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Weather and Operational Uncertainty in Electricity Market Operations: Stochastic Nodal Adequacy Pricing Approach

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SUMMARY

Power systems are increasingly dependent on weather and the impacts of extreme weather events. This is driven by rapid integration of variable renewable resources and increased inter-dependency between power and fuel supply networks. Evaluating the adequacy of systems with increasingly complex probabilistic interactions among individual system components requires high fidelity models with realistic representation of operational and grid constraints, hence can capture operational flexibility and limitations, and the outcome of decision-making processes. Traditional assessments of resource adequacy omit many of these details and are insufficient to identify system needs with correlated impacts of weather in space and time.

In this paper, we introduce a probabilistic extension of electricity production cost minimization tools that supports the use of high-fidelity models. These tools are able to accurately simulate the temporal and spatial relationships affecting system physics and economics. The ability to use high-fidelity models enables accurate calculation of dual variables and their use in defining reliability metrics that accurately represent the economic and engineering characteristics of all resources. In particular, the use of dual variables captures impacts of time-coupled resources and constraints such as storage and limited fuel supply. By bringing economic metrics directly into reliability analysis, we can supplement traditional reliability metrics with economically justified reliability criteria for use by system planning and operations.

High fidelity probabilistic models rich with operational and engineering details are computationally intensive, and using these models in the Monte Carlo fashion for probabilistic analysis has been considered computationally intractable. In this paper, we demonstrate that tractability can be achieved by combining parallel cloud computing technology with efficient math programming and multi-layered scenario reduction techniques. These techniques can be applied to multiple dimensions, such as weather scenarios, time, and random outages.

We illustrate these techniques and their computational performance using a high-fidelity model of a real-sized US market, more specifically ERCOT (Electric Reliability Council of Texas). The model includes MIP based security-constrained unit commitment, realistic operational details, and co-optimization of energy and reserves.

KEYWORDS

Resource Adequacy, Probabilistic Analysis, Extreme Events in Power Systems

1. INTRODUCTION

According to the North American Electric Reliability Corporation (NERC) [1], definition of power systems reliability consists of two fundamental concepts: adequacy and operating reliability. *Adequacy* is defined as "the ability of the electric system to supply the aggregate electric power and energy requirements of electricity consumers at all times, taking into account scheduled and reasonably expected unscheduled outages of system components". *Operating reliability* is "the ability of the electric system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system components."

In practice, *adequacy* has been, and still is, the primary goal of planning criteria applied through traditional centralized planning by utilities or in the context of capacity markets. Traditionally, adequacy has been concerned with how much capacity to build and to provide broad (i.e., without connection to the power grid) guidance on where that capacity should be located to support reliability.

Operating reliability is the key determinant of a Balancing Authority's reserve procurement policy. Traditionally, operational reliability has been concerned with near to short-term scheduling of existing capacity.

Historically, there has been almost no connection between the two concepts. Operational flexibility of resources that are critical from the operating reliability standpoint has rarely been a factor formally considered at the planning stage. This approach to reliability emerged in the middle of the past century and was intended for relatively self-sufficient territories served by vertically integrated utility companies with few concerns for deliverability within each territory. Over time, however, interconnection and integration of territories into power pools and regional transmission organizations (RTOs) have increased concerns for deliverability [2, 3, 4]. In many regions, adequacy criteria have been modified to reflect the impact of transmission constraints, such as through the establishment of localized (i.e., zonal) capacity requirements. These use ad-hoc rules with little or no economic justification [5].

The ongoing energy transition, with its' rapid electrification and penetration of variable resources, calls for a fundamental revision of adequacy concepts, criteria, and methodologies. There are two fundamental problems must be addressed.

First, traditional reliability metrics must be revisited. Simple and strict metrics using reserve margins and/or loss of load probabilities are economically inefficient and miss many reliability impacts. With anticipated energy investments at a scale of **$2.7 trillion dollars annually** to achieve Net Zero by 2050 [6], the economics of reliability must be addressed by adequacy metrics. New, economically-justified criteria for adequacy need to be defined and implemented as soon as possible.

Second, planners and operators need new tools and processes. To capture and quantify the adequacy and reliability impacts of power systems dominated by weather-driven variable resources requires a foundational revision of analytical methods and tools. Extreme events driven by weather are increasingly threatening reliable operation of the grid. Impacts of weather are driven not just by wind and solar generation, but also by load, transmission, thermal generation, and other connected energy systems such as gas pipelines and storage. Weather-driven spatial and temporal dependency among and between resources and loads turn the reliability assessment into an inherently dynamic problem. For example, contingency events are no longer probabilistically independent, and this dependency elevates the importance of incorporating detailed engineering impacts into resource adequacy (RA) analysis.

Temporal dependency on weather also elevates the importance of operational flexibility of resources to respond in time and the impact of control room policies in deploying this flexibility. It is no longer sufficient to consider unplanned outages and the dispatch of energy limited resources to be independently distributed random quantities that can be added together at some snapshot in time to evaluate the reliability of a system. To quantify correlated weather impacts, it is necessary to adopt dynamic high-fidelity physical and operational models that capture the fundamental relationship between resource availability and system impacts in time and in space.

Traditional RA tools and metrics fall short of capturing these relationships and, thus, correlated weather impacts. Modelling these impacts is the matter of technical and economic detail, of accurately representing system flexibility, and the response to variability and uncertainty driven by contingencies and forecast errors. Models must enable planners and operators to simulate outcomes from this variability and uncertainty and to understand how decisions in different decision timeframes (e.g., recourse and non-recourse decisions in day-ahead and real-time) impact these outcomes. Capacity not usable in the system due to operational constraints (transmission limits, ramp rates, minimum up and down times, startup times, energy limits, adjacent energy systems) has a significant impact on adequacy. For example, the deployment of contingency reserves (and other ancillary services) play a significant role in outcomes observed in the real system.

Broadly, appropriate understanding of system adequacy requires identification of and ability to model flexible and inflexible decisions at each stage of the operating process. When making inflexible commitment decisions for the next operating day (e.g., commitment of slow-starting coal units), not all outages are known in advance and inflexible decisions must be made based on outages known at that time. Outages that occur during the operating day (surprising or random outages), on the other hand, need to be addressed with whatever flexibility remains in the system, subject to the base plan made with known outages.

Power systems are shifting away from independent outages of large generating units and other components in the system to more complex correlated interactions. Conservative planning reserve margins cannot be used to resolve these increasingly complex interactions: These will become economically impractical and do not capture risks associated with the increasing range of uncertainties from extreme weather and surprising (unexpected) outages.

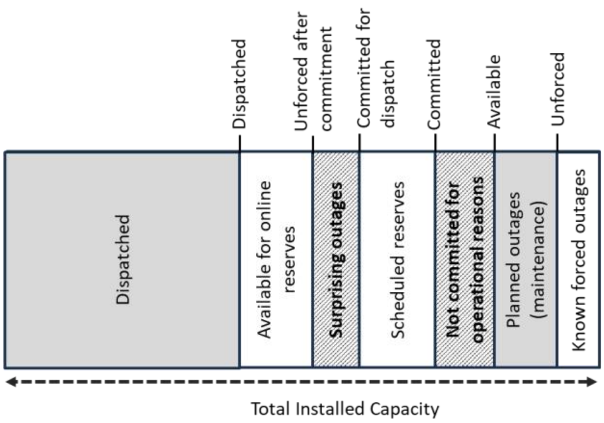

Figure 1 - Breakdown of installed capacity (Capacity Classification)

System inadequacy is increasingly driven by energy shortages that are not identifiable by reserve margins and instantaneous power capacity. The impact of operational decisions on outcomes is magnified with increasing dependence on storage and on unavailable capacity due to operational reasons and surprising outages (outages that occur after inflexible decisions are made for the operating day) (Figure 1). We can no longer assume that planning reserve margins are sufficiently conservative to address system needs.

This paper addresses the needs and theoretical foundation for economically justified locational and temporal probabilistic RA methods. It uses an integrated market framework as a template, but is in no way limited to market environments. The methodology can be employed to assess the reliability and economic impacts of decisions made in different time frames.

This paper will focus on annual assessment of day-ahead commitment decisions for planning purposes and on assessment of operational decisions a few days into the future. With short-term adequacy assessment, the objective is to reflect the stochastic risk of supply disruptions and other scarcity conditions in short-term energy, ancillary service, and transmission pricing. The need for RA assessment in shorter time frames (e.g., to capture the impact of reserve policies and maintenance scheduling) is increasingly being recognized [7].

The paper also introduces the use of shadow prices (i.e., dual prices) to define "Stochastic Nodal Adequacy Price" (SNAP) metrics that reflect the expected change in system shortage with respect to an increase in demand at each location in the network. At each location and time, dual variables identify the quantitative values of adequacy and reliability contributions of each system asset, including generation, storage, transmission, and demand resources. Of particular importance, dual-variable based metrics capture the time-coupled nature of storage and other energy limited resources when a system is under stress.

Section 2 presents the theoretical foundation behind SNAP and other metrics. Section 3 outlines the probabilistic methodology and computational approach. Section 4 illustrates the methodology and metrics using a real-world system at scale, including results on computational performance.

2. METRICS

SNAP applies nodal shadow-price based mathematics of power network economics to the valuation of RA, drawing on concepts from spot pricing of electricity [8]. The original derivation of nodal adequacy metrics was introduced in [9] as a foundation for the nodal probabilistic capacity market structure. An extended formulation defining concurrent capacity-market auction for generation and transmission investments was introduced in [10].

As an extension of these previous concepts, SNAP is used to *(i)* assess the adequacy of the system at every location, and *(ii)* define financial compensation for adequacy and reliability contributions of each system component (e.g., generating unit, transmission line, or load side participant). Our interpretation of SNAP is substantially broader than the original concept of Locational Stochastic Reliability Price (LSRP) introduced in [9,10]. The methodology discussed in this paper allows for a more flexible and comprehensive definition of scarcity (i.e., dispatch of demand response units, violation of ancillary service requirements) and is not limited to load shed events.

The core concept of SNAP is that efficient prices maximize social welfare. This occurs when the marginal cost of added capacity equals the marginal cost (or damage) associated with failure to serve load. For a simple single-area system, this relationship is summarized by Equation (1).

$$LOLH \times VOLL = MCC \tag{1}$$

$LOLH$ is Loss of Load Hours, $VOLL$ is Value of Lost Load, and MCC is Marginal Cost of Capacity. The product of $LOLH$ and $VOLL$ is the marginal cost of not serving load, and MCC is the marginal cost of adding and/or maintaining generation capacity[1].

Equation (1) also identifies an economic criterion at the nodal level [10]: a resource is needed if:

$$\boldsymbol{E}[C_n] \leq VOLL \times \sum_{t=1}^{T} \frac{\partial}{\partial L_n} \boldsymbol{E}[\theta_n(t,\omega)U(t,\omega)] \tag{2}$$

[1] A single VOLL does not recognize the diversity of impacts arising from a failure to serve load, and should be understood as the VOLL of the last load served or curtailed. However, due to historical limits on participation by loads in system balancing or in markets, VOLL has often been administratively defined.

$\boldsymbol{E}[C_n]$ is expected annualized capacity cost of a resource at node n, L_n is load at node n, $\theta_n(t,\omega)$ is capacity factor of the resource at time t and in scenario ω, and $U(t,\omega)$ is unserved system energy at time t and in scenario ω. If the condition in Equation (2) is not satisfied, building new resources is not justified and retirement may be justifiable. Annualized cost is per-unit of installed capacity and includes avoidable fixed cost and revenues.

The right-hand side of Equation (2) indicates the marginal damage of unserved load valued at $VOLL$ apportioned to the capacity factor of the resource at time of scarcity. Note that capacity factor of a resource and unserved energy are correlated variables and that this correlation impacts resource economics. The higher the available capacity factor of a resource at the time of scarcity (when unserved energy is above zero), the greater the economic value of the resource. The product $VOLL \times \partial U(t,\omega)/\partial L_n$ is the locational marginal price (LMP) at a node n from failure to serve load. If a market allows $VOLL$ to set prices, LMP identifies scarcity prices for both generating and load resources, as well as scarcity prices for contributions by other resources (e.g., transmission). If a resource is not available at the time of scarcity, it receives no compensation.

We refer to hourly locational values of right-hand side of the above equation as $SNAP_n(t,\omega)$, the stochastic nodal adequacy price of location n at time t and stochastic scenario ω:

$$SNAP_n(t,\omega) = VOLL \times \frac{\partial}{\partial L_n} U(t,\omega) \tag{3}$$

At each node, $SNAP_n(t,\omega)$ represents the value of injecting or reducing an additional unit of MW at location n for adequacy of the entire system. Thus, SNAP represents a contribution to the Locational Marginal Price (LMP) made by the event of the load shedding anywhere in the system. In the absence of load shedding, that contribution is uniformly zero. If the load shedding takes place, the contribution could be identical in all locations in the absence of transmission constraints. If transmission is limited, constrained out resources would see lower SNAP due to the reduced ability to address scarcity. Computationally, the value of SNAP can be determined by the same nodal mathematics as used for computing LMPs.

$SNAP_n(t) = VOLL \times \partial \boldsymbol{E}[U(t,\omega)]/\partial L_n$ is the adequacy price at node n and time t. This is based on the assumption that identification of scarcity requires load shedding. However, scarcity could be defined in other ways such as the deployment of emergency resources, reserve shortages, or transient transmission violations. With high penalty costs, these impacts are also included in LMP and, thus, a more general formulation of SNAP is:

$$SNAP_n(t,\omega) = \frac{\partial}{\partial L_n} \sum_k \pi_k V_k(t,\omega) \tag{4}$$

Where index k refers the type of system violations considered as contributing to scarcity event, $V_k(t,\omega)$ is the magnitude of that violation and π_k is the associated penalty. In this formulation, load shedding is only one type of shortage event.

Generating units and storage resources are compensated for their contribution to adequacy based on SNAP. If, during a simulated scarcity condition a generating unit is not able to dispatch power, it is not compensated for adequacy contribution. 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 adequacy. At time t, ELCCd of unit i is given by:

$$ELCCd_i(t) = \boldsymbol{E}[P_i(t,\omega) | \omega \in \omega^{S_t}] \tag{5}$$

where $P_i(t,\omega)$ is the dispatch of unit i at time t and stochastic scenario ω, and ω^{S_t} is the set of scenarios with scarcity at time (i.e., scenarios where LMP is greater than or equal to the *shortage threshold price*.

Similarly, load participants at location n are assumed to be exposed to the scarcity payment based on SNAP and assessed on the net load consumption (demand minus shed load). This creates an economic basis for defining the adequacy and reliability impacts of load. For example, when variable loads are correlated with other loads or anti-correlated with variable generation, they have a greater impact on RA requirements than loads that are dispatchable. Also, loads have a greater impact on RA requirements when distant from generation than loads co-located with generation. Thus, SNAP can be used to define financial incentives and to implement programs that encourage efficient participation of load in system balancing requirements. By defining prices that are grounded in engineering fundamentals, SNAP can also provide efficient and predicable price signals for future infrastructure investment in transmission and new technologies such as electrolyzers.

Of particular importance, SNAP provides a transparent and efficient mechanism to define shortage events. Shortage events are identified whenever SNAP is greater than a threshold price (*shortage threshold price*) determined by penalty costs of violations that contribute to shortage. This accurately calculates the missing contributions of resources regardless of timing and location. Traditional RA formulations focus on the occurrence of shortage events, but this fails to recognize the impact that resources in systems that have significant storage constraints and transmission congestion. With storage (including constraints on fuel and emissions), resource availability and dispatch in one hour can affect shortages in other hours. With congestion, resources may have limited or no impact on shortages that are electrically distant.

2.1 Transmission metrics

Value of transmission in carrying electricity to wherever is needed in time of scarcity is well understood but not well quantified in the context of adequacy. Using nodal SNAP pricing, adequacy contribution of transmission resources can be compensated based on the SNAP differential between the source and sink node of the transmission line using the following:

$$AP_b^{Tx}(t) = \boldsymbol{E}\left[f_b(t,\omega) \times \Delta SNAP_{n',n}(t,\omega)\right] \tag{6}$$

where b is the index for a transmission line, f_b is the flow on transmission line b and n', n are the source and sink nodes of the line. That definition is consistent with the transmission economic criteria [9] according to which the transmission branch would be considered needed if:

$$\boldsymbol{E}[TC_n] \le \sum_{t=1}^{T} \boldsymbol{E}\left[f_b(t,\omega) \times \Delta SNAP_{n',n}(t,\omega)\right] \tag{7}$$

Where $\boldsymbol{E}[TC_n]$ represents the capacity cost of the transmission branch.

Transmission metrics for adequacy can also be used to value the contribution from/to neighbouring entities during times of shortage.

Another metric revealing the system-wide or local nature of the scarcity conditions is Shortage Localization Index (SLI), which measures the ratio of dispatch exposed to shortage (i.e., being dispatched at locations with shortage) to total dispatch in a given hour with shortage conditions:

$$SLI(t) = \frac{\sum_{n \in n^s} \boldsymbol{E}[P_n(t,\omega]}{\sum_n \boldsymbol{E}[P_n(t,\omega]} \tag{8}$$

where n^s is the set of nodes at time t with shortage conditions (price above *shortage threshold price*), and $P_n(t,\omega)$ is the total dispatch at location n at time t. If the above value is equal to 1, this means that every generation resource is generating at locations with shortage (i.e., all of dispatch is exposed to shortage). Conversely, the closer the above value is to 0, the more local is shortage.

3. PROBABILISTIC METHODOLOGY AND COMPUTATIONAL APPROACH

As discussed earlier, general definition of SNAP (Equation 4) allows to flexibly define *(i)* which events are shortage events, *(ii)* the order of actions taken to avoid shortage events. Shortage in the probabilistic methodology is identified through prices that exceed a threshold (*shortage threshold price*).

The use of prices (dual variables) to detect shortage events identifies scarcity conditions even when there is no shortage observed in primal variables (e.g., no unserved energy). The optimization solution of dual variables captures indirect impacts of all engineering constraints, including time-coupled constraints on storage, limited fuel availability, and transmission congestion. As a result, these prices provide economically justified metrics that can be used as basis for payment from/to market participants.

Using optimization to simulate a wide range of events impacting system adequacy, RA can identify shortages that occur within a wide range of outcomes driven by weather and outages. These results can be combined to calculate the value of additional capacity at each time (hour of day, season of year) and location (by balancing authority and electrical node). However, due to the large number of uncertainties of system components and the probabilistic space, computational cost can be very large. To reduce computational costs and time, we employ multiple efficiency techniques and utilize cloud computing.

There are two layers to the Monte Carlo simulation methodology for RA evaluation: *(i)* integrated scenario reduction for random system outage conditions using a multi-step approach and *(ii)* a bi-level stratified sampling method to efficiently allocate samples to weather scenarios or historical weather years as well as time periods in long-term (e.g., annual planning) studies.

Filtering of random outage samples is integrated within the SCUC/SCED production cost optimization. The multi-step approach first solves the optimization problem in full detail (e.g., Day Ahead SCUC/SCED) in an "estimation" step. This is followed by a "filter" step that solves a simplified optimization problem (where certain decisions are fixed to the previous estimation step) for a range of random outage draws. A final "analysis" step solves with full detail only those outage draws identified as having potential shortages in the filter step.

Stratified sampling is applied to efficiently allocate outage samples to each weather scenario and time segment. The first step estimates the variance of shortage probability for each weather scenario and time segment. Additional outage samples are then allocated in proportion to the variances estimated in the first step. If there is no shortage detected for a particular combination of weather scenario and time segment, no additional samples are evaluated. Both steps in the stratified sampling approach utilizes cloud computing technology and solve each weather scenario and time segment in parallel.

4. ILLUSTRATION USING A REAL-SIZE US MAKET – ERCOT

We illustrate the methodology and metrics calculation on an annual model of the Electric Reliability Council of Texas (ERCOT). The goal of this illustration is to identify weeks and locations within ERCOT with shortages and to calculate both traditional and economic adequacy metrics. This annual assessment is partitioned into weekly time segments run in parallel using cloud computing.

We apply the 2022 weather year to a projection of ERCOT system conditions in the year 2024. The input data (e.g., generation stack, fuel price forecasts) in the ERCOT model as well as load and renewable availability forecast of the weather year is based on the ENELYTIX® data service and platform [11] [12].

In the first round, 100 outage samples are evaluated for each week with a total computation time of 88.5 hours and a turn-around time of 3 hours. Turn-around time is defined by the largest computation time among all weekly segments. For this particular weather year, the results show an LOLH (Loss of Load Hours) of 0.26 hours out of 8670 hours. In the second round using stratified sampling, 5,000 additional outage samples are evaluated distributed to weeks according to their variance and parallelized over 50

Virtual Machines. For this round, the resulting computational time was around 200 hours and turn-around time was 8 hours.

4.1 Model Setup

The model is a SCUC/SCED daily rolling-horizon optimization model with a 72-hour horizon. Decisions for each horizon are made 15 hours in advance of the beginning of the horizon, limiting visibility of forced outages to those that begin at least 15 hours before the start of a day. For instance, decisions for Tuesday are made at 9 AM the day before (Monday) and any outage that begin afterward is a surprising (random) outage. Surprizing outages must be managed by ancillary-service deployment such as dispatch of contingency reserves and commitment of fast-start generators. Outages that begin before 9 AM Monday and continue into Tuesday are known and factored into commitment decisions.

4.2 Results

Figure 2.a shows the peak load in each month for each weather zone in ERCOT, as well as peak and average load in the entirety of ERCOT. The load profile shows higher peak and average load in summer months. System-wide generation availability in Figure 2.b accounts for known forced outages (i.e., outages known at the time of making decisions for the next operating day) but excludes surprising outages. It also includes maintenance outages and units that are not available due to operational limitations (e.g., minimum down times following a failed startup). The month of August has the lowest renewable generation available on average due to low wind availability.

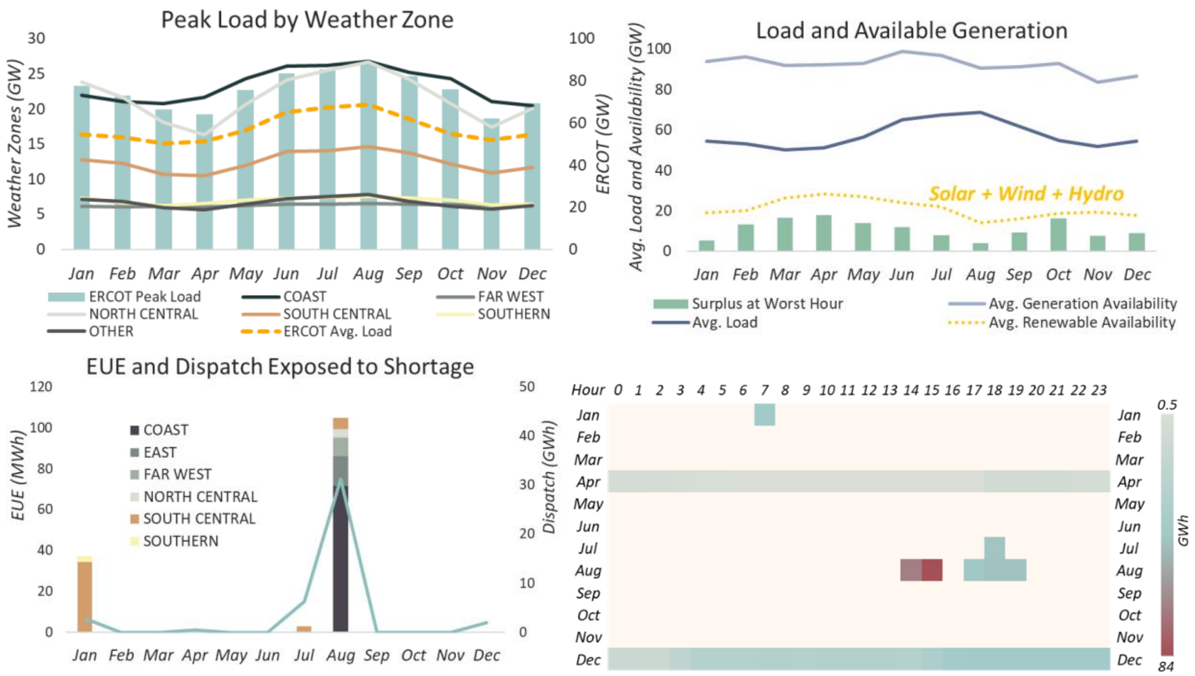

Figure 2- Left to Right: ***(a)*** *Peak load by weather zone and in peak and average load in all ERCOT,* ***(b)*** *Average load and generation availability in ERCOT. Generation availability accounts for maintenance and known forced outage.* ***(c)*** *EUE for each weather zone and total dispatch in all ERCOT exposed to shortage,* ***(d)*** *Hourly profile of generation exposed to shortage*

System-wide, Figure 2.b reveals that month of August has tighter conditions than other months given the balance between average load and generation availability. The tighter conditions are also reflected in EUE (Expected Unserved Energy) in the system for each month (Figure 2.c). In August load shed is observed in almost every weather zone in varying levels. The system-wide impact of shortage in the month of August is also apparent from the total dispatch exposed to shortage (Figure 2.d), which is the basis for the calculation of "Shortage Localization Index (SLI)" (Equation 8). In Figure 3.a, distribution of SLI across random outage samples in each month shows that in August, there are multiple draws with SLI close to 1, indicating generation in almost all locations is exposed to shortage, whereas the remainder of months consistently have an SLI index close to 0, revealing the local nature of shortages.

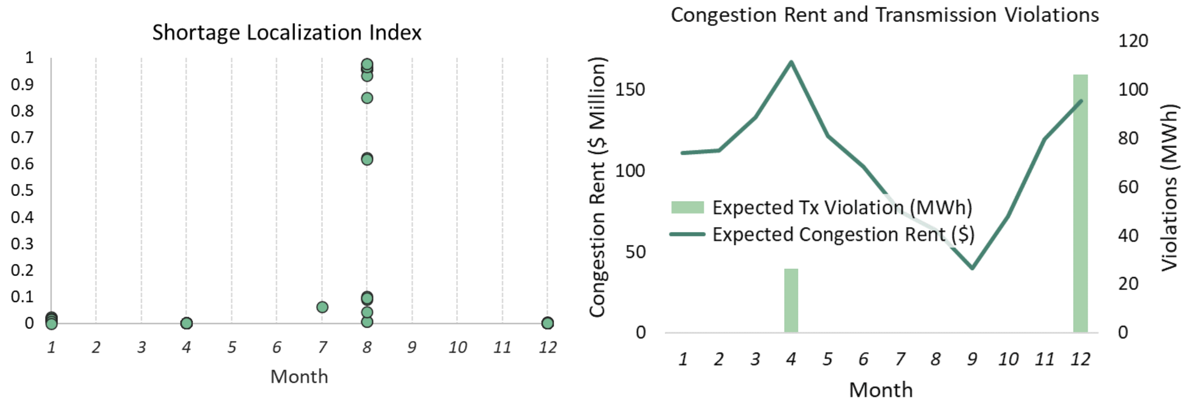

*Figure 3 – Left to Right : **(a)** Distribution of SLI across outage samples in each month **(b)** Congestion rent and violation of transmission (Tx) constraints*

Interestingly, the months of December and April have some dispatch albeit small in locations exposed to shortage, even though there are no load shed events, meaning that *(i)* shortage is due to other events in the system that set the price higher than the *shortage price threshold (ii)* and shortage is local.

In fact, Figure 3.b shows the total congestion rent (shadow price of each transmission constraint multiplied by flow on the transmission line) for each month and total violation amount of transmission constraints (total flow above or below the limit of each transmission line), revealing that the local shortages observed in the months of April and December are due to transmission congestion . Comparing the heatmap of adequacy prices in Figure 4 between the months of August and December shows the high system-wide adequacy prices in the month of August due to low supply margins and local nature of shortage conditions in December in the Coast zone due to transmission congestion.

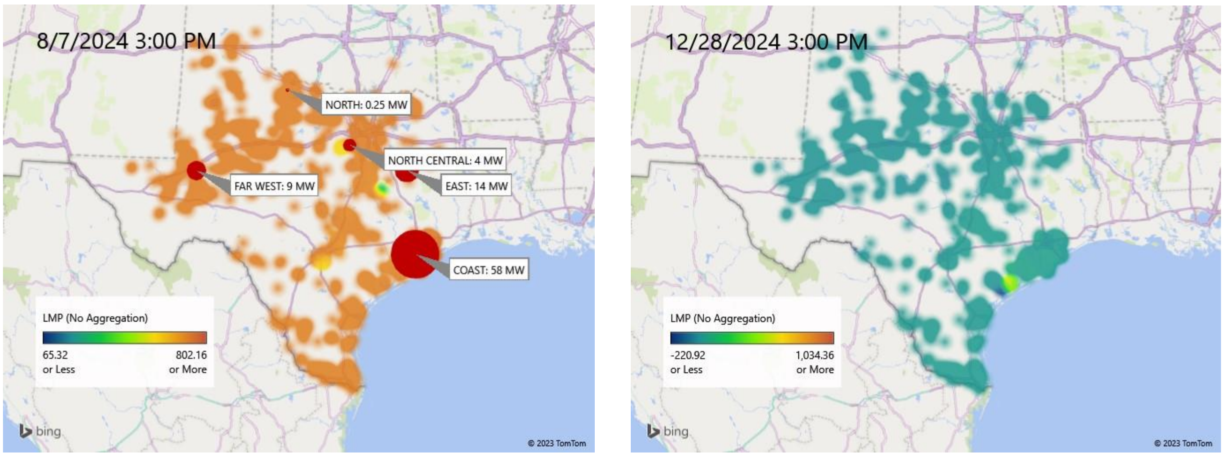

Figure 4 – Heat map of SNAP prices in a given hour in August and December. Bubbles in red represent load shed (MW) in each weather zone.

Transmission congestion is caused by simultaneous scheduling of maintenance for generating units in the same location. Combined with random outages that further affect available generation in this location, the transmission constraint is violated since shortage is resolved more economically rather than zone level load shed. In that case, the penalty price associated with violating transmission constraints sets the price higher than *shortage price threshold* in these locations (Equation 4), triggering a *shortage event* . In this case, staggering the maintenance of units in the same location resolves shortage, indicating the importance of dynamic maintenance scheduling and operational decisions around that.

Generator performance during shortage events categorized by unit type, measured by ELCCd values (Equation 7) is shown in Figure 5. More specifically, ELCCd for a generating unit is calculated as the average dispatch of the unit during shortage events in its location, divided by its capacity.

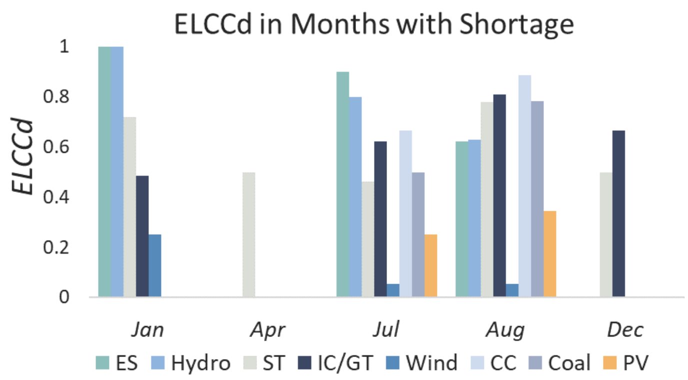

Figure 5 - ELCCd values in shortage event periods categorized by unit type. ST : Steam Turbine, ES : Energy Storage, CC : Combined Cycle

Figure 5 summarizes the different levels of capability in addressing shortages across different generation technologies. ELCCd values for certain unit type categories are missing in some periods since there is no shortage event observed at the location of these units in those periods. In summer months, wind units have low ELCCd due to shortages mostly being observed during mid-day when wind availability is low.

In summary, different metrics reveal different aspects of shortage events: *(i)* whether the issue is system-wide or local (i.e., shortage location index), *(ii)* duration of the event (i.e., number of hours), and *(iii)* severity of the event (i.e., EUE).

4.3 Stratified Sampling

Based on the initial round of 100 outage samples evaluated for each week, the month of December is allocated the most additional outage samples by the stratified sampling process (Figure 6.a).

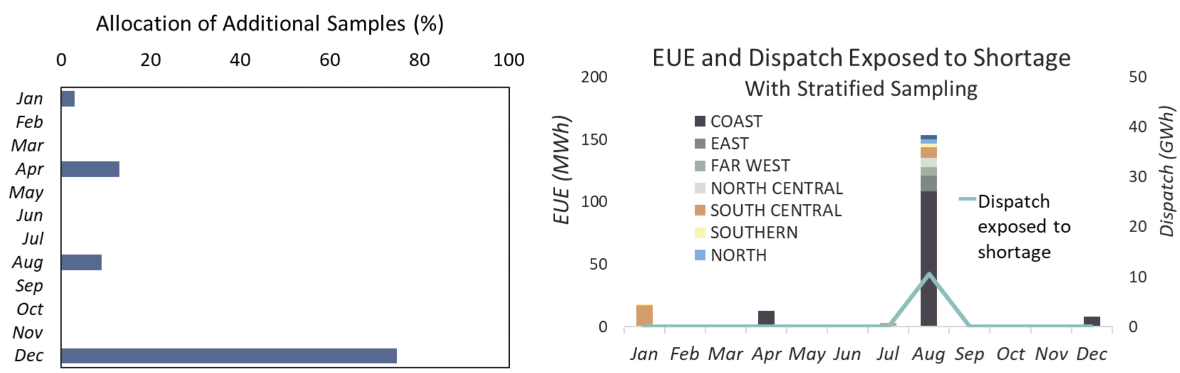

Figure 6 – Left to Right: ***(a)*** *Monthly allocation of additional outage samples as a result of stratified sampling analysis* ***(b)*** *Revised EUE with additional 5,000 random outage samples*

A total of 5,000 additional random outage samples are allocated to segments according to monthly proportions in Figure 6.a. Although the general outlook of severe months and regions with large amounts of load shed is the same as the first stage (Figure 2.c), the analysis with additional samples reveals load shed events in the months of April and December and in additional weather zones (North and West) that are not detected in the first stage with only 100 samples for each week (Figure 6.b).

In the first round of analysis with 100 outage samples per week, average standard error of shortage estimate over all shortage periods is 0.0124, while the standard error given the 5,000 additional outage samples drops to 0.003, revealing an increased precision of shortage estimate through stratified sampling allocation.

5. SUMMARY AND CONCLUSION

In this paper, we have laid out the foundation for a probabilistic nodal resource adequacy methodology that yields economically-justified metrics to value the contribution of generation, transmission, and load to times of scarcity. In particular, through the use of dual variables, the methodology addresses weaknesses of traditional adequacy methods by accurately simulating the impacts of storage, other time-coupled constraints, and transmission congestion. The methodology is applicable to decisions made in all time frames (e.g., build and retire, commitment, dispatch, storage targets, fuel allocations, emissions management), supporting analysis of an increasingly dynamic power system. A multi-layered computational approach is employed to improve computational performance and focus analysis on critical events driven by weather and random outages. Combined with cloud computing technology, the computational enhancements allow resource adequacy assessment to be performed with rapid turn-around time without engineering simplifications with important operational details. As illustrated in the application of the methodology to ERCOT system in US, operational decisions such as maintenance scheduling and engineering limits of transmission have major impacts to the adequacy of this system.

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