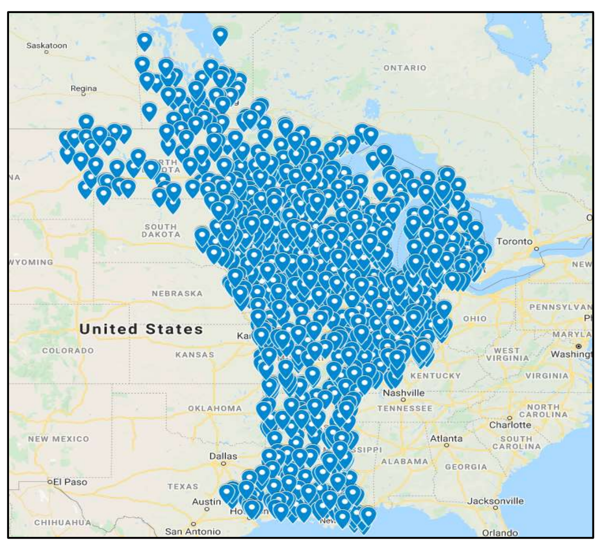

Figure 1. METAR locations in MISO.

Figures 2a and 2b show the forecasted spread (gray shaded area) and the actual temperature (blue line) for an extreme cold period in Jackson, Mississippi (February 11-19, 2021) and an extreme warm period in Minneapolis, Minnesota (June 4-17, 2021), respectively.

Using the single variable of temperature as an example, Figure 2 illustrates that the probability spread can be quite large, capturing the uncertainty in any central tendency forecast. The broader the range, the more uncertain is the outcome, i.e., the less certain is the mean value to be a reliable forecast. When extended to locational forecasts of wind and solar availability or consumer demand, the stochastic nodal value of weather variables provides the input to the SNAP calculation of supply adequacy or inadequacy.

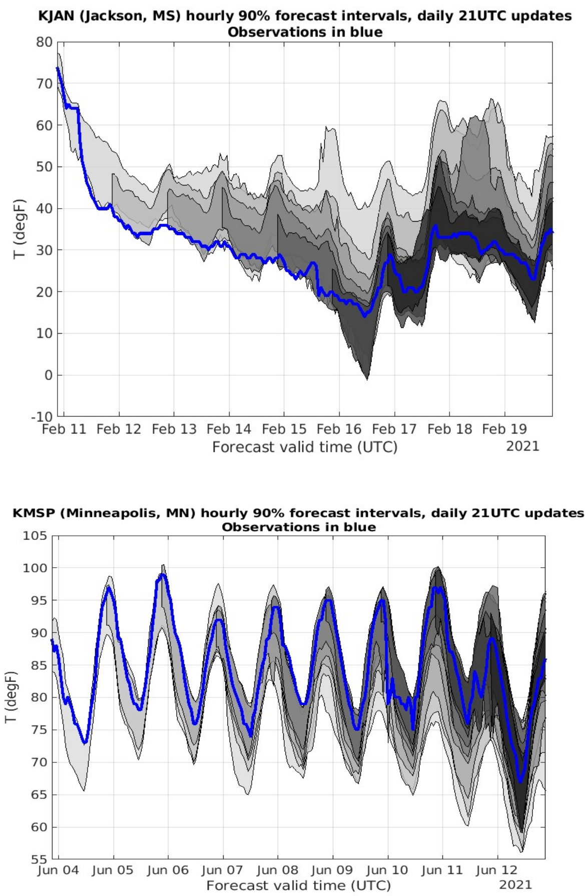

Figure 2a (top) and 2b (bottom). Forecasted and actual temperatures during an extreme cold period in Jackson, Mississippi (top) and an extreme hot period in Minneapolis, Minnesota (bottom).

A key challenge to the implementation of SNAP is the ability to translate the 100 probabilistic forecasts of individual weather variables into an equal number of forecasts of electric generation from each renewable resource in the system, as well as forecasts of net demand acknowledging behind the meter generation and weather affects. SNAP builds upon the weather variable forecasts to develop 100 equally probable location-specific, hourly forecasts of wind, solar, load, and outages to create stochastic scenarios of hourly resource availability and net demand.

To produce the probabilistic wind forecast, for example, each wind farm is modeled at the turbine level. The probabilistic wind forecast, provided at ground level at the location of each wind farm, is interpolated with a deterministic wind forecast provided at several different heights to create a probabilistic wind speed forecast at each turbine's individual hub height. Wind turbine power curves, which parameterize power output as a function of wind speed, are used to convert wind speed to wind power generation for each probabilistic scenario. Power curves are empirical functions based on observed data, and height- and manufacturer-specific power curves are used for each turbine, even within a single wind farm.

Wind energy represents a highly stochastic input to the resource adequacy mix for any system operator. Building upon a combination of wind speed, air density, humidity, hub height, and specific turbine characteristics, SNAP generates probabilistic forecasts of wind output for each windfarm. These probabilistic forecasts become an input into the expected quantity of resource adequacy as the operator looks forward multiple hours or multiple days. Figure 3 illustrates the value of the stochastic forecasting of wind energy. The solid blue line provides the mean value of the 100 scenarios for an example wind farm in MISO, while the blue shaded area shows the full range across all scenarios. It is important to note that, while the mean may remain high, there is often a non-zero probability that the actual output will be dramatically lower (zero) or higher.

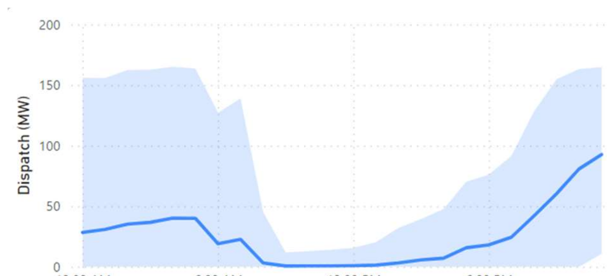

Figure 3. Generation from an example wind farm in MISO (Walnut Wind) on June 10, 2021 over 100 probabilistic scenarios.

The process for converting forecasts of weather variables into energy from utility scale solar installations parallels that of wind energy. Multiple weather variables are combined to create solar-to-energy forecasts. As with wind, the forecast space is 100 independent forecasts for each utility scale solar installation in MISO.

Weather-based net demand forecasting for MISO follows a similar logic to that of wind and solar but requires a more complex calculation procedure. To produce the probabilistic load forecast, MISO is subdivided into its 38 constituent local balancing authorities (LBAs). Each LBA is assigned a probabilistic forecast based on representative weather station(s) in the urban areas within that balancing authority. An ensemble machine learning model developed by Newton Energy Group produces a load forecast for each probabilistic weather scenario. This weather-to-load model is trained on 11 years of historical data from the period January 1, 2009 to August 16, 2021. The data are organized by MISO LBA and include load, temperature, dew point, wind speed, cloud cover, solar radiation, and rainfall. Figure 4 shows an example demand forecast for the Alliant Energy – East LBA, where the solid blue line shows the mean value, and the blue shaded area shows the full range, of the 100 weather scenarios.

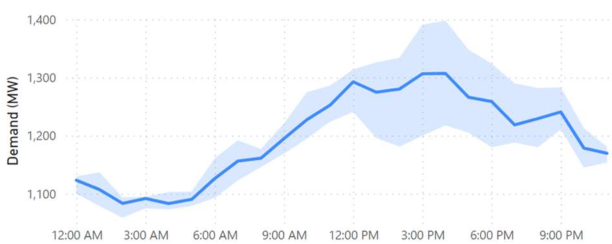

Figure 4. Forecasted demand for an example MISO LBA (ALTE) on June 10, 2021.

The final stochastic dataset incorporated into SNAP is the probability of outage of traditional generation and transmission resources which reflects the analytic levels used by the RTO/ISOs in analyses of resource adequacy.

4. The SNAP platform

The SNAP modeling platform is comprised of two core components: Power System Optimizer (PSO), a Security Constrained Unit Commitment (SCUC) and Security Constrained Economic Dispatch (SCED) power system simulator, operating within the ENELYTIX modeling environment, a cloud-based data and processing environment. Each weather-based scenario of a power system is paired with scenarios simulating random behavior of grid equipment – generating units and transmission outages, availability of demand response measures, and inter-market transactions. Through a uniquely flexible representation of decision cycles in PSO, system operational planners/operators are able to use SNAP to assess system adequacy (inadequacy) at different decision points in time, including expansion planning, maintenance scheduling, week-ahead scheduling, day-ahead scheduling, intra-day scheduling, and real-time scheduling.

Figure 5 provides, schematically, the calculation structure of SNAP. External to the calculation process of ENELYTIX, SNAP accesses the commercially available probabilistic weather forecasts produced by IBM, the Weather Company. In addition, ENELYTIX accesses a full catalogue of data on the existing condition of the grid that includes the initial and forward status of all generation, the topology and availability of all elements of the transmission system and the current plan to cover adequacy for each hour of the operational planning horizon.

Given access to the external data, and internal to the ENELYTIX platform, the weather dependent (and standard utility) probability analyses are parallelized for rapid computation. Once the full deck of resources and load is available, supply and demand outage values are incorporated to create roughly 100,000 Monte Carlo draws. ENELYTIX operates on the AWS cloud and automatically manages the entire SNAP workflow from managing data feed to parallelization of computations, provisioning and monitoring of machine instances, post-processing results, and providing access to results.

Developed for SNAP, ENELYTIX optimally allocates resources to specific parallel tasks to deliver high precision adequacy estimators quickly and at low costs. ENELYTIX architecture pairs 100 weather-driven scenarios load forecasts, wind and solar resources and transmission line ratings with over 1,000 scenarios of generation and transmission outages. The system is capable of running through over 100,000 simulation scenarios of security constrained unit commitment of a large electrical system the size of MISO. ENELYTIX processes the results of the parallelized computations and reports the metrics described in Section 2.

The computational efficiency of the SNAP implementation was shown in a case analysis of June 10, 2021 that utilized 100,000 stochastic scenarios of SCUC/SCED analyzed for the entirety of MISO using 500 Virtual Machines with a solution delivered in 45 minutes at a cost of $200 using on-demand VM instances or $120 using spot VM instances. This case analysis is discussed in the next section.

5. Case analysis: MISO – June 10, 2021

The SNAP methodology was tested on a 24-hour period, June 10, 2021, for which the authors had a full set of data. The date was chosen by project partners at MISO as a representative date on which the MISO system was significantly stressed.

After running the SNAP analysis, output data is displayed in a graphical dashboard, allowing operational planners easy access to the results. The dashboard is designed to help operators answer the following questions:

- WHEN is there potential for inadequacy?
- WHERE will the inadequacy occur?
- WHY is there potential for inadequacy?
- WHAT options are available to avoid the inadequacy?

Figure 6 shows the "Load View" dashboard page, which displays results at the LBA level. A table in the bottom-right allows operational planners to quickly identify hours in which there is potential inadequacy while a map displaying LBAs color-coded to the probability of inadequacy allows operational planners to quickly identify where the potential inadequacy is located. Additional summary statistics are displayed, including load, expected unserved energy, and the SNAP value. As shown in Figure 6, for the period analyzed, there is a nonzero probability of inadequacy in the Big Rivers Electric Corporation (BREC) LBA between the hours of 12:00-9:00 pm, which peaks at 0.016 during the 4:00 pm hour.

A "Generator View," shown in Figure 7, allows operational planners to drilldown to generator-specific information. In this example, multiple key generating units in BREC had a relatively high outage probability during the at-risk hours (e.g., ranging from 0.07-0.15 during the 4:00 pm hour) which was coupled with generally low production from wind facilities in MISO-N (where BREC is located) during those same hours. In Figure 7, the Walnut Wind facility is shown as a representative example. Similar visualizations exist in the dashboard for other weather-dependent variables, including solar generation and net demand. Operational planners can use this same information to identify potential actions to avoid a shortage event. For example, a planner could quickly identify units with the requisite capacity and location that are on planned outage but could be brought online to provide additional generation.

6. Conclusions

The increasing penetration of weather-dependent renewable resources necessitates new methods for analyzing and quantifying resource adequacy, especially in large-scale electric systems exposed to significant transmission constraints.

SNAP provides an efficient Monte Carlo approach allowing for the development and solution of approximately 100,000 SCUC/SCED analyses principally derived from the stochastically applied forecast of weather variables developed by IBM, The Weather Company.

Using PSO and ENELYTIX, it is possible to solve the 100,000 stochastic scenarios in a period of less than 45 minutes at a cost of between $120 to $200 as a function of spot or demand machine time on the AWS cloud.

The resulting metrics provide operational planners with the information needed to identify when and where a potential for inadequacy exists, what system conditions lead to inadequacy, and what options are available to prevent a shortage event.

In addition, the $SNAP_n(t)$ value, the adequacy price at location *n* and time *t,* is an hourly marginal resource adequacy price at every node in the system that can be seamlessly integrated into existing power market design.

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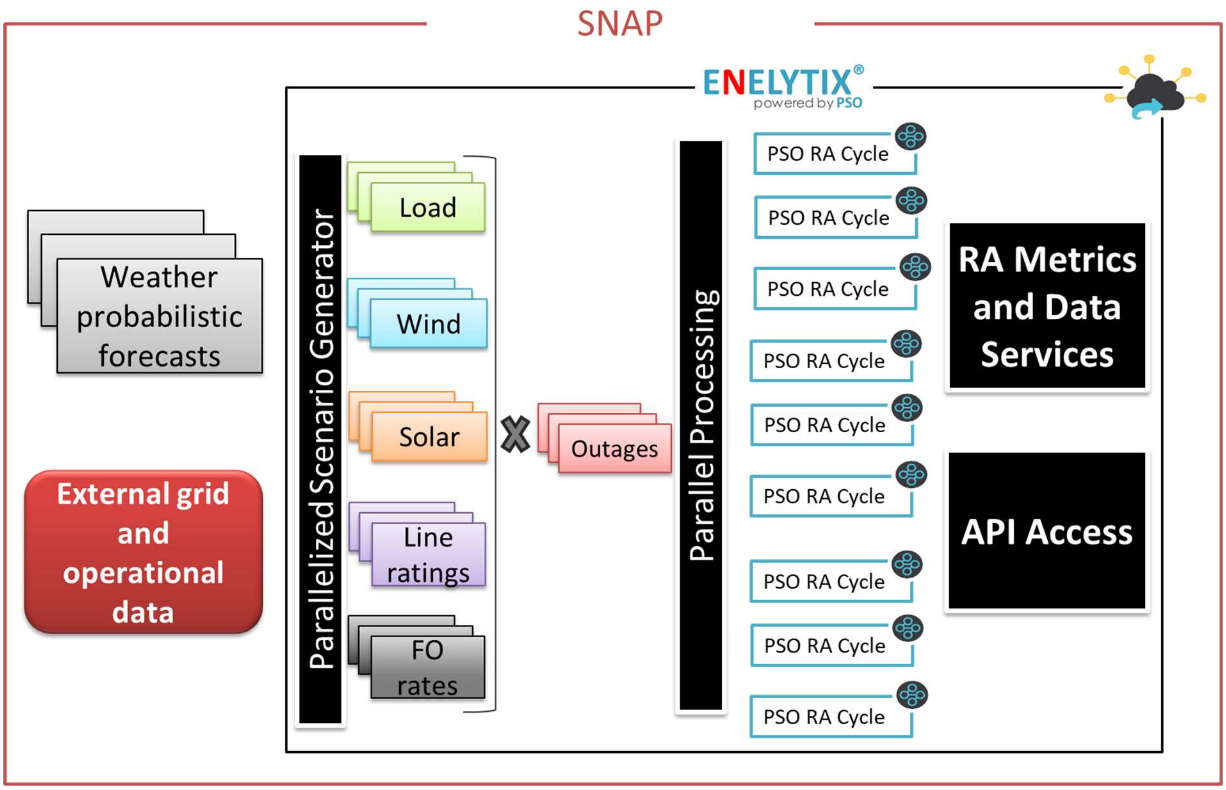

Figure 5. SNAP schematic flow diagram.

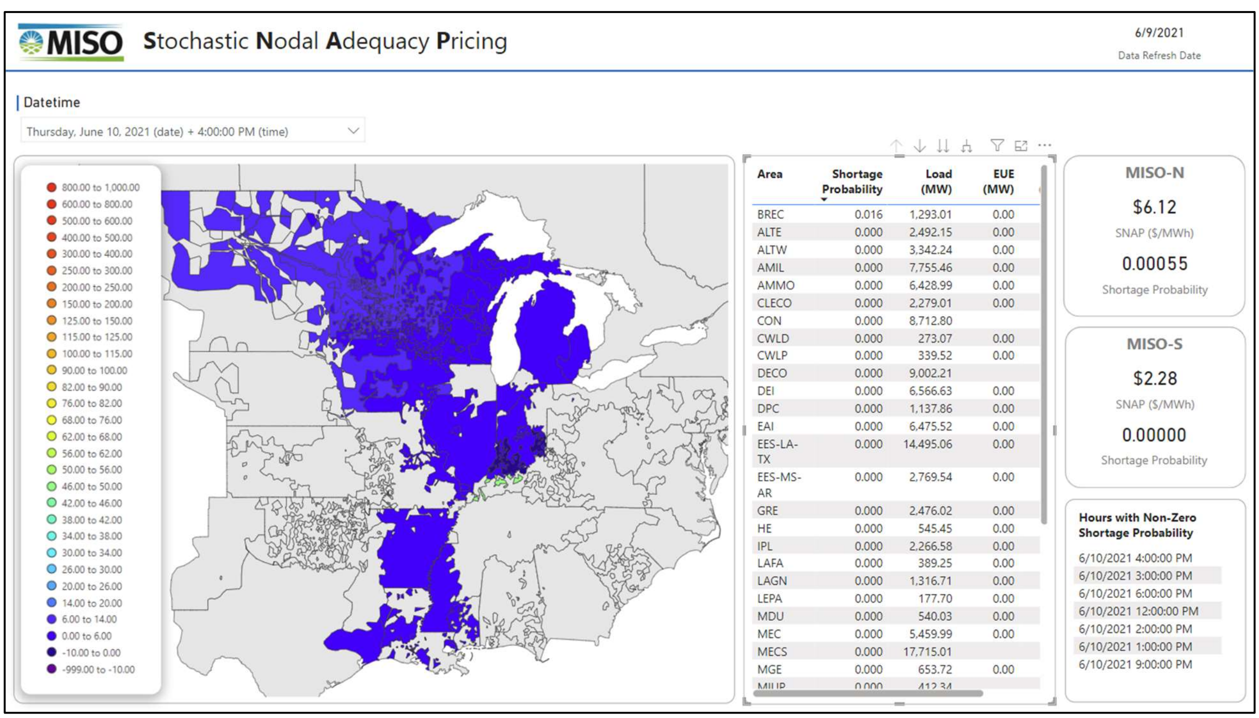

Figure 6. SNAP “Load View” visualization showing a nonzero probability of inadequacy in the BREC LBA at 4:00pm on June 10, 2021.

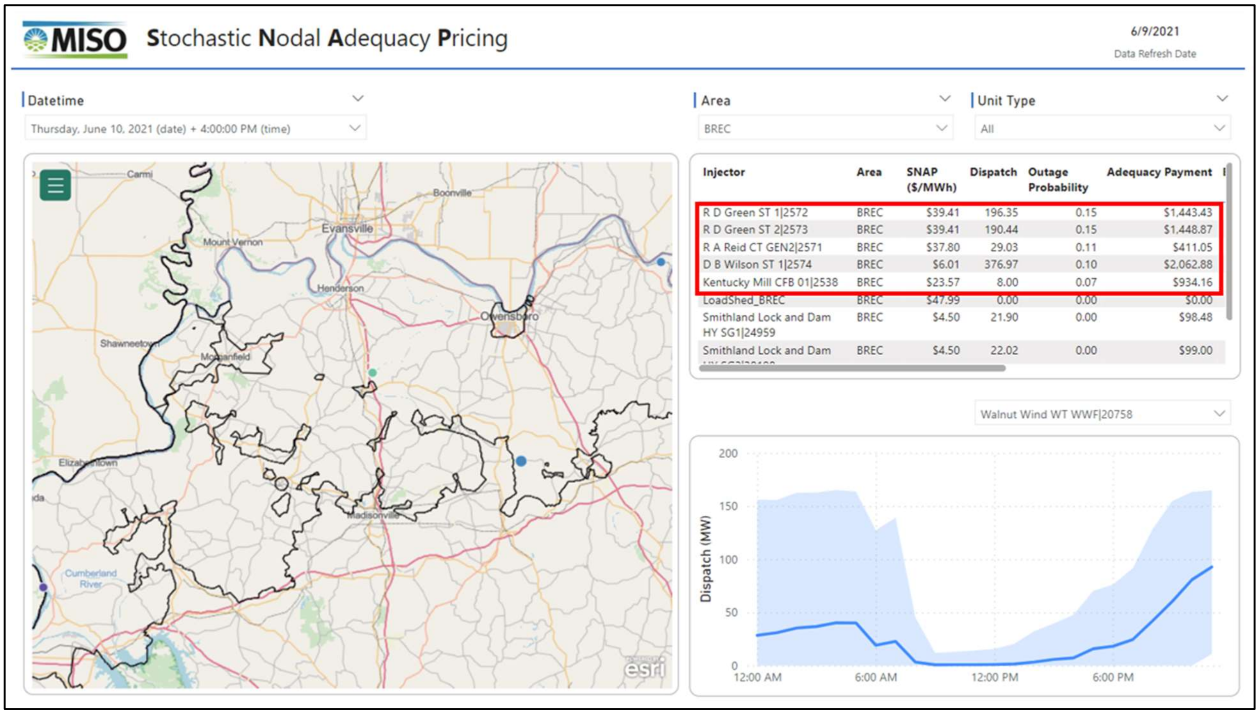

Figure 7. SNAP “Generator View” visualization.