Informed Prosumer Aggregator Bidding Strategy via Incorporating Distribution Grid Outage Risk Predictions

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ABSTRACT FERC Order 2222 paves the way for aggregated distributed energy resources (DERs) participation in the wholesale electricity market. A particular DER assumed to be widely available in the future is the distributed prosumer (DP), also called virtual power plant (VPP), which may host PV generation, and stationary and mobile battery energy storage systems, in addition to the on-site passive load. DP aggregation and participation in the day-ahead market ancillary service products (ASPs) require managing uncertainties associated with load consumption and photovoltaic generation, electric vehicle (EV) scheduling, market-clearance prices, etc. Outages in the distribution grid may distort these energy-limited resources from their optimal operating point, potentially impacting their ability to deliver the committed ASPs in real-time. To address these challenges, first, we develop a machine learning algorithm to predict the risk of outages in distribution feeders. Next, we incorporate the distribution feeder State of Risk (SoR) predictions with the bidding model of the DP aggregator to provide an informed decision-making tool for optimal participation in the energy and ASP markets. The simulation results demonstrate the efficacy and scalability of the proposed model in improving the aggregator profitability and preventing penalties for the inability to deliver ASPs due to unexpected energy capacity limits of DP assets.

INDEX TERMS Aggregator, Bidding strategy, Distributed prosumer, Outage prediction, Wholesale market.

NOMENCLATURE

PARAMETERS

$\Lambda_t^e, \Lambda_t^{sr}$	DAM energy and SR price forecasts.
λ_{jt}^e	RTM energy price forecast for scenario j.
δ_{kt}	EV charging/discharging price according to EV contract with DPs.
Π_j	Weight of scenario j.
U	Unavailability of DP a.
A	Availability of DP a ($A = 1 - U$).
ϑ_{jt}	Expected portion of spinning reserve to be activated in real-time.
ρ^{sr}	Penalty per unit of undelivered SR in real-time.
ρ^e	Penalty per unit load loss in disconnected DPs.
τ	Portion of SR activated in real-time.
PV	PV generation.
L^{nc}	Non-controllable electric load of DP.
$\bar{P}^b$	Maximum BESS power limit.
$\underline{E}^b, \bar{E}^b$	Minimum and maximum BESS energy limits.
η^b	BESS efficiency.
θ^{amb}	Ambient temperature.
β_a, R_a	Building's thermal constant and resistance.
C_a	Air conditioner's coefficient of performance.
ϑ	Building's heat gains and losses.
$\underline{\theta}_a, \bar{\theta}_a$	Minimum and maximum building temperature.
$\bar{L}_a^{th}$	Maximum thermal power.
L^{df}	Deferrable load.
dc_a	Duty cycle of deferrable load.
PL, QL	Active and reactive load of the node.
r, x	Resistance and reactance of the line.
α	Confidence level.
ω	CVaR weighing factor.

VARIABLES

E^{da}, E^{rt}	Traded energy in DAM and RTM.
SR	Awarded spinning reserve in DAM.
Φ^{sr}	Penalty for not delivering the committed SR.
Φ^e	Penalty for load loss of disconnected DPs.

p	Power output.
sr	SR capacity without outage.
$\breve{sr}$	SR capacity after outage clearance.
psr	Power under spinning reserve.
l^{th}, l^{df}	Thermal and deferrable loads.
p^{u}	Stored energy used for power generation during outage.
$\tilde{p}^{u}$	Load loss during outage.
p^{d}	Extra PV generation stored during outage.
$\tilde{p}^{d}$	Spilled PV generation during outage.
x^{b}	Binary variable for BESS operating mode (0: charging, 1: discharging).
$\bar{e}_{t}^{b}$	Expected stored energy at BESS at the end of timestep t (weighted by risk of outages).
e^{b}	Stored energy at BESS at the end of timestep t, without an outage.
$\tilde{e}$	Stored energy at BESS at the end of timestep t, in case of outage.
θ	Building temperature.
pn_{m}^{a},qn_{m}^{a}	Active and reactive powers injected by DPs to node m.
pf, qf	Active and reactive power in the line.
V^{sq}	Variable denoting the square of node voltage.
ϕ	Value-at-risk.
γ_{j}	Excess of profit is scenario j over VaR.

SETS

t	Set of time steps.
j	Set of real-time scenarios.
a	Set of DPs.
k	Set of EVs.
DP_{a}	Set of EVs connected to DP a.
m, n	Set of nodes in distribution grid.

SUPERSCRIPTS

da, rt	Day-ahead, real-time
e, sr	Energy, spinning reserve (SR)
ch, dis	Charging and discharging modes
a	Distributed prosumer
ev	Electric vehicle
b	Battery energy storage
nc	Non-controllable load
th, df	Thermal load (HVAC) and Deferrable load
u, d	Positive and negative net-load during outage

I. INTRODUCTION

A. PROBLEM STATEMENT

Distributed prosumer (DP) is a unique type of distributed energy resource (DER) located in buildings potentially equipped with rooftop photovoltaic (PV) generation, battery energy storage system (BESS), and electric vehicle (EV) chargers [1], [2]. DP owners can profit by offering energy resources in different scenarios: a) distribution grid support services [3]–[5], b) participation in distribution markets with transactive energy exchanges through peer-to-peer energy trading [6]–[9], and c) ancillary service product (ASP) procurement for the wholesale electricity market (WEM) through aggregation [10], [11]. The independent system operator (ISO) may benefit from additional energy resources acquired through ASPs to secure reliable grid management. The Federal Energy Regulatory Commission (FERC) order 2222 is a milestone development that mandates the USA ISOs in the Eastern and Western Interconnection to facilitate ASP procurement by DER aggregators with the intent of lowering energy costs through enhanced competition, improving grid resilience, flexibility, and reliability, and stimulating more innovation in DER technologies [12]. However, the DP resources are energy-limited and subject to uncertainty stemming from (i) the risk of outages in the distribution grid leading to the drain of their stored energy to supply their load, and (ii) unexpected utilization of energy resources such as load and PV generation, EV initial state of charge (SOC), arrival and departure times. These sources of uncertainty, if not captured precisely, may result in the inability of the DP aggregator to deliver the committed ASPs resulting in monetary losses and potential penalties.

B. PRIOR RESEARCH

Different research efforts have focused on improving the profitability of DPs through energy trading and ASP procurement in the WEM. In [13], a distributionally robust optimization via a scenario-wise ambiguity set model was proposed for a collaborative DP bidding strategy in the day-ahead market (DAM). On this basis, a robust counterpart of the optimization problem by applying scenario-based affine recourse approximation was presented. In [14], the information gap decision algorithm was adopted to maximize the aggregator risk level per a preset level of the expected payoff. In [15], a tri-layer bidding framework for the aggregator bidding in the energy and regulation reserve market was developed. In this framework, bidding plans for the superordinate ISO and dynamic price curves for the subordinate DER owners were formulated. The authors in [16] used a regrouping algorithm with scenario trees to model the EV fleet market participation as a virtual battery. The participation of an EV aggregator in energy and different regulating reserve products was explored in [17]. In this model, the aggregator compensated the EV owners based on their battery degradation costs. In [18], a robust decision-making tool for an EV aggregator participating in the energy and regulation reserve markets was proposed. The aggregator participation in the demand response (DR) programs was assessed in [19]–[25]. A quantitative compensation mechanism to guarantee DP profitability in DR programs considering price volatility was presented in [19]. In [20], the regret-based approach in a bi-level optimization was proposed for proper contribution in a DR program, where the CVaR measure is employed for risk management. In [21] and [22], stochastic scenario-based provision of DR by the aggregator of DERs was discussed.

Uncertainty in renewable generation was addressed in [23] by implementing DR programs and EV aggregators via a coordinated stochastic decision-making model. In [24], the aggregator utilized the agents' load curtailment and load shifting abilities to participate in DR programs, and the agents were compensated based on pre-contracted incentive programs. In [25], a spatiotemporal transfer characteristic-based bidding strategy for participation in a DR program was developed. The Shapley value method was implemented to design proper incentive mechanisms based on which agents are rewarded. A bidding strategy model that considers the uncertainties of DP resources to optimally offer energy and secondary reserve in DAM and RTM was proposed in [26]. A two-stage stochastic optimization model was developed, in which the uncertainties of renewable generation, ambient temperature, load, and house occupancy were modeled through a set of scenarios. In [27], the authors developed the curves for price-quantity bidding of a thermal load aggregator in day-ahead and quantity-only bids in the real-time. They leveraged the flexibility of the thermal load in real-time to address the load and weather-related uncertainties. The authors in [28] proposed a hierarchical model predictive control (MPC) to ensure the delivery of energy under the committed ASPs in real-time. The aggregator benefited from this MPC to control the heterogeneous flexible resources of the DPs in real-time. The provision of flexibility by DP aggregators was discussed in [29]–[31]. A scenario-based optimization was developed in [29] to exploit DP flexibility in energy and tertiary reserve markets. The impacts of such DP aggregators on the market operation were explored in [30]. In [31], the joint participation of an aggregator in the wholesale energy and local flexibility markets was studied, where a robust adjustable optimization was used to tackle the uncertainties.

Research on the outage risk assessment offers various approaches. Authors in [32] used remote sensing data to enhance the performance of the outage prediction model. Random Forest is the core Machine Learning (ML) algorithm used in [33] to predict the number of customers losing power during hurricanes. Neural Network (NN) that exploits repair logs from a utility was trained to predict the duration of outages in [34]. The Long short-term memory (LSTM) cells captured temporal patterns in data to predict weather-related outages in [35]. Granular modeling of wind fields over a large area was demonstrated to improve prediction accuracy in [36].

C. OUR CONTRIBUTION

The previous studies ignore the impacts of outages in the distribution grid on the aggregator's ASP delivery and energy trading. During outages, the DPs rely on their stored energy to supply their load. If the DP is suddenly disconnected due to an outage, the aggregator must sell the surplus energy, purchased in the DAM, back in the RTM, which is subject to high price fluctuations. More importantly, ASP delivery by the temporarily disconnected DPs after reconnection can be impeded since less reserve capacity may be available due to supplying their load during the outage.

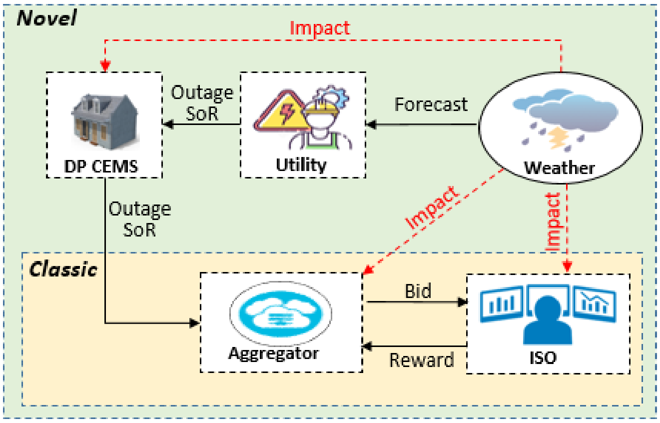

FIGURE 1. The risk-based approach to Aggregator bidding strategy.

The main novelty of this study is proposing an optimal aggregator bidding strategy model that (i) considers the impacts of risk of outages in distribution feeders on DP aggregator market participation and (ii) captures the uncertain behavior of different DP assets, which requires adequate modeling of the risk and uncertainty. Fig.1 depicts the general concept that distinguishes our approach. With reference to Fig. 1, our contributions are as follows:

- The weather-caused outages in the distribution feeder are predicted using a gradient boosting ML algorithm. The outage State of Risk (SoR) prediction algorithm output is incorporated into the aggregator bidding strategy model providing a decision-making tool for avoiding the ASP over-procurement, and excessive energy trading.
- The aggregator bidding strategy model is formulated as a stochastic scenario-based optimization problem for participation in the day-ahead energy and spinning reserve (SR) markets. The uncertainties associated with the DP resources are captured via representative scenarios. The aggregator profit risk is managed via conditional value-at-risk (CVaR).
- An optimal resource management algorithm for the disconnected DPs is proposed such that the comfort requirements of the building occupants are met, and the energy storage resources are minimally distorted from their optimal operating point soon after the DPS are reconnected.

D. PAPER ORGANIZATION

The coordination between the involved entities, i.e., aggregator, DP owner, ISO, and distribution utility, is described in Section II. The machine learning algorithm for outage SoR prediction in the distribution feeders is presented in Section III. The proposed bidding strategy model is outlined in Section IV and the disconnected DP resource management strategy is discussed in Section V. The case studies are provided in Section VI, and conclusions are stated in Section VII.

II. NEED FOR COORDINATION AMONG ENTITIES

The FERC Order 2222 does not specify the coordination requirements between the ISO and the utilities involved in the ASP procurement by the DERs (in our case DPs) aggregators in the wholesale market. It only mandates that such procurements should be available through the ancillary service bidding provisions.

We envisioned the proposed coordination shown in Fig. 2. The ISO clears the WEM at the transmission level, the distribution utility is responsible for maintaining the operating conditions of the distribution grid, and the aggregator aims to aggregate the DPs, which are the end-users of the grid services to trade energy and offer ASPs to the WEM. The distribution grid connection allows the physical means for the ASP delivery by the aggregator and is highly vulnerable to weather-caused outages. Based on the machine learning algorithm described in Section III, we assume the distribution utility provides the DPs with the SoR predictions of weather-caused outages in the distribution feeders through the customer energy management system (CEMS). In our use case, we assume that the CEMS receives control signals from the aggregator and SoR data from the utility and sends energy resource status and SoR data to the aggregator. The aggregator, based on the DP resource status, SoR data, the forecast of uncertain parameters in DP resources, WEM prices, and distribution grid technical constraints, runs the bidding strategy model presented in Section IV. Next, it submits energy and SR bids to the market. The ISO clears the day-ahead market where all the traded energy and rewarded ASPs are binding.

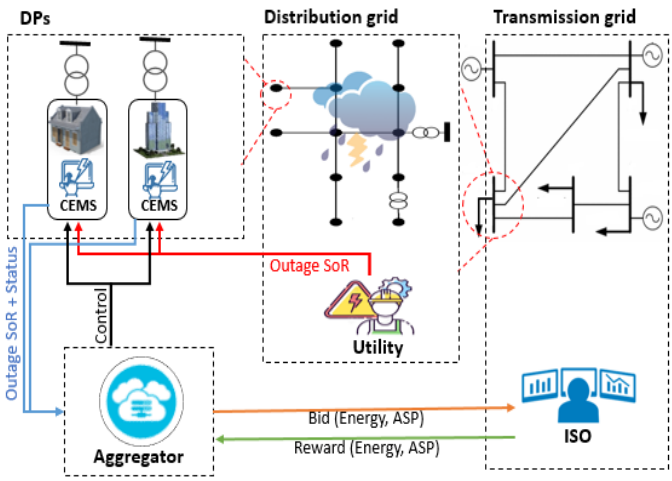

FIGURE 2. Coordination among aggregator, DPs, utility, and ISO.

III. PREDICTION OF THE SoR OF WEATHER-CAUSED DISTRIBUTION FEEDER OUTAGEs

This section describes the approach for predicting outages. The approach begins by collecting relevant data, including historical outage records from the utility company, geographical disposition of the distribution grid, weather information for the area of study, and any additional datasets that provide insight into conditions during grid operation (such as land cover, tree canopy, and leaf index) [37]-[39]. All input data is then preprocessed, cleansed, and transformed into a table-like form. The resulting datasets are subjected to a spatiotemporal correlation process, which matches the past outage occurrences to external environmental conditions. The ML algorithm is then trained on temporally separated data to predict the likelihood of outages in each part of the network. We use Catboost, a gradient boosting algorithm based on decision trees [36]. The algorithm was demonstrated to perform well on the task of outage prediction [36], [40]. To estimate the performance of the resulting prediction model, we use the testing dataset, which was not used during the training phase. The model is then finely tuned to achieve the best performance. The output of the model is the state-of-risk (SoR) of weather-caused outages in the distribution feeders.

Using weather forecasts for the future, the utility can utilize the model to obtain the outage SoR predictions in the grid. In our case, since the aggregator aims to participate in the day-ahead market, we use the SoR predictions for the 24 hrs of the next day. The utility sends SoR prediction data to the DP CEMS. The DP shares the data with the aggregator and aggregator incorporates the data within its bidding strategy model. The process is depicted in Fig. 3.

We define the outage SoR as:

$$SoR = Hazard \times Vulnerability = \mathbb{P}(inclemment\ weather) \times \mathbb{P}(outage|inclemement\ weather) \quad (1)$$

Here, *hazard* is the probability of inclement weather occurring, and *vulnerability* indicates the conditional probability of outage occurrence in the feeder if inclement weather occurs.

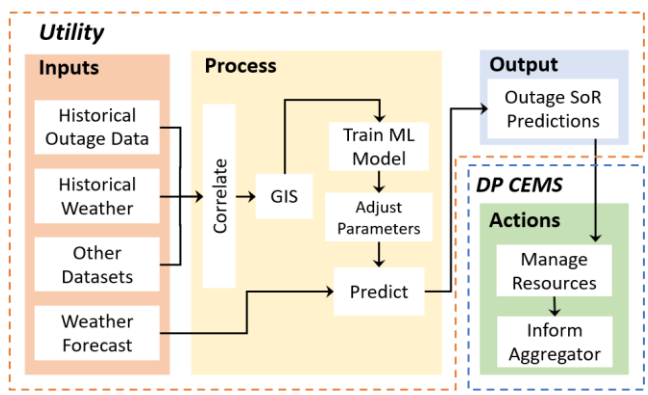

FIGURE 3. Distribution grid outage SoR prediction algorithm as a part of the DP awareness that may affect DP aggregator bidding strategy.

IV. BIDDING STRATEGY

We assume the aggregator participates in the DAM for energy and SR ASPs. The assumption is that the aggregator is able to directly manage the DP resources through CEMS. The ISOs in the US, such as California ISO and ERCOT, attempt to procure 100% of their SR capacity requirements in the DAM. To be eligible for SR procurement, the market participants must be connected to and synchronized with the grid and be able to activate the offered SR capacity in less than 10 min when required [40], [42]. Currently, only upward SR is procured in the U.S. markets. We assume that the aggregator attempts to trade all its energy needs and SR capacity in the DAM. The aggregator participates only in the energy market in the RTM and trades the required energy to meet its real-time demand. Note that during outages, the disconnected DPs are excluded from delivering the committed ASPs, and their constraints are enforced only when they are connected back to the grid.

The aggregator's objective function is to maximize its profit from DAM and RTM participation:

$$OF = \max\left\{\text{prof}^{da} + \mathbb{E}\left(\sum_j \text{prof}_j^{rt}\right)\right\}$$
$$= \max\left\{\sum_t \left(E_t^{da}\Lambda_t^e + SR_t\Lambda_t^{sr}\right) + \sum_j \Pi_j \sum_t \left(E_{jt}^{rt} + psr_{jt}\right)\lambda_{jt}^e \right.$$
$$\left. -\Phi_{jt}^{sr} - \Phi_{jt}^{e} + \sum_k \left(p_{jkt}^{ev,ch}\delta_{kt}^{ch} - p_{jkt}^{ev,dis}\delta_{kt}^{dis}\right)\right\} \tag{2}$$

The aggregator’s total profit consists of (i) the day-ahead profit coming from energy trading and SR procurement in DAM, and (ii) expected profit in real-time, including extra energy trading in RTM minus penalty for the inability to deliver the committed SR, minus penalty for load loss of disconnected DPs, plus profit/cost associated with charging/discharging EVs. Note that the EV charging and discharging prices for residential DPs are assumed to be zero, and are non-zero for commercial DPs. The objective function (2) is subjected to the constraints given below.

A. AGGREGATION CONSTRAINTS

The constraints for the aggregation of DPs are given below:

$$E_t^{da} + E_{j,t}^{rt} \le \sum_a p_{jat}^a A_{at} \qquad \forall j,t \tag{3}$$

$$SR_t \le \sum_a sr_{jat}^a \qquad \forall j,t \tag{4}$$

$$\Phi_{jt}^{sr} \ge \rho^{sr}\left(\sum_a \breve{sr}_{jat}^a U_{a,t-1} - SR_t\right) \qquad \forall j,t \tag{5}$$

$$\tau_{jt}.SR_t = psr_{jt} \qquad \forall j,t \tag{6}$$

$$\Phi_{jt}^{e} \ge \rho^{e}\sum_a \tilde{p}_{jat}^u U_{at} \qquad \forall j,t \tag{7}$$

$$\Phi_{jt}^{e}, \Phi_{jt}^{sr}, SR_t \ge 0 \qquad \forall j,t \tag{8}$$

Note, U_{at} and A_{at} stand for the unavailability (outage SoR) and availability of DP a at hour t, such that $U = 1 - A$. Based on (3), the total energy traded in DAM and RTM must meet the aggregated need of DPs multiplied by their availability at hour t. Per (4), the total offered SR in DAM must be limited to the total available SR capacity in DPs. The portion of the rewarded SR not delivered in real-time is penalized per (5). Parameter ρ^{sr} denotes the penalty for not delivering 1 MWh of the committed SR set by the ISO. This portion comes from the difference of the expected SR capacity of the DPs after the outage multiplied by their associated outage SoR and the total rewarded SR in DAM. The expected SR called for power generation in real-time as a portion of the total procured SR is set in (6). Equation (7) sets the penalty for load loss of the disconnected DPs. This constraint ensures that DPs have enough stored energy to supply their load in case of an outage. The non-negativity of load loss and SR shortage penalties and SR capacities is enforced in (8).

B. INDIVIDUAL PROSUMER CONSTRAINTS

The constraints for each DP are provided below:

$$p_{jat}^a = PV_{jat} - L_{jat}^{nc} - l_{jat}^{th} - l_{jat}^{df} + p_{jat}^{b,dis} - p_{jat}^{b,ch} + \sum_{k\in DP_a}\left(p_{jkt}^{ev,dis} - p_{jkt}^{ev,ch}\right) \qquad \forall j,a,t \tag{9}$$

$$sr_{jat}^a = sr_{jat}^{th} + sr_{jat}^{b,dis} - sr_{jat}^{ch} + \sum_{k\in DP_a}\left(sr_{jkt}^{ev,dis} + sr_{jkt}^{ev,ch}\right) \qquad \forall j,a,t \tag{10}$$

$$p_{jat}^u + \tilde{p}_{jat}^u \ge L_{jat}^{nc} + l_{jat}^{th} - PV_{jat} \qquad \forall j,a,t \tag{11}$$

$$p_{jat}^u = p_{jat}^{b,u} + \sum_{k\in DP_a} p_{jkt}^{ev,u} \qquad \forall j,a,t \tag{12}$$

$$p_{jat}^d + \tilde{p}_{jat}^d \ge PV_{jat} - L_{jat}^{nc} - l_{jat}^{th} \qquad \forall j,a,t \tag{13}$$

$$p_{jat}^d = p_{jat}^{b,d} + \sum_{k\in DP_a} p_{jkt}^{ev,d} \qquad \forall j,a,t \tag{14}$$

$$\breve{sr}_{jat}^a = \breve{sr}_{jat}^{b,dis} + \breve{sr}_{jat}^{b,ch} + sr_{jat}^{th} + \sum_{k\in DP_a}\left(\breve{sr}_{jkt}^{ev,dis} + \breve{sr}_{jkt}^{ev,ch}\right) \qquad \forall j,a,,t \tag{15}$$

$$p_{jat}^u, \tilde{p}_{jat}^u, p_{jat}^d, \tilde{p}_{jat}^d, sr_{jat}^a, \breve{sr}_{jat}^a \ge 0 \qquad \forall j,a,t \tag{16}$$

The above constraints can be divided into two cases:

- DP normal operation (9)-(10): the power balance for each DP is enforced in (9). The net power injection of a DP equals the summation of PV generation and storage discharging power minus total load and storage charging power. Per (10), the total SR capacity in normal operation is the summation of the SR capacities of DP resources.

- DP outage (11)-(15): in case of DP outage, the following two scenarios can happen:
  1) Positive DP net-load ($L^{nc}_{jat} + l^{th}_{jat} - PV_{jat} \geq 0$). In this case, the DP uses the stored energy in its BESS and EVs (if they are plugged in) to supply the extra load not supplied by PV generation. Per (11), the total power generation from the stored energy (p^{u}_{jat}) plus the load loss ($\tilde{p}^{u}_{jat}$) is equal to the DP net-load. Based on (12), the total power generation from stored energy equals the corresponding values from BESS and the plugged EVs.
  2) Negative DP net-load ($L^{nc}_{jat} + l^{th}_{jat} - PV_{jat} \geq 0$). In this case, the DP must store extra PV generation. Per (13), the PV generation stored in batteries (p^{d}_{jat}) plus the spilled PV generation ($\tilde{p}^{d}_{jat}$) is equal to the net-load. Enforced in (14), the total stored PV generation is equal to the corresponding amounts of the BESS and plugged EVs.

  Based on (15), the total SR delivered by DP <u>after outage clearance</u> is equal to the summation of SR capacities of DP resources.

The non-negativity constraints are enforced in (16).

C. BATTERY STORAGE SYSTEM CONSTRAINTS

The technical constraints associated with the BESS power output and SR capacity are presented below:

$$p^{b,dis}_{jat} + sr^{b,dis}_{jat} \leq x^{b}_{jat}\bar{P}^{b,dis}_{a} \qquad \forall j,a,t \qquad (17)$$

$$sr^{b,ch}_{jat} \leq p^{b,ch}_{jat} \leq (1 - x^{b}_{jat})\bar{P}^{b,ch}_{a} \qquad \forall j,a,t \qquad (18)$$

$$p^{b,u}_{jat} \leq \bar{P}^{b,dis}_{a} \qquad \forall j,a,t \qquad (19)$$

$$p^{b,d}_{jat} \leq \bar{P}^{b,ch}_{a} \qquad \forall j,a,t \qquad (20)$$

Constraints (17), (18) are for normal operation, and constraints (19), (20) are for the case of outage. Based on (17), the summation of the power output and SR capacity in discharging mode does not surpass the maximum output power limit. In other words, the SR capacity in discharging mode must be limited to the extra power generation capacity that is available. Per (18), the SR capacity in charging mode is limited to the current power output, which is consequently restricted to the maximum output power limit. In charging mode, the BESS can offer SR up to the current power output. In case of outages, the discharging or charging power is limited to the corresponding maximum limits enforced in (19) and (20).

The relationship between the stored energy in BESS and power output is as follows:

$$\begin{aligned}\bar{e}^{b}_{jat} = \bar{e}^{b}_{jat-1} &+ (p^{b,ch}_{jat}\eta^{b}_{a} - p^{b,dis}_{jat}/\eta^{b}_{a})A_{at} \\ &+ (p^{b,d}_{jat}\eta^{b}_{a} - p^{b,u}_{jat}/\eta^{b}_{a})U_{at} \quad \forall j,a,t\end{aligned} \qquad (21)$$

$$e^{b}_{jat} = \bar{e}^{b}_{jat-1} + p^{b,ch}_{jat}\eta^{b}_{a} - p^{b,dis}_{jat}/\eta^{b}_{a} \quad \forall j,a,t \qquad (22)$$

$$\tilde{e}_{jat} = \bar{e}^{b}_{jat-1} + p^{b,d}_{jat}\eta^{b}_{a} - p^{b,u}_{jat}/\eta^{b}_{a} \qquad \forall j,a,t \qquad (23)$$

$$\underline{E}^{b}_{a} \leq \tilde{e}_{jat}, e^{b}_{jat}, \bar{e}^{b}_{jat} \leq \bar{E}^{b}_{a} \qquad \forall j,a,t \qquad (24)$$

Here, three variables for the stored energy in BESS are defined: (i) the expected stored energy ($\bar{e}^{b}_{jat}$) the end of timestep t in which the outages SoR is weighted, (ii) the stored energy (e^{b}_{jat}) at the end of timestep t in case of normal operation, and (iii) the stored energy (e^{b}_{jat}) at the end of timestep t in case of outage. According to (21), the expected stored energy in BESS at the end of t is a function of the stored energy at $t-1$, and charging and discharging power weighted by the outage SoR. Based on (22), the stored energy at the BESS in the case of normal operation without outages is a function of the expected energy at $t-1$, and charging and discharging power in normal operating mode at t. As enforced in (23), the stored energy in case of outage depends on the charged/discharged power during the outage, and the energy before the outage. Per (24), the three stored energy variables must fall within the minimum and maximum limits of the battery storage capacity.

The connection between the SR capacity and the stored energy is given below:

$$sr^{b,dis}_{jat} \leq \left(e^{b}_{jat-1} - \underline{E}^{b}_{a}\right)\eta^{b}_{a} \qquad \forall j,a,t \qquad (25)$$

$$\breve{sr}^{b,dis}_{jat} \leq \left(\tilde{e}_{jat-1} - \underline{E}^{b}_{a}\right)\eta^{b}_{a} \qquad \forall j,a,t \qquad (26)$$

$$\breve{sr}^{b,ch}_{jat} \leq sr^{b,ch}_{jat} \qquad \forall j,a,t \qquad (27)$$

$$p^{b,dis}_{jat}, p^{b,ch}_{jat}, sr^{b,dis}_{jat}, sr^{b,ch}_{jat} \geq 0 \qquad \forall j,a,t \qquad (28)$$

Ensured in (25), the offered SR in normal operation in discharging mode must be limited to the available stored energy. Similarly, per (26), the SR capacity after outage clearance must be limited to the corresponding stored energy. The SR capacity in charging mode after outage clearance at t cannot exceed the SR capacity in normal operation at that timestep enforced in (27). The non-negativity constraints are set in (28).

D. ELECTRIC VEHICLE CONSTRAINTS

A set of constraints similar to the BESSs is enforced for the connected EVs. Note that the EV constraints are applied only for $t \in [t^{arr}_{jk}, t^{dep}_{jk}]$ where t^{arr}_{jk} and t^{dep}_{jk} are the arrival and departure time of EV k, forecasted in scenario j. For the sake of conciseness, the EV constraints are not repeated here.

E. CONTROLLABLE LOAD CONSTRAINTS

The thermal and deferrable loads account for the controllable loads of DPs. The building temperature can vary between the minimum and maximum comfortable temperatures set by building occupants to offer SR capacity. The deferrable load is defined as the load currently in use which can be postponed to later times such as dishwasher and laundry appliances. The thermal load and deferrable load can be used for ASP procurement. We do not consider the lighting loads for ASP delivery. The lighting load cannot be adjusted per ISO's demand for SR delivery since the SR is used frequently which impacts the comfort of occupants. The lighting load can be adjusted by the building occupants during the times with low occupancy (for example during weekends/holidays in commercial buildings) to lower the DP demand. Our assumptions only apply to the normal grid operation and regular ASP procurement/delivery. In cases of high impact low frequency (HILP) events, such as infrequent winter storms, hurricane, earthquake, and wildfire, non-critical loads (including non-critical lighting) may be shed for ASP delivery under demand response or emergency reserve. Such cases are out of the scope of this study.

According to [43], the technical constraints for thermal load are as follows:

$$\theta_{jat} = \beta_a\theta_{jat-1} + (1-\beta_a)(\theta_{jt}^{amb} - C_a R_a l_{jat}^{th}) + \vartheta_{jat} \quad \forall j,a,t \tag{29}$$

$$\underline{\theta}_a \le \theta_{jat} \le \bar{\theta}_a \quad \forall j,a,t \tag{30}$$

$$0 \le sr_{jat}^{th} \le l_{jat}^{th} \le \bar{L}_a^{th} \quad \forall j,a,t \tag{31}$$

$$\beta_a\theta_{jat-1} + (1-\beta_a)(\theta_{jt}^{amb} - C_a R_a(l_{jat}^{th} - sr_{jat}^{th})) + \vartheta_{jat} \le \bar{\theta}_a \quad \forall j,a,t \tag{32}$$

The building temperature as a function of the AC load and building parameters is provided in (29). The building temperature must fall within the comfort range of building occupants set in (30). Per (31), the AC SR capacity is limited to its current load, which in turn is limited to the AC maximum power. Constraint (32) ensures that the building temperature does not exceed its maximum limit when the offered SR is activated, i.e., the AC load is called to lower its power consumption.

According to [43], the constraints for deferrable load are:

$$\sum_t l_{jat}^{df} = \sum_t L_{jat}^{df} \quad \forall j,a \tag{33}$$

$$l_{jat}^{df} \le \sum_{h=\max(1,t-dc_a)}^{t} L_{jah}^{df} \quad \forall j,a,t \tag{34}$$

Based on (33), the total deferrable load supplied throughout the day is equal to the forecasted deferrable load. Constraints (33)-(34), ensure the deferrable loads are supplied during their duty cycle set by building occupants.

F. GRID CONSTRAINTS

The underlying distribution grid technical constraints must be regarded. In this vein, a linear approximation of the distribution grid power flow model is used as follows [44]:

$$pn_{mt}^{a} - PL_{mt} = \sum_{n,n\neq m} pf_{mnt} \quad \forall m,t \tag{35}$$

$$qn_{mt}^{a} - QL_{mt} = \sum_{n,n\neq m} qf_{mnt} \quad \forall m,t \tag{36}$$

$$qn_{mt}^{a} = pn_{mn}^{a}\left(\frac{QL_{mn}}{PL_{mn}}\right) \quad \forall m,t \tag{37}$$

$$V_{mt}^{sq} - V_{nt}^{sq} = 2(r_{mn}pf_{mnt} + x_{mn}qf_{mnt}) \quad \forall mn,t \tag{38}$$

$$\underline{pf}_{mn} \le pf_{mnt} \le \overline{pf}_{mn} \quad \forall mn,t \tag{39}$$

$$\underline{qf}_{mn} \le qf_{mnt} \le \overline{qf}_{mn} \quad \forall mn,t \tag{40}$$

$$\underline{V}_{m}^{sq} \le V_{mt}^{sq} \le \overline{V}_{m}^{sq} \quad \forall m,t \tag{41}$$

Equations (35), (36) ensure that the active and reactive powers injected into each node are equal to the corresponding values in the distribution lines connected to that node. Per (37), the reactive power of DPs follows the same portion of the reactive to active power of other loads connected to that node. The voltage drop across a line as a function of line power and impedance is given in (38) where V^{sq} is a linear variable representing the square of node voltage. This variable is used to linearize the power flow constraints. Lastly, constraints (39)-(41) set the minimum and maximum limits for the line active and reactive powers and the node voltages.

G. PROFIT RISK MEASURE

The CVaR risk measure is implemented as follows [43]:

$$\max\left\{(1-\omega).\mathrm{OF} - \omega\Big(\phi + \frac{1}{1-\alpha}\sum_j \Pi_j\gamma_j\Big)\right\} \tag{42}$$

$$\mathrm{prof}_j^{rt} + \phi \ge -\gamma_j \;;\quad 0 \le \gamma_j \quad \forall j \tag{43}$$

Here, ϕ is the value-at-risk (VaR) denoting the maximum profit the aggregator can reach for a given confidence level α, where the probability of the profit not exceeding the VaR is lower than $(1-\alpha)$. Variable γ_j is the excess of profit in scenario j over the VaR. The CVaR denotes the expected profit if the profit falls below the VaR. Weighing factor ω provides a trade-off between the aggregator profit and the risk management from CVaR.

H. SOLUTION PROCEDURE

The solution procedure for aggregator bidding in the DAM is provided in Fig. 4. The aggregator, based on its historical data of PV generation, load, EV scheduling, SR activation, and market prices, generates real-time forecast scenarios. It also receives the grid status forecast from the distribution utility, and the weather-related outage SoR prediction from DP CEMS. Based on these input data, the aggregator runs the bidding optimization with objective function (42) subject to constraints (3)-(41) and (43). The outputs of this optimization are the aggregator's desired energy and SR capacity in DAM. Then, the aggregator submits energy and SR bids to the market. After receiving the bids from all market participants, the ISO clears the day-ahead market, where all of the rewarded energy and ASPs are binding. The aggregator controls the DP energy resources through CEMS to deliver ASPs and comply with ISO dispatch commands. The disconnected DPs manage their resources through the CEMS based on the algorithm described in Section V.

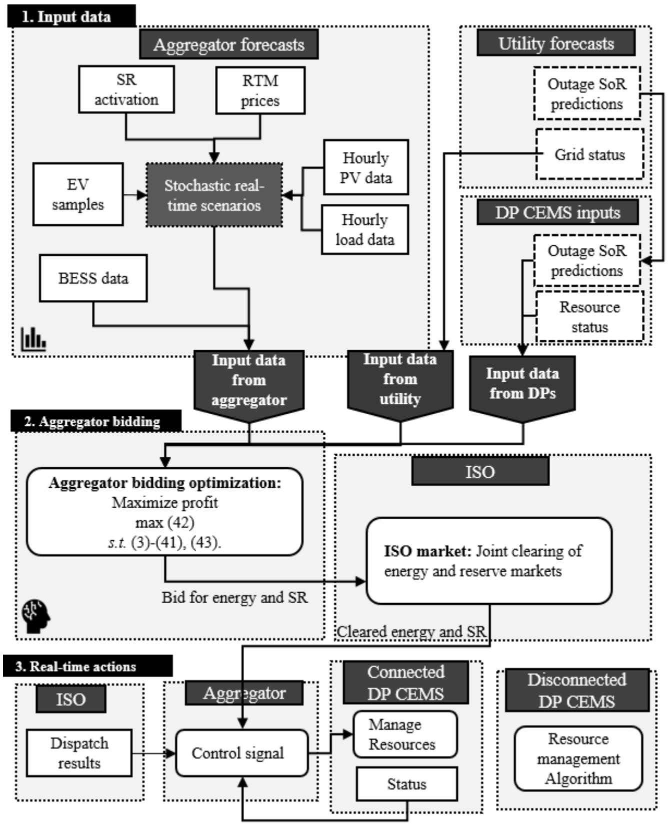

FIGURE 4. Solution Procedure.

V. RESOURCE MANAGEMENT DURING OUTAGE

When an outage occurs and several DPs are disconnected, DP resource management's goal is to meet DP occupants' convenience requirements, supply the loads or absorb the extra power generation. To do so, we propose the resource management strategy given in Fig. 5. This algorithm is run by the DP CEMS during outages. On this basis, first, the thermal load is lowered to its minimum level set by building occupants and the deferrable loads are postponed to later times. Then, if the PV generation is greater than the remaining load, the extra energy is stored in EVs and BESS; otherwise, the BESS and EVs are discharged to supply the remaining load. Note that the EVs, if connected, are charged before the BESS and discharged after BESS. The reason is that the energy stored in EVs is of a higher priority for the owners since they may need to use it for trips.

Algorithm: DP resource management in outages

raise temperature to maximum ($\theta \rightarrow \bar{\theta}$)
postpone deferrable load (l^{df})

if load lower than PV output ($L^{nc} + \underline{l}^{th} \leq PV$)
  store in the plugged EVs ($p^{ev,d}$)
    if more PV energy left
      store in BESS ($p^{b,d}$)
        if more energy left
          set temperature (θ) to normal
    remaining PV energy is spilled energy ($\tilde{p}^{d}$)

else ($L^{nc} + \underline{l}^{th} \geq PV$)
    use BESS energy ($p^{b,u}$)
    if more energy needed
      use plugged EVs ($p^{ev,u}$)
    remaining load is load loss ($\tilde{p}^{u}$)

FIGURE 5. Resource management strategy for disconnected DPs.

VI. CASE STUDIES AND SIMULATION RESULTS

A. MAIN ASSUMPTIONS

We assume a distribution grid with 10 feeders, and 100 DPs connected to each. Of the total of 1000 DPs, we assume that 800 are residential, and 130 are small, 50 medium, and 20 large commercial buildings. The buildings' PV generation and electric load data are discussed in [45], [46]. Currently, 28% of the residential PV projects in Texas include BESS, compared to 99% in California [47]. To have a realistic assumption, we consider that half of the buildings are equipped with BESS (400 BESSs in residential and 100 BESSs in commercial buildings). The BESS capacity follows a discrete uniform distribution in the range of [5kWh, 10kWh] in residential, and [10kWh, 25kWh] in commercial buildings. The maximum power run-time for BESSs is randomly selected from [2hr, 4hr, 6hr]. Since the primary source of SR in DPs comes from energy storage, the aggregator only contracts with the DPs that own BESS and/or EV, and would offer their availability. Hence, we assume 500 EVs in residential buildings and 500 EV chargers in commercial buildings. The EV battery capacity in kWh is randomly selected from [30, 40, 50, 60] with a maximum charging power in the range of [7kW, 12kW]. We also assume that the minimum and maximum temperature comfort ranges set by building occupants are uniformly distributed between [67°F, 75°F] and [72°F, 80°F], respectively. The deferrable load accounts for 20% of the total load in residential and 0 in commercial DPs. We set $\alpha = 0.95$ and $\omega = 0.5$ in the CVaR.

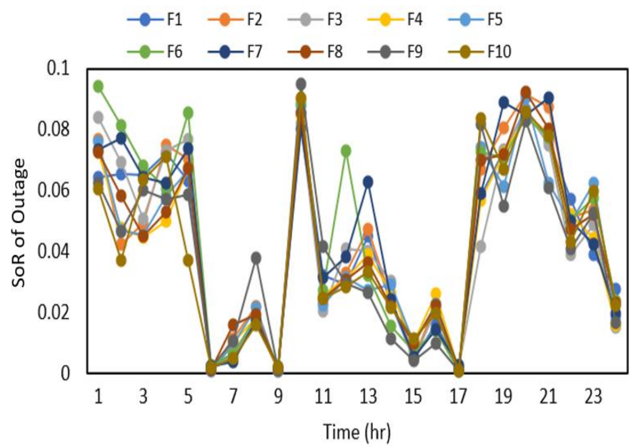

FIGURE 6. Outage SoR for 10 distribution feeders.

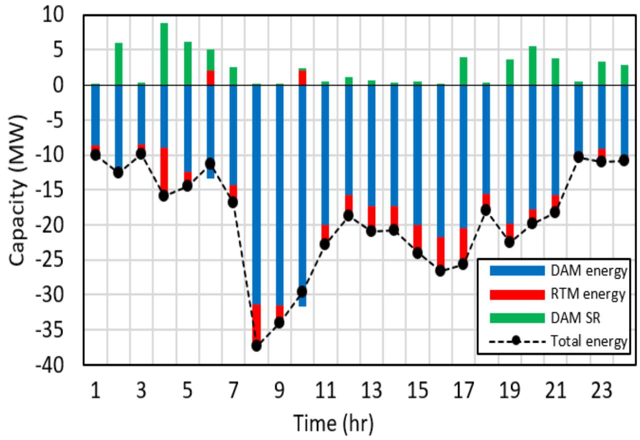

FIGURE 7. Average traded energy and SR in DAM and RTM in UCI.

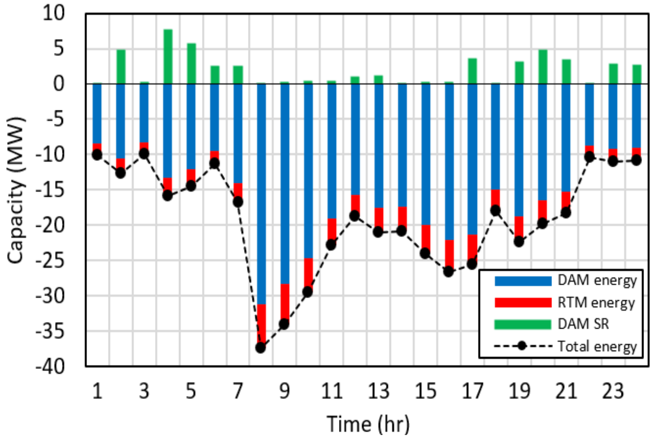

FIGURE 8. Average traded energy and SR in DAM and RTM in UCII.

The scenario generation process for PV generation, loads, RTM prices, building occupancy and heat gains and losses, EV arrival, departure times and the initial stored energy is elaborated in [26], [43]. The algorithm used for DAM energy and SR price forecasts described in [43]. The outage SoR predictions in the 10 distribution feeders for the 24 hours of the next day are given in Fig. 6. According to Fig. 6, inclement weather is expected during hours 1-3, 10, and 18-21. To remove any biases, we assume that the aggregator participates in 5 days of the CAISO day-ahead market from 9/5/2022 to 9/9/2022 [48]. Two use cases (UCs) are considered, and their results are compared:

- UCI: without outage SoR prediction data,
- UCII: with outage SoR prediction data.

The simulations were conducted in the Python programming language, and the IBM CPLEX solver was utilized for solving the problems. The PC had 64GB of RAM and 2GB of SSD hard drive. In the MILP model, the minimum optimality gap was set to 0.5%. The average computation time was 4650 s.

B. BIDDING STRATEGY

The total procured SR in the DAM and traded energy in the DAM and RTM for the five-day case study for UCI and UCII are shown in Fig. 7 and Fig. 8. Ignoring the risk of outages in UCI, the aggregator has over-purchased energy in the DAM and as a result, it has traded higher amounts of energy in RTM. This imposes energy trading profit risks on the aggregator since it will be exposed to highly uncertain prices in the real-time energy market. Considering the risk of outages in UCII assisted the aggregator in accurate energy need estimation leading to less energy trading in RTM. In addition, the aggregator has committed to less SR capacity in UCII compared to UCI. The total procured SR for five days in UCI is 55.1 MW and in UCII is 49.4 MW. The reason is that by having the outage risk predictions, the aggregator acts more conservatively in SR bidding and avoids excessive SR capacity commitment and subsequent penalties associated with capacity unavailability. Another point worth mentioning is that during hours 7 to 16, the aggregator has barely procured SR in both use cases. Since the DP load and energy price were high during these times, the aggregator used the stored energy in BESSs and EVs to supply a portion of the load.

TABLE I
ENERGY & SR COST/PROFIT FOR 5 DAYS IN UCI & UCII

	Energy Cost DAM	Energy Cost RTM	SR Profit DAM	SR Penalty	Total Cost
UCI	$61,808	$9,315	3,397	$1,334	$69,060
UCII	$59,063	$9,968	$3,012	0	$66,019

Total energy costs in DAM and RTM, SR procurement profit and penalties for the inability to deliver the committed SR capacity in real time for the two use cases are provided in Table I. In UCII, the aggregator has purchased less energy in the DAM, leading to less DAM energy cost than UCI. The aggregator RTM energy cost in UCII is higher than UCI since, in the latter, the aggregator over-purchased energy in the DAM that is traded in the RTM. Note that the traded energy in the RTM imposes high profit risks on the aggregator due to high RTM price fluctuations. The total energy cost in UCII is $69,031, roughly 3% lower than UCI. In UCII, the aggregator has made less profit from offering SR in the DAM. However, it has managed to deliver all the committed SR and has faced no penalties. On the other hand, the aggregator has offered excessive SR capacity in UCI, which was unable to deliver in real-time and has faced penalties accordingly. All in all, the total cost in UCII is ~4.5% lower than UCI, demonstrating the effectiveness of the proposed informed bidding strategy model in the aggregator profit securement.

C. DISCONNECTED DP RESOURCE MANAGEMENT

The performance of the disconnected DP resource management algorithm in terms of load loss and PV generation spillage is depicted in Fig. 9.

The total critical load of the disconnected DPs for the 5-day case study was 6.65 MWh and the total load loss was 0.026 MWh. These numbers for the total PV generation and spillage

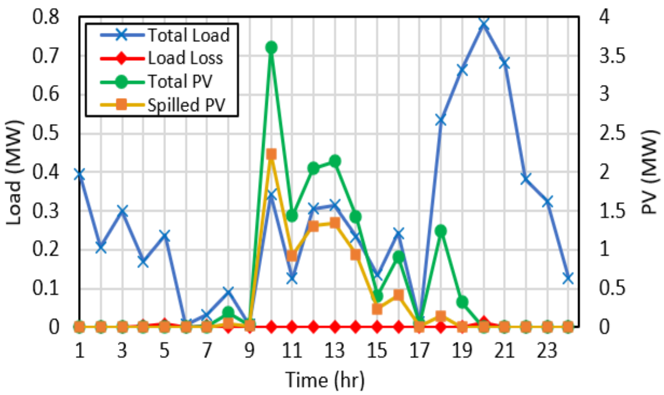

FIGURE 9. **The DP resource management algorithm's performance in load loss and PV power spillage prevention for the 5-day case study.**

were 13.81 MWh and 7.61 MWh. The algorithm's performance in load loss mitigation was more significant than PV generation spillage. The reason is that PV generation is high during the day when the residential building occupants are away. During these times, the residential electric load is low, and EVs are usually unavailable. Hence, there is a limited capacity to store or consume the extra PV generation during outages. That being said, the load loss is of higher importance for customers, and in our case study, the load loss was trivial.

VII. CONCLUSIONS AND RECOMMENDATIONS

A significant challenge for DP aggregator participation in the WEM is the high risk of weather-caused outages in the distribution grids impacting the delivery of ASPs. We incorporated the outage SoR prediction with the aggregator bidding strategy model to avoid penalties for not delivering the committed ASP. We also developed an algorithm for optimal energy resource management of disconnected DP so that they are minimally distorted from their optimal operating point. The significant findings of this research are:

1) Considering the outage SoR prediction, the total SR delivery profit increased by 46%, from $2,063 (w/o outage prediction) to $3,012 (with outage prediction).
2) The total energy cost decreased from $71,123 (w/o outage prediction) to $69,031 (with outage prediction). The aggregator avoided ASP penalties and reach the highest rewarding market participation.
3) By implementing the disconnected DP resource management algorithm, we supplied 99.6% of the critical electric load and stored/consumed 45% of PV generation during outages.
4) The algorithm's performance for PV generation storage/consumption was weaker since the total PV generation in the disconnected DPs (with a peak of 3.6 MW) was comparatively higher than the load (with a peak of 0.78 MW).

The outage SoR predictions can be used for other purposes such as peer-to-peer energy trading schemes, retail market, and back up services for the distribution grid. These topics are recommended for the future work.

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