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Impacts of Weather-Related Outages on DER Participation in the Wholesale Market Energy and Ancillary Services

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SUMMARY

Distributed energy resources (DERs) are valuable assets which bring about engagement of electricity consumers with the power grid. An important type of DER is nano-Grid (n-Grid) also known as distributed prosumer. An n-Grid is a residential or commercial building equipped with rooftop photovoltaic (PV) generation, fixed battery energy storage system (BESS), electric vehicle (EV) charger(s) serving the electric load. These resources can offer high flexibility to the power grid given proper incentives. A particular option is to offer ancillary service products (ASPs) through aggregation to the wholesale electricity market (WEM). The Federal Energy Regulatory Commission Order 2222 paves the way by mandating the WEM operators across united states to enable participation of DER aggregators in ASP markets. DERs, however, are connected to the distribution grid where the number of outages is much higher than the transmission grid. Also, they are usually energy limited resources whose stored energy might be drained during outages to supply their local loads when the grid is unable to do so. Therefore, they may be vulnerable to large distribution grid outages where many of them might be disconnected, and the aggregator might be unable to deliver the ASPs support in real-time.

In this paper, the impact of weather-related distribution feeder outages on the performance of n-Grid aggregator participating in the WEM ASPs is investigated. First, the probability of failure of distribution grid feeders is derived using novel machine-learning (ML) based algorithms. Using a past weather conditions, geographical features, aerial imagery and historical outages, the ML model is trained to predict the risk levels for each part of the distribution grid. Next, a novel bidding strategy for n-Grid aggregator participation in the day-ahead market (DAM) for energy and spinning reserve (SR) products is proposed. The feeder outage probabilities are incorporated in the proposed model for informed decision making of the aggregator. The simulation results demonstrate the aggregator can leverage this decision-making model to optimally trade energy and ASPs and hedge the financial risks associated with over-committing n-Grid resource availability to support these products.

KEYWORDS

Ancillary Service Product, Bidding Strategy, Distributed Energy Resources, nano-Grids, Feeder Outage Risk Forecast, Wholesale Electricity Market.

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1. INTRODUCTION

The advancement in DER technologies has brought significant advantages to the power grids. Amongst many, improving the resilience and reliability, demand response programs, peak shaving and load scheduling are worth mentioning [1]-[4]. In order to encourage more customers to install DERs and participate in smart demand management programs, the profitability of these technologies must be assured. An opportunity the DER owners may leverage to improve their profitability is by participating in the WEM through an aggregator that aims at ASP procurement [5]-[7]. The FERC order 2222 provides a formal framework for such incentives [8].

The n-Grid resources, namely, EV charging station, BESS, controllable electric loads (CELs) and rooftop PV, due to their high ramp capacities, are eligible options for participating in ASPs at the WEMs [9]-[10]. Due to their relatively small size, the n-Grid owners need a load serving entity, also known as an aggregator, to aggregate their demand and participate in the WEM on their behalf as shown in Fig. 1 [11]. According to Fig. 1, the aggregator submits energy and ASP bids to the WEM operator. Based on the rewarded energy and ASPs, it manages the resources of each agent by sending control signals to those resources and receiving measurement signals from them through home energy management system (HEMS).

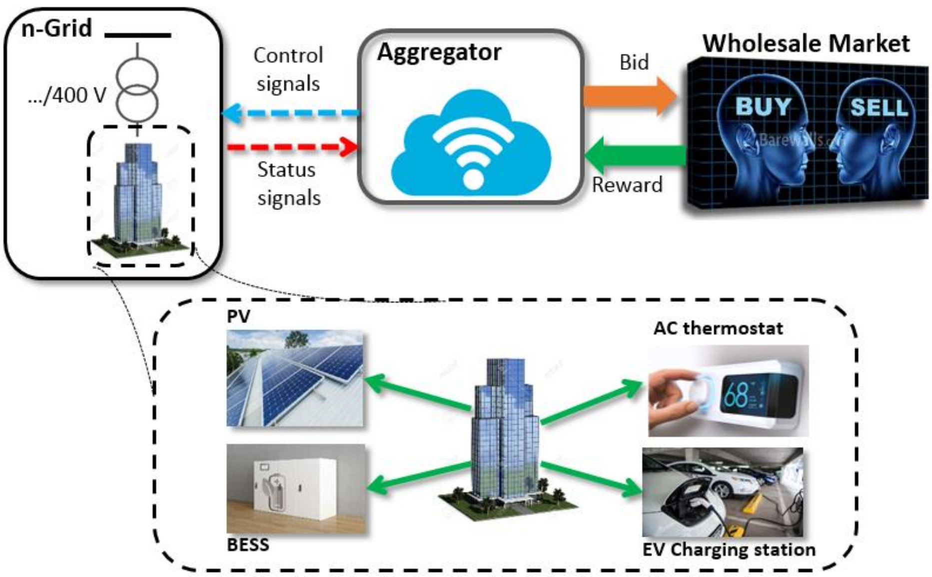

Figure 1 The n-Grid aggregator framework for participation in the WEM

The DERs can participate in peer-to-peer energy trading schemes [12]-[13], offer back-up services to the distribution grid [14]-[15] and offer different ASPs to the WEM [9]-[10], [16]-[17]. In [9], a bi-level optimization is proposed for aggregator participation in energy and SR markets considering n-Grid ability to manage its own resources. In [10], the n-Grid ability to provide flexible ramping product in California ISO market was assessed where the simulation results justified the high flexibility levels provided by n-Grids. A distributionally robust bidding strategy is proposed in [16] for collaborative participation of DERs in the market. Similar problem is solved using the information gap decision making in [17].

The n-Grids interfaced to the distribution systems may not be ready to offer their services due to many circumstances, such as distribution feeder outages, n-Grid failure, etc. In such instances, n-Grids are no longer able to deliver the rewarded ASPs requirements. One of the major reasons are weather-related events such as storms and other forms of inclement weather. The weather-related feeder outage prediction using artificial intelligence and machine learning based algorithms has brought a useful tool for the DER aggregators to manage the risks associated with the n-Grid availability for ASP participation [18]-[20]. This paper will answer the question "*How can the weather-related probability of failures in the distribution system affect the DER aggregator's energy management for participation in the energy and ASP markets*?" To answer this question, first, we introduce novel machine learning algorithms based on which such outage risk forecasting is performed. Second, we propose an aggregator market participation model which uses the outage forecasting data as an input to making informed decisions in terms of energy and ASP trades. This framework enables DER aggregators to prepare for unexpected outage situations and hedge the risks of profit loss due to the aforementioned circumstances.

2. OUTAGE RISK PREDICTION MODEL IN DISTRIBUTION GRID

Short circuits have always posed a significant threat to operation of power systems. Weather related outages constitute a major part of all outages in the system. Faults can adversely affect ability of DERs to fulfill their obligations in APSs. Recent advances in ML applications combined with Big Data and Geographic information systems allow for predicting outage risk levels in different parts of the distribution system, which can be utilized to take preventive actions to reduce total amount and mitigate duration of outages in the system. Risk levels also can accommodate aggregators with crucial information, which is then utilized to guide their bidding strategies in WEM [21]-[23].

The ML risk prediction models are first trained on historical data and then are put utilized to predict risk levels using weather forecasts and other predictors. The input features (predictors) for the model may include a variety of data: weather parameters (temperature, humidity, dew point temperature, atmosphere pressure, wind speed and direction etc.), lightning data, vegetation data, aerial and satellite imagery, land use and land cover maps etc. The model is then trained and tested, the accuracy metrics are analyzed, and the best combination of features is selected. The output of the model is conditional probability of outage occurrence for each part of the system in predefined time period in the future, under given weather forecast. The spatial and temporal granularity of the output risk predictions can be tuned for specific application. For instance, it has been shown that risk levels on a feeder can be used for optimal tree trimming scheduling [24]. In our case, we propose using hourly temporal resolution for a day-ahead predictions and spatial resolution is different feeder segments. Next an abbreviated discussion about process of ML model training and tuning is presented.

One begins with selecting a historical dataset of past outages and correlates it spatially and temporally with corresponding weather conditions and other predictors. After that the resulting dataset is wrangled: preprocessed, cleaned and transformed into applicable format. Depending on the application, the loss function and the ML algorithm are selected. Then ML algorithm is trained on the final dataset, using cross-validation technique. The latter is essential to acquire a non-biased performance metrics and use all of available data. The trained model is then validated on a separate validation dataset to assess its performance on new data. One also needs to tune hyper parameters of the algorithm. Grid search can be utilized for that purpose, which allows selection of optimal hyper parameters to improve model accuracy.

The process of establishing the final version of the ML risk prediction model is iterative. After acquiring first version of the model, various additional features are added to the training dataset to evaluate their effect on the performance. The new versions of the model (with additional features) are compared against the baseline model. Useful features are then identified and are incorporated into final version.

The results of the model can be represented graphically using GIS software by means of risk maps. The risk levels are mapped to the respective parts of the system. Then the color scheme is used to represent the different levels of risk: red for higher levels and blue for lower levels. Two examples of the risk maps are depicted in Figure 2. Left one shows normal risk levels for calm weather, the second one – elevated outage risk levels for severe weather conditions. Such risk maps present a graphical intuitive way of assessing overall outage risk level in entire system. The aggregators should use risk levels of the parts where the DERs are connected to the distribution grid to evaluate likelihood of the outages and refine their WEM bidding strategies for ASPs. Further analysis to develop risk mitigation strategies may be introduced, but that consideration will be the topic of a future paper.

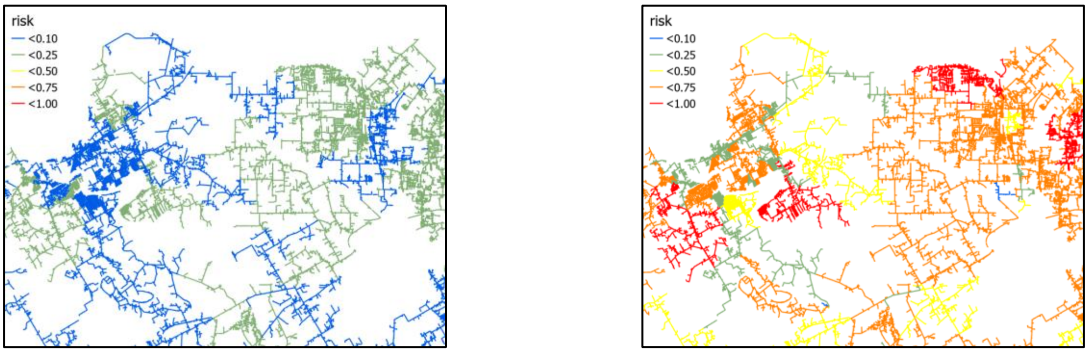

Figure 2 Risk Maps: normal (left), and elevated (right)

3. BIDDING STRATEGY MODEL

The aggregator needs to derive the availability of each n-Grid based on the feeder failure probabilities. To do so, at first, it picks up l^p number of the feeders with highest probability of failure at each hour ($l^p \subseteq L$ where L is the total number of feeders). Then, it generates feeder states with the combination of failures up to n^{out} simultaneous outages. Total number of feeder states will be: $\binom{l^p}{0} + \binom{l^p}{1} + \cdots + \binom{l^p}{n^{out}}$. For each feeder state, the grid state will be determined. A grid state is an array of length N (number of nodes) showing the availability of each grid node; if there is a path from node i to the point of common coupling, then the node is available and the value of element i in the grid state array is 1, otherwise it is unavailable and the value of element i is 0. The probability of each grid state is the product of the probabilities of the feeders being in that state.

By doing so for all the feeder states, we will derive $S \times N$ grid state matrix denoted by GS and a $S \times 1$ grid state probability matrix denoted by GSP, where S is the total number of unique grid states and N is the total number of nodes. The elements of GSP matrix will be normalized so the summation of probabilities becomes 1.0.

The aggregator aims to profit out of energy and spinning reserve APSs. The SR is mainly procured to respond to the contingencies in the power system. In order to be eligible for this ASP, the resources must be synchronized with the system and be able to deliver the ASP in less than 10 min. The objective function it attempts to maximize is to bid in the day-ahead market (DAM) is as follows:

$$OF = \max \sum_t (prof_t^{p,da} + prof_t^{sr,da} + prof_t^{p,rt} + prof_t^{sra}) \tag{1}$$

The first term indicates the profit of energy trading in the DAM, the second term stands for the profit of procuring spinning in the DAM, the third term is the profit of energy trading in the real-time market (RTM) and the last term is the profit of power under reserve in the RTM.

Note, if the aggregator sells p^{da} in the DAM, it must trade the difference of p^{da} and its realized power in the RTM based on the RTM energy prices. Assuming the expected power of the DERs at each node to be p_t^n, the profit out of energy based on the grid states probability can be written as:

$$\begin{aligned} prof_t^{p,da} + prof_t^{p,rt} &= p_t^{da}\lambda_t^{p,da} + \Delta p_t^{rt}\lambda_t^{p,rt} = p_t^{da}\lambda_t^{p,da} + \left(p_t^{rt} - p_t^{da}\right)\lambda_t^{p,rt} \\ &= p_t^{da}\left(\lambda_t^{p,da} - \lambda_t^{p,rt}\right) + \lambda_t^{p,rt}\int_{-\infty}^{+\infty} pr^p . \tilde{p}_t^{rt} . dp \\ &= p_t^{da}\left(\lambda_t^{p,da} - \lambda_t^{p,rt}\right) + \lambda_t^{p,rt}\sum_s pr_{s,t} . p_t^s = p_t^{da}\left(\lambda_t^{p,da} - \lambda_t^{p,rt}\right) + \lambda_t^{p,rt}\sum_n pr_{n,t} . p_t^n \end{aligned} \tag{2}$$

Here, $\lambda_t^{p,da}$ and $\lambda_t^{p,rt}$ are the energy LMPs for the DAM and RTM. pr_s and p_t^s are the probability of grid state s and available power of that state. Lastly, $pr_{n,t}$ and p_t^n are the probability of availability of node n and Expected power of that node (the matrix of availability of nodes can be calculated by $[PR^n] = [GS]^T[GSP]$). The expected power in the real-time is the expected power output of each node multiplied by the availability of that node.

The profit out of SR and SR activation is given as follows:

$$prof_t^{sr,da} + prof_t^{pur,da} = sr_t^{da}\lambda_t^{sr,da} + sra_t\lambda_t^{p,rt} \tag{3}$$

Where sr_t^{da} and sra_t are the SR and SR activation, and $\lambda_t^{sr,da}$ indicates the SR marginal price in the DAM.

The objective function (1) is subject to the following constraints. The total energy, SR and SR activation must be equal to the corresponding amounts of n-Grids:

$$p_t^{da} + p_t^{rt} = \sum_a (p_{a,t}^{pv} - D_{a,t}) + \sum_b \left(p_{b,t}^{dis} - p_{b,t}^{ch}\right) + \sum_k \left(p_{k,t}^{dis} - p_{k,t}^{ch}\right) \qquad \forall t \tag{4}$$

$$sr_t^{da} = \sum_b (sr_{b,t}^{dis} + sr_{b,t}^{ch}) + \sum_k (sr_{k,t}^{dis} + sr_{k,t}^{ch}) + \sum_d sr_{d,t}^{th} \qquad \forall t \tag{5}$$

$$sra_t^{da} = \sum_b (sra_{b,t}^{dis} + sra_{b,t}^{ch}) + \sum_k (sra_{k,t}^{dis} + sra_{k,t}^{ch}) + \sum_d sra_{d,t}^{th} \qquad \forall t \tag{6}$$

Where superscripts pv, dis and ch indicate PV, discharging and charging modes, respectively. Sets a, b, k and d, in order, stand for agents, BESS, EVs and thermal load. $D_{a,t}$ represents the load of agent a. According to (4), the total energy traded in the DAM and RTM equals the aggregated net-load of n-Grids. Based on (5) and (6), the total SR and SR activation equal the corresponding amounts procured by n-Grid resources.

The BESS technical constraints are enforced as follows:

$$p_{b,t}^{dis} + sr_{b,t}^{dis} + sra_{b,t}^{dis} \le x_{b,t}^{bs} \bar{P}_b^{dis} \qquad \forall b,t \tag{7}$$

$$p_{b,t}^{ch} - sr_{b,t}^{ch} - sra_{b,t}^{ch} \ge 0 \qquad \forall b,t \tag{8}$$

$$p_{b,t}^{ch} \ge \left(1 - x_{b,t}^{bs}\right) \bar{P}_b^{ch} \qquad \forall b,t \tag{9}$$

$$sr_{b,t}^{dis}.\frac{\Delta t}{\xi_b^{bs}} \le soc_{b,t}^{bs} - \underline{soc}_b^{bs} \qquad \forall b,t \tag{10}$$

$$sr_{b,t}^{ch}.\Delta t.\xi_b^{bs} \le soc_{b,t}^{bs} - \underline{soc}_b^{bs} \qquad \forall b,t \tag{11}$$

$$soc_{b,t}^{bs} - soc_{b,t-1}^{bs} = \left((p_{b,t}^{ch} - sra_{b,t}^{ch}).\xi_b^{bs} - (p_{b,t}^{dis} + sra_{b,t}^{dis})/\xi_b^{bs}\right)\Delta t \qquad \forall b,t \tag{12}$$

$$\underline{soc}_b^{bs} \le soc_{b,t}^{bs} \le \overline{soc}_b^{bs} \qquad \forall b,t \tag{13}$$

$$soc_{b,T}^{bs} \ge soc_{b,0}^{bs} \qquad \forall b \tag{14}$$

$$p_{b,t}^{dis}, sr_{b,t}^{dis}, psr_{b,t}^{dis}, p_{b,t}^{ch}, sr_{b,t}^{ch}, psr_{b,t}^{ch} \ge 0 \qquad \forall b,t \tag{15}$$

Where, $x_{b,t}^{bs}$ is the binary variable determining the operating mode of the BESS (0: charging mode and 1: discharging mode). Parameters $\bar{P}_b^{dis}$ and $\bar{P}_b^{ch}$ are the maximum discharging and charging power levels. $soc_{b,t}^{bs}$, $\underline{soc}_b^{bs}$ and $\overline{soc}_b^{bs}$ represent the stored energy and minimum and maximum energy levels, respectively. Lastly, ξ_b^{bs} is the efficiency of the BESS. The relationship of power output, SR and SR activation is presented in (7)-(9). Eq. (10) and (11) ensure the offered SR does not exceed the available energy. The energy stored at t is derived by (12), which is limited to its threshold based on (13). Constraint (14) assures the BESS is not drained at the end of time horizon. The non-negativity of variables is enforced in (15).

Similar constraints are enforced for each EV except that they are only applied at the times the EV is connected to the grid, i.e., $t \in [T_k^{arr}, T_k^{dep}]$.

The constraints of the AC are given below:

$$p_{d,t}^{th} - sr_{d,t}^{th} - sra_{d,t}^{th} \ge 0 \qquad \forall d,t \tag{16}$$

$$p_{d,t}^{th} \le \overline{L}_d^{th} \qquad \forall d,t \tag{17}$$

$$\theta_{d,t}^{in} - B_d \theta_{d,t-1}^{in} = (1 - B_d)\left(\theta_t^{amb} - COP_d.R_d^{th}.\left(p_{d,t}^{th} - sra_{d,t}^{th}\right)\right) \qquad \forall d,t \tag{18}$$

$$\underline{\theta}_d^{in} \le \theta_{d,t}^{in} \le \overline{\theta}_d^{in} \qquad \forall d,t \tag{19}$$

$$B_d \theta_{d,t-1}^{in} + (1 - B_d)(\theta_t^{amb} - COP_d.R_d^{th}.(p_{d,t}^{th} - sr_{d,t}^{th})) \le \overline{\theta}_d^{in} \qquad \forall d, t \in [2,T] \tag{20}$$

Where parameter $\overline{L}_d^{th}$ is the maximum power of AC, and B_d is the thermal constant. θ_t^{amb}, COP_d and R_d^{th} are the ambient temperature, thermal capacity and thermal resistant of the building. Lastly, $\theta_{d,t}^{in}$, $\underline{\theta}_d^{in}$ and $\overline{\theta}_d^{in}$ represent the building temperature and its minimum and maximum limits (these limits are set by the building occupants). According to (16), the maximum SR capacity the AC can offer is limited to its current power output. The power output is limited to its cap in (17). The building temperature at each time-step is obtained using (18). This temperature must fall in the comfort range set by occupants per (19). Lastly, based on (20), the offered SR must not exceed the energy needed to keep the inside temperature below the maximum limit.

4. CASE STUDY

We run the proposed model on the modified IEEE 13-bus radial distribution system as shown in Fig. 3. The data of this system are given in [25]. Each node contains 100 smart buildings with PV, BESS and EV charging stations. To simplify the analysis, we assume the outage probability of each line at hours 9 and 15 is 0.2 and for the rest of time-steps is 0. The priority of n-Grids when disconnected from the grid is to supply their own load.

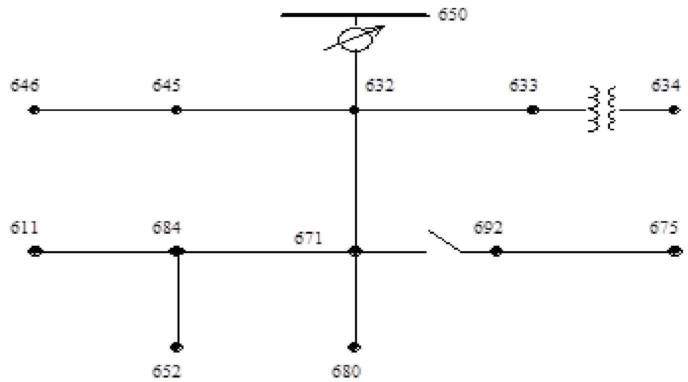

Figure 3 The IEEE 13-bus radial distribution test system topology.

We compare two test cases:

- TCI: The proposed model in which the probability of weather-related feeder outages is considered,
- TCII: A deterministic model in which the probability of feeder outages is ignored.

The profits and penalties associated with these two cases are given in the Table I.

Table 1. Profit and Penalties in TCI and TCII (k$)

Test Case	Energy cost DAM	Energy cost RTM	Profit SR	Penalty SR	Profit SRA	Penalty SRA	Total Cost
TCI	20.51	2.55	3.09	0	0.7	19.27	20.51
TCII	21.84	1.62	3.13	0.94	0.72	20.55	21.84

As can be seen, in TCII, the feeder outages are ignored. That has led to the excessive purchase of energy in DAM, which is traded in the RTM. This is important since the RTM energy prices are subject to high uncertainty and may impose high costs to the aggregator. Furthermore, by considering feeder outage probabilities in TCI, we see much lower penalty of spinning reserve and much higher profitability (total reserve profit is 3.79 k$ in TCI and 2.93 k$ in TCII). Since usually a small amount of spinning reserve is summoned for energy generation, we do not see any penalties for power under reserve. All in all, the total cost in TCI is 20.51 k$ which is low compared to 21.84 k$ in TCII which demonstrates the effectiveness of our proposed method.

The day-ahead energy purchase and SR procurement in the given test cases are depicted in Fig. 4. The faults are forecasted to occur at hours 9 and 15. As it is observed in Fig. 4 (a), in TCI where such outages are considered in energy purchased from the WSM, the aggregator purchased less energy during and after these hours. In fact, during these hours, a number of n-Grids are disconnected and cannot use the main grid to supply their demand. However, ignoring the possible outages in TCII, had led to over-purchasing of energy. The extra energy must be sold in the real-time market which is subject to high price fluctuations and may cause profit loss based on Table 1. The SR procurement in the test cases is given in Fig. 3 (b). Ignoring the probability of outages in TCII, has led to over-procurement of SR at hours 9-11 and 15-17 which must be delivered in real-time. Since the aggregator could not deliver the offered capacity in real-time and is penalized as given in Table 1.

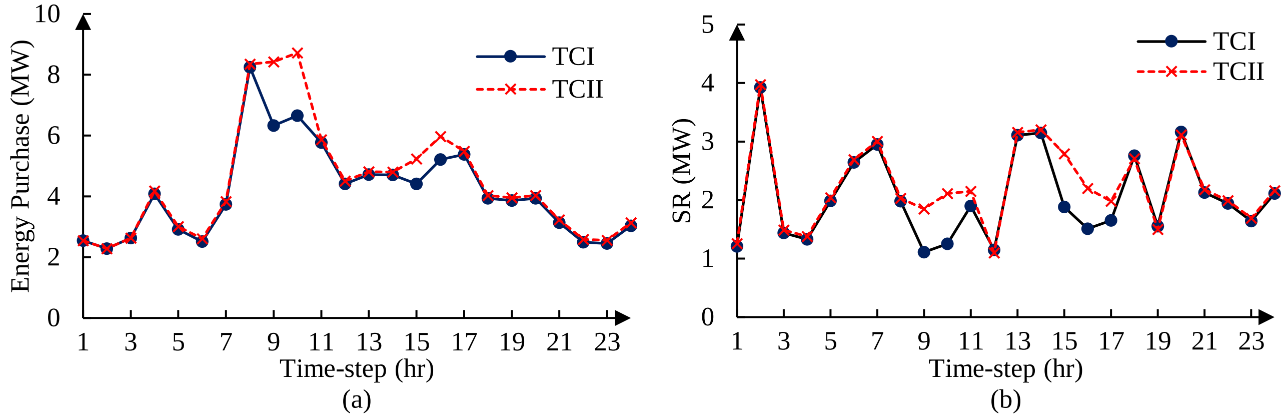

Figure 4 Energy purchase and SR procurement in TCI and TCII

On the other hand, in TCI, the aggregator has forecasted unavailability of n-Grid resources and therefore has offered SR capacity optimally and was not penalized for inability to deliver it in real-time. In neither of the test cases, the aggregator encountered inability to deliver SR activation and did not incur any penalties.

5. CONCLUSION

DERs are eligible resources for trading energy and procuring ASPs to the WEM. These resources are usually energy limited and any disconnect from the grid may affect their optimal operation by draining their energy to supply local load. We assessed the impacts of weather-related outages in the distribution system on the performance of DER aggregation participating in the wholesale energy and ASP markets. The distribution feeder outage probabilities are derived using Gradient Boosting Algorithm to feed the proposed optimization method. We conducted a case study on the modified IEEE 13-bus radial test system. The simulation results demonstrate the vital necessity of considering the probability of distribution feeder outages in scheduling DERs for participation in the WEM. We only considered probability of weather-related outages for 2 hours-ahead time horizon. In our case study, it is observed that such a framework has raised the total SR profit by ~29.3% and reduced the total costs by ~6.3%.

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