A Data-driven Method for Adaptive Reserve Requirement Estimation via Probabilistic Net Load Forecasting

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***Abstract*—With the increasing penetration of renewable energy, power systems are subject to more uncertainty. This makes power system reserve scheduling more challenging. Most of the current reserve requirement determination methods calculate reserve requirements based on historical data, which does not consider the real-time or future system uncertainty. In this paper, a data-driven method is developed to determine the non-spinning reserve requirement (NSRR) in the Electric Reliability Council of Texas (ERCOT) system. The method follows the procedure of the current ERCOT method while adaptively determining the NSRR based on probabilistic net load forecasts. Case studies with two years of ERCOT data show that the developed method significantly reduces the NSRR by introducing an adaptive temporal resolution and update rate. Sensitivity analysis with different forecasting and percentile thresholds indicates the flexibility of the developed method.**

***Index Terms*—Non-spinning reserve, reserve requirement, probabilistic forecasting**

I. Introduction

POWER systems are subject to inherent uncertainty, mostly due to the variability of system load, as well as uncertainty associated with generation. Even though forecasting techniques are able to partially mitigate the uncertainty, forecasting errors cannot be avoided. Therefore, power system operators maintain ancillary services through operating reserves to ensure the reliability and stability of the grid. These operating reserves are provided for the regulation, forecasting errors, equipment outages, and local area protection.

Different power markets offer their own ancillary services, where definitions and requirements of reserves are distinctive [1]. For example, The Electric Reliability Council of Texas (ERCOT) requires generation units that provide spinning reserves to respond in a shorter time (within the first few minutes) than other Regional Transmission Operators (RTOs) or Independent System Operators (ISOs). The Midcontinent ISO provides two separate products for both spinning and non-spinning reserves, which is different from most other ISOs/RTOs. Generally, all the ISOs/RTOs maintain at least three types of reserves, namely, regulation reserves, spinning reserves, and non-spinning reserves. Regulation reserves are usually used to correct the system area control error, while the others are used for contingency events. Compared to the first two categories of reserves, non-spinning reserves are less studied in the literature.

With the increasing penetration of renewable energy into power systems, the reserve scheduling problem becomes more challenging. Most ISOs/RTOs estimate reserves empirically from historical data. For example, the California ISO's requirement for contingency reserves is equal to the largest credible contingency or five percent of the load served by hydro generation and seven percent of the load served by thermal generation [2]. ISO New England requires the sum of ten-minute spinning reserves and ten-minute non-spinning reserves to be at least equal to the capacity of the largest single system contingency multiplied by a contingency reserve adjustment factor in the most recent operating quarter [3]. In addition, the contingency reserve requirement in the Midcontinent ISO is set to 2,000 MW, in which around 50% is spinning reserve and the rest is supplemental reserve [4]. Most of these reserve requirement determination algorithms fail to consider the information about system uncertainty available in real-time.

Recently, several works have improved reserve requirement determination by considering renewable power uncertainty, load forecasting errors, and control area imbalance in the historical data [5]. The consideration of system uncertainty (in terms of renewable generation, load, or net load) as one random variable neglects the heterogeneity of randomness over time. For example, Wang *et al.* [6] developed a distributionally robust optimization method, which determined the reserves by taking the wind power forecasting error distribution into account. However, the method exhausted all the error distribution scenarios, which did not differentiate the wind power distributions at forecasting time steps in the real-world operation. Similarly, the net load uncertainty information is quantified from the historical forecasts in Ref. [7], which was used to

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estimate the spinning reserve requirements.

In this paper, a data-driven method is developed to determine the adaptive non-spinning reserve requirement (NSRR) in ERCOT. The method balances the practical possibilities in daily operations and the utilization of an advanced uncertainty quantification method. Specifically, we follow the ERCOT NSRR determination procedure and estimate adaptive NSRR based on probabilistic net load forecasting. Three dimensions of adpativeness are introduced by the method to dynamically update NSRR by utilizing more recent forecasts with updating uncertainty information.

The remainder of the paper is organized as follows. Section II introduces the background of the current ERCOT method for NSRR determination. Section III describes the developed data-driven method with three-dimensional adaptiveness. Results are analyzed in Section IV, while Section V concludes the paper.

II. Background on the ERCOT Non-spinning Reserve Requirements

ERCOT determines ancillary service requirements annually and posts them by December 20th for the entire coming year (i.e., 1-year-ahead). The requirements can be updated 1-day-ahead or even closer to real-time if needed. In the ERCOT system, the non-spinning reserve service consists of generation resources capable of being ramped to a specified output level within 30 minutes or load resources that are capable of being interrupted within 30 minutes and that are capable of running (or being interrupted) at a specified output level for at least one hour [8].

The daily non-spinning reserve profile has six distinctive values, each of which indicates the requirement for a four-hour block (e.g., 2 AM–6 AM). Data that falls within the time block from the same month of the previous three years is used to determine one specific value, which also means that the daily profile is consistent within every month. Specifically, the hourly *net load uncertainty* data is used to determine the NSRR. The net load uncertainty is defined as:

$$\bar{\mathbf{y}}_{nl} := |\hat{\mathbf{y}}_{nl} - \mathbf{y}_{nl}| \tag{1}$$

where $\hat{\mathbf{y}}_{nl}$ and $\mathbf{y}_{nl}$ indicate net load forecast and actual net load vectors, respectively.

The net load and net load forecast are defined as: $\mathbf{y}_{nl} := \mathbf{y}_l - \mathbf{y}_w - \mathbf{y}_s$ and $\hat{\mathbf{y}}_{nl} := \hat{\mathbf{y}}_l - \hat{\mathbf{y}}_w - \hat{\mathbf{y}}_s$, where $\mathbf{y}_l$, $\mathbf{y}_w$, $\mathbf{y}_s$ are the actual ERCOT system-wide load, wind power generation, and solar power generation, respectively. $\hat{\mathbf{y}}_l$, $\hat{\mathbf{y}}_w$, $\hat{\mathbf{y}}_s$ are forecasts of the ERCOT system-wide load, wind power generation, and solar power generation, respectively.

The percentile of net load uncertainty from the same month of the previous three years is set as the sum of NSRR and regulation-up reserve requirement for one four-hour block of a month:

$$RR_{nlr,h} := P_{PC,\bar{\mathbf{y}}_{nl,h}} = f^{-1}_{\bar{\mathbf{y}}_{nl,h}}(PC) \tag{2}$$

where $P_{PC,\bar{\mathbf{y}}_{nl}}$ is the PCth percentile of the net load uncertainty and PC ranges from 70 to 95 based on the hourly net load ramp in ERCOT. f is the probability density function. h is the hour index.

Finally, the NSRR is calculated by subtracting the average regulation-up reserve of the same four-hour block:

$$RR_{nsp,h} = RR_{nlr,h} - RR_{regup,h} \tag{3}$$

where RR_{regup} is the regulation-up reserve.

There are a few areas in which the current ERCOT method could potentially be improved: (i) the current method lacks an updating mechanism. Even though the reserve profiles can be adjusted, the decision relies on the experience of the operator; (ii) the timeline of the reserve determination is not consistent with the daily operation schedule; (iii) the reserve levels are mainly based on historical data, thus the current and future system uncertainty is not considered.

III. Methodology

In this section, the overall framework of the developed method for determining the NSRR is introduced. Then the key components of the method are described, including net load forecasting and adaptive percentile thresholding.

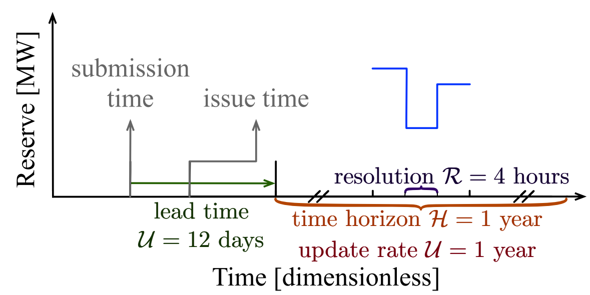

Figure 1. The reserve determination timeline.

A. The Overall Framework

To ensure the practical value, the developed method follows the procedure of determining the NSRRs in ERCOT's daily operations. There are four time-related requirements that need to be taken into account, which are lead time ($\mathscr{L}$), time horizon ($\mathscr{H}$), time resolution ($\mathscr{R}$), and update rate ($\mathscr{U}$) [9]. As shown in Fig. 1, the lead time indicates the difference between the reserve posting time and time of the first reserve value.[1] Time horizon is the span of the reserve profile generated at each issue time. Resolution is the interval between two distinctive reserve values. The update rate is the interval between two issue times. In the ERCOT system, the lead time is 12 days, the time horizon is 1 year, the time resolution is 4 hours, and the update rate is 1 year.

In this work, improvements of the developed method are made by introducing three-dimensional adaptivness into the ERCOT procedure, namely, (i) the adaptive time resolution,

[1] Submission time means the time that the data should be submitted and issue time means the time that a certain operation or process should be run. For example, there should be sufficient time between the submission time for NSRR and issue time to run the real-time economic dispatch model, so that data can be transferred, loaded, and prepared properly. In this paper, we assume issue time and submission time are the same for the simplicity purpose.

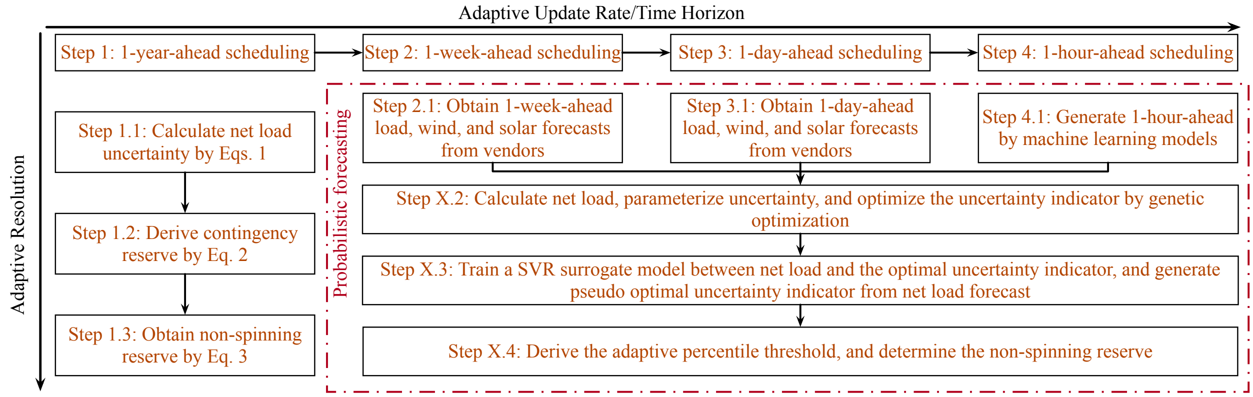

Figure 2. Overall framework of the developed method for NSRR estimation.

(ii) the adaptive update rate/time horizon, and (iii) the adaptive percentile thresholds. In more detail, the developed method calculates hourly NSRR instead of every four hours, since the four-hour block requirement is not a technical constraint. Second, in addition to the 1-year-ahead scheduling for the entire year, NSRRs are adaptively adjusted 1-week-ahead every week, 1-day-ahead every day, and 1-hour-ahead every hour. In this procedure, probabilistic load, wind, and solar forecasts with three different time horizons are utilized to provide uncertainty information of the power system, which is used to adjust the percentile threshold.

The overall process of the developed method is shown in Fig. 2. Based on the update rate/time horizon, the method contains four major steps, which provide NSRRs with ($\mathscr{L}^{12\text{ days}}$, $\mathscr{H}^{1\text{ year}}$, $\mathscr{R}^{1\text{ hour}}$, $\mathscr{U}^{1\text{ year}}$), ($\mathscr{L}^{1\text{ week}}$, $\mathscr{H}^{1\text{ week}}$, $\mathscr{R}^{1\text{ hour}}$, $\mathscr{U}^{1\text{ week}}$), ($\mathscr{L}^{1\text{ day}}$, $\mathscr{H}^{1\text{ day}}$, $\mathscr{R}^{1\text{ hour}}$, $\mathscr{U}^{1day}$), and ($\mathscr{L}^{1\text{ hour}}$, $\mathscr{H}^{1\text{ hour}}$, $\mathscr{R}^{1\text{ hour}}$, $\mathscr{U}^{1hour}$). The procedure of step 1 is similar to that described in Section II, except for the different resolution (i.e., 2-hour or 1-hour). In steps 2–4, probabilistic net load forecasting with different time requirements is used to predict the future system uncertainty. A novel two-step probabilistic forecasting method is adopted in these three steps, which quantifies the net load uncertainty dynamically at every forecasting step. At last, the percentile threshold is adaptively determined based on the probabilistic forecasts and is used to estimate the non-spinning reserve.

B. Net Load Forecasting

The key component in steps 2–4 is net load forecasting, which measures the system uncertainty and therefore directly impacts the NSRRs. In the developed method, a two-step probabilistic method is used to produce the probabilistic net load forecasts, which is shown in the red dashed box in Fig. 2. In the first step, the deterministic net load forecasts are obtained from vendors or produced by a machine learning method (i.e., random forest) [10]. Specifically, the base estimators in the random forest are classification and regression trees (CARTs), `ntrees`=1,000, and `mtry=5`. Then, the uncertainty is added to the deterministic forecasts by an optimal uncertainty indicator in the second step (steps X.3 and X4). The procedure of probabilistic net load forecasting is described as follows:

- ***Step X.1***: Obtaining load, wind power generation, and solar power generation from vendors for short-term forecasts or from the random forest forecasting model for very short-term forecasts.
- ***Step X.2***: Calculating net load and parameterizing the uncertainty of the net load in terms of μ and σ, where μ is assumed to be the net load value itself. Then, the quantile, q, and its corresponding pinball loss, L_q, are derived and expressed by q and σ:

$$F_t(y_{nl,t}|\mu_t,\sigma_t) = F_t(\sigma_t) \tag{4}$$

$$Q_t(p) = F_t^{-1}(p) = F_t^{-1}(p,\sigma_t) \tag{5}$$

$$L_{q,t}(q,\sigma_t) = \{q - H(y_t - Q_t(q))\}\{y_t - Q_t(q)\} \tag{6}$$

where t is a time index, which means the predictive distribution differs at different forecasting times; $F(\cdot)$ and $F^{-1}(\cdot)$ are a cumulative distribution function (CDF) and its corresponding inverse function, respectively; $Q(\cdot)$ is the quantile function; p and q are probability and a quantile, respectively; $H(\cdot)$ is the Heaviside step function.
Next, the net load uncertainty indicator, σ (the only unknown parameter), at each forecasting time step is optimized by minimizing the average pinball loss of all quantiles with a genetic algorithm (GA):

$$\begin{aligned} \sigma_t^* &= \arg\min_{\sigma_t} \frac{1}{N_q}\sum\nolimits_{q=1}^{N_q} L_{q,t}(\sigma_t) \\ s.t. &\qquad \zeta_1 < \sigma_{q,t} < \zeta_2 \end{aligned} \tag{7}$$

where σ^* is the optimized standard deviation; $N_q = 99$ is the number of quantiles; ζ_1 and ζ_2 are the lower and upper bounds of σ, which are 0.001 and 1, respectively.
- ***Step X.3***: A support vector regression (SVR) surrogate model, Ψ , is constructed to fit the actual net load and σ^* set $\{\mathbf{y}_{nl},\sigma^*\}$ in the training stage, which is used to generate unknown pseudo standard deviations, $\hat{\sigma}^*$, in the forecasting stage.

The random forest model and SVR model were empirically selected based on experience [10]–[12]. Note the focus of this paper is to develop a NSRR determination method that mitigates the uncertainties associated with forecasting errors rather than reducing forecasting errors by building the most accurate forecasting model.

C. Adaptive Percentile Thresholding

Different from most probabilistic forecasting that takes forecast target as a random variable, the developed probabilistic net load forecasting considers the forecast at each timestamp as a random variable. Therefore, the pseudo standard deviation at each forecasting timestamp, $\hat{\sigma}_t^*$, is an adaptive indicator of the future system uncertainty. The pseudo standard deviation is used to determine the adaptive percentile threshold:

$$PC_t = \frac{(\hat{\sigma}_t^* - \sigma_{min}^*)(PC_{max} - PC_{min})}{\sigma_{max}^* - \sigma_{min}^*} + PC_{min} \quad (8)$$

where σ_{max}^* and σ_{min}^* are the maximal and minimal optimized standard deviation, respectively. PC_{max} and PC_{min} are the maximal and minimal percentile threshold, respectively. Then, the net load percentile is obtained by plugging PC_t into Eq. 2. Finally, the non-spinning reserve is derived by Eq. 3.

IV. Experimental Results

This section introduces the dataset for case studies, the forecasting evaluation (including both historical net load uncertainty and future net load uncertainty), reserve requirement profiles determined by different steps, and sensitivity analysis of the reserve requirements in terms of the forecasting time horizon in the historical net load uncertainty and the uncertainty lower bound. All the experiments are conducted in `R`.

A. Data Description and Case Studies

In this research, the ERCOT hourly system-wide load, wind, solar data, and their short-term forecasts (up to 1-week-ahead) are used for case studies. The data spans from 2017-01-01 to 2018-12-31. The data in 2017 is used to determine the reserve requirement profiles in 2018. Ideally, the previous three years of data should be used for the reserve requirement calculations. However, only one year of data is used in the process due to the data limitation, whose impacts on the different methods are considered equivalent.

In case studies, the current ERCOT NSRR determination method (denoted as ERCOT) is considered as the baseline method, which is compared to results from the four steps described in Section III. Specifically, two reserve resolution cases, i.e., 2-hour and 1-hour (denoted as Step 2-2 and Step 2-1), are tested in step 2, and three forecasting update rates/time horizons, i.e., 1-week-ahead, 1-day-ahead, 1-hour-ahead (denoted as 7DA, 1DA, and 1HA), are analyzed in steps 2–4.

B. Forecasting Evaluation

Two sets of net load forecasts are used in the NSRR determination process, which are historical forecasts and real-time forecasts. Both forecasts are critical to the NSRRs. The forecasting normalized mean absolute percentage error (MAPE), normalized mean absolute error (nMAE), and mean root mean square error (nRMSE) are used to evaluate the deterministic forecasting. The probabilistic net load forecasting is evaluated by the normalized average pinball loss (nPL) [10].

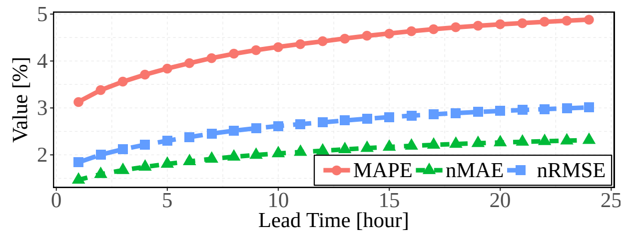

Figure 3. Forecasting error vs. lead time.

The deterministic forecasting errors of the ERCOT 2017 net load with respect to lead time are shown in Fig. 3. It is observed that the forecasting errors increase with the lead time. The impact of increasing forecasting errors will be analyzed in Section IV-D. The real-time forecasting results are listed in Table I. Similar to the historical forecasting, the real-time forecasting errors increase with the lead time for both deterministic and probabilistic forecasts.

Table I. Forecasting result evaluation metrics [%]

Step	Deterministic forecasting nMAE	nRMSE	MAPE	Probabilistic forecasting nPL
2	4.05	5.42	8.69	1.52
3	2.37	3.04	5.04	0.94
4	1.55	1.98	3.37	0.67

C. Reserve Requirement Comparison

NSRRs determined by the current ERCOT method and four steps of the developed method are calculated based on 3-hour-ahead net load forecasting uncertainty in the historical data (results with other lead time forecasts will be studied later). The minimal percentile threshold is set as 0.7 in this section (other thresholds will be discussed in the sensitivity analysis). The average hourly reserve requirements are listed in Table II. Please note that the NSRR calculated is different from the real ERCOT NSRR, since only 1-year of data is used and the net load uncertainty forecasting time horizon is short-term instead of mid-term. It is observed that by changing the update rate in step 2, the hourly NSRR is decreased by 6.11%. The hourly NSRR is reduced by 13.93%, 21.10%, and 50.62%, respectively, by the adaptive percentile thresholding based on forecasts with 7DA, 1DA, and 1HA time horizons.

Table II. Hourly average non-spinning reserve [MW]

Method	Note	Hourly average
ERCOT	The current ERCOT method	2353.87
Step 1 ($\mathscr{R}^{2\text{ hour}}$)	Result from step 1 with a 2-hour resolution	2268.05
Step 1 ($\mathscr{R}^{1\text{ hour}}$)	Result from step 1 with a 1-hour resolution	2210.16
Step 2	Weekly updated reserve	2026.09
Step 3	Daily updated reserve	1857.32
Step 4	Hourly updated reserve	1165.33

The hourly NSRRs in each month and each hour are shown in Figs. 4 and 5, respectively. The reserve reductions of the 1DA scheduling and 1HA scheduling are consistent and significant in all hours and months. On the contrary, 7DA scheduling may estimate larger reserve requirements, compared to the baseline method, due to the larger forecasting errors. It is

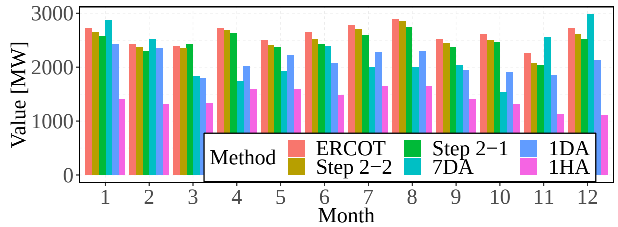

Figure 4. NSRR in each month.

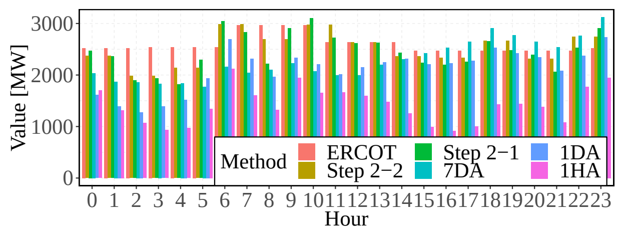

Figure 5. NSRR in each hour.

also found that the NSRRs with adaptive scheduling indicate a diurnal pattern.

D. Sensitivity Analysis

NSRRs estimated by the six models are all based on the historical net load uncertainty (previous 1-year forecasting errors), which are directly affected by the forecasting lead time and time horizon. Sensitivity of the NSRRs with respect to forecasting time horizon is shown in Fig. 6. It is observed that the NSRR increases with the time horizon of historical forecasts. The lower bound of the percentile in Eq. 8 also impacts the NSRR, which is shown in Fig. 7. These two parameters can be adjusted based on the ISO's need, which makes the developed method flexible to different requirements. For example, in seasons with more outages or larger forecasting errors, a larger lower percentile bound can be used in the method to hold more NSRRs.

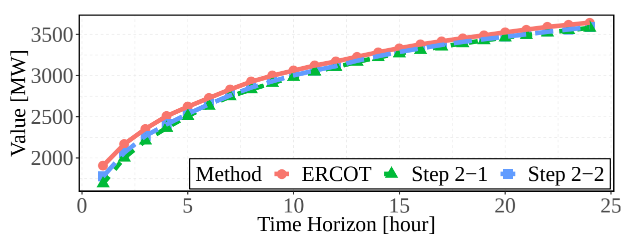

Figure 6. NSRR vs. time horizon of historical forecasts.

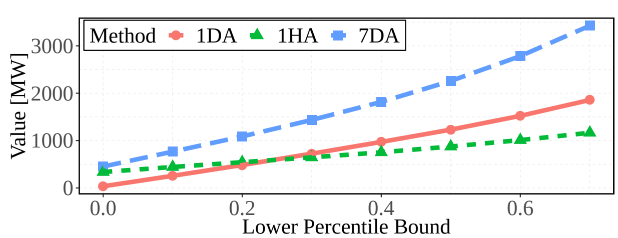

Figure 7. NSRR vs. lower percentile bound.

V. Conclusion

This paper developed a data-driven method for the Electric Reliability Council of Texas (ERCOT) system non-spinning reserve requirement (NSRR) determination. The method followed the ERCOT procedure to determine the NSRR, which made the developed method easy to implement in practice. In addition, the method took into account the future system uncertainty by relying on probabilistic net load forecasts. Three dimensions of adaptiveness were introduced in the developed method to dynamically updated the NSRR with higher temporal resolutions and varying confidence thresholds. Case studies showed that the developed method significantly reduced the NSRR while keeping flexibilities to adjust the NSRR reduction. Future work will validate the estimated NSRR with simulations of multi-timescale power system operations from both reliability and economic perspectives [13]. Impacts of additional years of data on the NSRR estimation will also be explored. In addition, methods without following the ERCOT procedure will be investigated, such as NSRR estimation by learning from NSRR and exogenous data using machine learning models.

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