Outage Forecast-Based Preventative Scheduling Model for Distribution System Resilience Enhancement

Preprint

Yiyun Yao,[1] Weijia Liu,[1] Rishabh Jain,[1]
Santhosh Madasthu,[2] Badrul Chowdhury,[2] and
Robert Cox[2]

1 National Renewable Energy Laboratory
2 University of North Carolina at Charlotte

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National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
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Outage Forecast-based Preventative Scheduling Model for Distribution System Resilience Enhancement

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[1]National Renewable Energy Laboratory
Golden, CO, U.S.A.
{yiyun.yao; weijia.liu; rishabh.jain}@nrel.gov

[2]University of North Carolina at Charlotte
Charlotte, NC, U.S.A.
{smadasth; b.chowdhury; robert.cox}@uncc.edu

***Abstract* — Distribution system resilience enhancement is an important topic to ensure customers have access to power supply during extreme events. In fact, certain weather-related extreme events can be predicted ahead of time. Therefore, it is important to investigate how to predict grid outages using extreme weather forecasts, and how outage predictions can be incorporated into distribution system resilience enhancement. In this paper, a preventative scheduling model for distribution systems is proposed. The model targets at allocating resources, especially mobile responsive resources such as mobile backup generators and mobile energy storage systems, to prepare for an extreme event in the day-ahead context. To achieve efficient resource allocation and scheduling, a machine learning-based outage prediction module is developed to predict vulnerable or risky segments of the distribution system based on historical operating records and extreme weather event forecast. By integrating the outage prediction results into the scheduling model, optimal resource allocation can be derived to help distribution systems prepare for an upcoming event and improve resilience performance. A real distribution feeder in North Carolina, U.S. is used in the case study to validate the proposed approach.**

***Index Terms*—Distributed energy resources, forecast-based preventative scheduling, machine learning, outage prediction, power system resilience, responsive resource allocation**

I. Introduction

Power system resilience has been a hot topic in recent years, which addresses the power supply reliability and security against high impact low probability events such as extreme weather events and cyberattacks [1]. As far as distribution systems are concerned, resilience focuses on securing the power supply to end customers during disastrous events to minimize economic and social losses associated with power outages. For typical distribution systems that rely heavily on the upstream transmission system for power supply, little can be done on the distribution end to enhance resilience other than strengthening the grid due to the lack of controllable generation resources.

With the growing integration of distributed energy resources (DERs), distribution systems could still have generation capability from their DERs when there is a major blackout at their upstream transmission system. Hence, reasonable utilization of DER capability becomes a key to improving distribution system resilience [2]. In [3], the authors formulate an islanding strategy in the event of line failures in distribution systems, and they propose a decentralized, multi-agent system to control the DERs. Reference [4] investigates the collaboration of various DERs and legacy devices in distribution system service restoration. Here, mixed-integer, second-order cone programming is used to model the restoration problem. The authors in [5] built a cooptimization method, in where the repair crew and mobile power source were jointly dispatched for electric service restoration. In [6], the authors focus on comparing the load restoration performances using fixed and variable time steps. Here, the restoration model for the distribution system is a mixed-integer, linear programming (MILP) problem. Reference [7] develops a new set of quantitative metrics with clear physical interpretation to comprehensively evaluate power system resilience and integrate them into power system optimization models for resilience enhancement. Behind-the-meter DERs were controlled to improve distribution system resilience in [8]. The restoration of secondary distribution network with distributed generators was studied in [9].

Overall, existing works have explored the feasibility of implementing DERs to assist distribution system service recovery and resilience enhancement. However, their focuses are either on long-term planning (e.g., grid strengthening) or real-time DER control. For certain extreme events such as hurricane and flood, it is possible to get a pretty good prediction of the event propagation hours or days ahead. If this event prediction information can be leveraged by utility operators, it is possible for them to adjust their operating schedules and allocate emergency responsive resources such as backup generators to the most vulnerable grid segments to improve resilience. To achieve this, the following two questions need to be addressed:

- For extreme events that can be predicted, how to efficiently map the extreme event prediction to grid outage prediction, and how to improve the outage prediction accuracy.
- With a credible outage prediction result, what measures can be taken to allocate responses and controllable assets to prepare for the outage event.

To this end, the major contents and contributions of this paper includes:

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- An outage forecast-based preventative scheduling (FPS) model is developed to incorporate outage prediction results and responsive resource allocation into conventional distribution system restoration problems. The FPS model is formulated as a mixed-integer linear programming model, where mobile resources are allocated to critical locations based on the outage predictions to improve system resilience.
- Two machine learning models, namely decision tree (DT) and ensemble boosted tree (EBT), are employed to generate outage prediction results based on historical data.
- The effectiveness of the proposed solution is demonstrated on the model of a real distribution feeder in North Carolina. The real outage data of the past ten years are utilized for outage prediction.

The rest of this paper is organized as follows. Section II briefly describes the FPS model. Section III introduces the outage prediction approach with machine learning techniques. Section IV demonstrates the simulation results on a real distribution feeder. Section V concludes the paper.

II. FPS Model with Mobile Responsive Resources

A. FPS Model Formulation with Outage Prediction and Mobile Responsive Resources Allocation

In the FPS model, the outage event is predicted and informed to the operator. The following assumptions are adopted when developing this FPS model:

- The developed FPS model targets a three-phase unbalanced microgrid. Power loss in the microgrid is ignored. This FPS model can easily be modified to model balanced distribution networks and transmission networks.
- Distributed generators (DGs), photovoltaics (PVs), and battery energy storage systems (BESSs) are the primary DERs in the microgrid. Other types of DERs can also be integrated into the proposed model.

In addition, the FPS model needs to consider the allocation of responsive resources in response to a given outage prediction. In this paper, three types of mobile resources are considered and explained in Table I.

TABLE I Mobile Resources for FPS Model

	Capability	Constraints
Mobile generator	Power generation	Capacity; Fuel; Rating power
Mobile BESS	Power generation or consumption	Capacity; Stage-of-charge; Rating power
Mobile transformer	Connection	Capacity

Among these three mobile resources, mobile generator (typically diesel generators mounted on the truck) can be used to generate electricity. Mobile BESS is more flexible because the BESS can be operated in charging mode as well. Mobile transformer, on the other hand, is not a traditional DER because it does not have any power generation or consumption capability. However, mobile transformer can restore the connection between critical node and the grid. Furthermore, we consider there will be a number of access points where mobile responsive resources can be connected to the feeder to provide power supply. The conceptual diagram is shown in Figure 1. In Figure 1, responsive resources are originally located at the substation. Along the feeders, there are multiple access points for the mobile resources, denoted by a green circle. In the FPS model, microgrid operators will allocate these mobile resources to candidate access points using outage predictions.

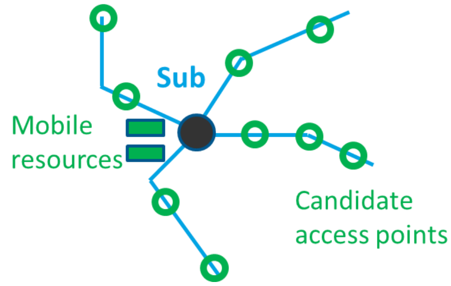

Fig. 1. Conceptual diagram of mobile resource integration

Based on the assumptions, the FPS model includes an objective function to maximize distribution system resilience while minimizing resource allocation costs. A compact version of the FPS model is described below due to space limit.

$$\begin{aligned} max: \quad & f^R(\boldsymbol{g},\boldsymbol{m}) - C(\boldsymbol{m}) \\ s.t.: \quad & h(\boldsymbol{g},\boldsymbol{m}) \leq \mathbf{0} \end{aligned}$$

where $\boldsymbol{g}$ and $\boldsymbol{m}$ are variables associated with DER and distribution system operation, and mobile responsive resource operation, respectively. f^R is a function to quantify distribution system resilience [10], and C is a function to quantify mobile resource allocation costs. h is the set of constraints that includes 1) power flow constraints; 2) DER operating constraints; and 3) mobile DER constraints. The mobile DER constraints will be elaborated in Section II.B, while the other constraints are conventional and can be referred to existing studies such as [3]-[9].

B. Mobile DER Contsraints

Mobile DERs are constrained by both their inherit operating boundaries such as rated power, power factor, and runtime, and by the transportation network constraints such as travel time from one location to another. In this section, a general mobile DER model is developed to cover the three types of mobile resources considered in this study.

The inherit mobile DER constraints can be expressed as:

$$\begin{gathered} \sum_i y_{m,i,t}\, P_m^{\mathrm{M,min}} \leq P_{m,t}^{\mathrm{M}} \leq \sum_i y_{m,i,t}\, P_m^{\mathrm{M,max}} \\ -\varphi_m^{\mathrm{M}} P_m^{\mathrm{M,min}} \leq Q_{m,t}^{\mathrm{M}} \leq \varphi_m^{\mathrm{M}} Q_{m,t}^{\mathrm{M}} \\ E_m^{\mathrm{M,min}} \leq \sum_t P_{m,t}^{\mathrm{M}} \leq E_m^{\mathrm{M,max}} \end{gathered}$$

where $P_{m,t}^{\mathrm{M}}$ and $Q_{m,t}^{\mathrm{M}}$ denote the active and reactive power output from mobile DER m at time t, respectively. $P_m^{\mathrm{M,max}}$ and $P_m^{\mathrm{M,mim}}$ are the maximum and minimum active power output, respectively. φ_m^{M} is the power factor limitation. $E_m^{\mathrm{M,max}}$ and $E_m^{\mathrm{M,min}}$ denote the maximum and minimum energy output, respectively. $y_{m,i,t}$ is a binary variable indicating whether the mobile DER m is connected to bus i at time t of the distribution system concerned. Hence, it is clear that the key variable in the mobile DER model is $y_{i,t}$. This variable will be linked to the transportation network for mobile resource dispatch.

The transportation network constraints can be described as:

$$\begin{gathered} y_{m,i,t} = y_{m,i,t-1} + \sum_j y_{m,ji,t}^{\mathrm{A}} - \sum_j y_{m,ij,t}^{\mathrm{D}} \\ \sum_{\tau=t}^{t+\Delta\tau} y_{m,i,t} \geq \Delta\tau (y_{m,i,t} - y_{m,i,t-1}) \\ \sum_i y_{m,i,t} \leq 1 \end{gathered}$$

$$y^{\mathrm{D}}_{m,ij,t} \geq y_{m,i,t-1} - y_{m,i,t}$$
$$y^{\mathrm{D}}_{m,ij,t} \leq y_{m,i,t-1}$$
$$y^{\mathrm{D}}_{m,ij,t} \leq 1 - y_{m,i,t}$$
$$y^{\mathrm{A}}_{m,ij,t+\Delta\tau_{ij}} = y^{\mathrm{D}}_{m,ij,t}$$
$$y^{\mathrm{A}}_{m,ij,t}, y^{\mathrm{D}}_{m,ij,t}, y_{m,i,t} \in \{0,1\}$$

where $y^{\mathrm{A}}_{m,ij,t}$ and $y^{\mathrm{D}}_{m,ij,t}$ are binary variables indicating whether the mobile DER m has departed from bus i to bus j or arrive at bus i from bus j, respectively. $\Delta\tau$ denotes the discretized loading/unloading time to constrain a mobile DER to be connected to the grid for at least $\Delta\tau$ time steps before being reallocated.

III. Outage Prediction with Machine Learning

In the FPS model discussed in Section II, the allocation of responsive resources and microgrid formation strategy are highly dependent on distribution system outage information. To improve the accuracy of system outage prediction, a machine learning-based outage prediction approach has been proposed to estimate which sections of the network will be out during an upcoming extreme weather event and which sections will experience actual physical damage.

In this paper, the focus is to provide zone-based, device-level predictions, i.e.:

i). Predict outages associated with each protection zone for the next time horizon (e.g., 24 hours);

ii). Provide an indication of the physically affected sections of each protection zone for the next time horizon.

A. Data Collection and Feature Selection

Protection zones are defined based on each recloser and its downstream fuses. Outage predictions for each protection zone include recloser and fuse-related components. Recloser outage prediction is essentially a classification problem that produces a 1 or 0 outcome. Fuse outage prediction is more complicated because of its large number. Therefore, the total number of fuse events will be predicted instead.

To build the dataset for model training, 10 years historical data of 25 substations are collected and processed. In addition to utility operating data such as recloser/fuse operations, number of customers influenced, and outage duration, the weather data is also included to build connection between outage and extreme weather event. Specifically, the following weather features are used in this paper:

- **R_{max}**: Maximum relative humidity each day (in %);
- **R_{min}**: Minimum relative humidity each day (in %);
- **T_h**: Average daily wind direction (in degrees clockwise from north);
- **t_{mmn}**: Daily minimum temperature (in ^{o}K);
- **t_{mmx}**: Daily maximum temperature (in ^{o}K);
- **v_s**: Daily average windspeed associated.

The complete dataset includes 18 extreme weather events and contains 22,050 records. Among these 18 extreme event data, 16 of them will be used for model training and 2 will be used for validation.

B. Machine Learning Models

In this paper, we implemented two machine learning models to predict outages, namely decision tree (DT) and ensemble boosted tree (EBT). The overall workflow of implementing the proposed machine learning models for outage predictions is also illustrated in Fig. 2.

- DT is a series of decision nodes ('if-then' statements) that, starting from a 'root node', allows to recursively split the training data into subsets of similar values for the response variable. During training, the DT is fitted with any historical data that is relevant to the problem domain and the true value we want the model to learn to predict. The model learns any relationships between the data and the target variable.

- EBT combines several decision trees to produce better predictive performance than utilizing a single decision tree. Boosting is an ensemble technique to create a collection of predictors. In this technique, learners are learned sequentially with early learners fitting simple models to the data and then analyzing data for errors. In other words, we fit consecutive trees and at every step, the goal is to solve for net error from the prior tree.

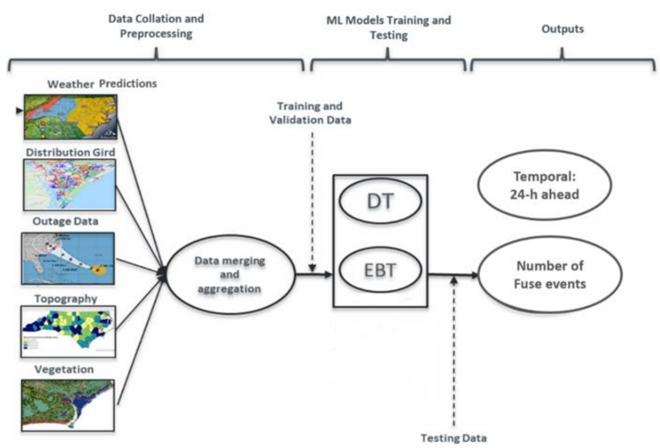

Fig. 2. Outage prediction workflow with machine learning models.

TABLE II Error Metrics for the Machine Learning-Based Outage Predictions on a Real Hurricane Event

Metric	DT	EBT
RMSE	0.3504	0. 3421
R^2 Score	0.79	0.83
NMAE	5.96%	5.37%

To verify the performance of the machine learning-based outage prediction models, three primary performance metrics – root mean square error (RMSE), normalized mean average error (NMAE) and R^2 – were considered. For RMSE and NMAE, smaller values imply better performance. On the other hand, larger R^2 values are desired. Table II listed the prediction error on a real hurricane event. Both DT and EBT produce good prediction of outages. Using other machine learning outage prediction techniques, such as deep neural network-based methods, implies using more complex architectures [10]; the choices of DT and EBT models are due to its simplicity and lightweight, in view of its implementation on an industrial level.

IV. CASE STUDY

To validate the developed translation scheme, we implement the tests on the model of a real feeder in North Carolina, the topology is shown in Fig. 3. The feeder model consists of 1,484 nodes, and it has a peak load of 3,970 kW. To simulate the impacts caused by predicted extreme events, here are the assumptions in the test:

- 7 reclosers are deployed across the system as shown in Fig. 3. There is 1 recloser deployed near substation, lower load cluster, and medium load cluster, respectively. 5 reclosers deployed in the upper cluster. 9 nodes of mobile DER connection are deployed based on the similar rule.
- The scheduling timeframe is 24-hour with 15-minute time-resolution, which contains 96-time steps in total. During this timeframe, the 7 reclosers and 9 nodes may be tripped off according to the outage prediction results. For each component, the recovery time is randomly generated using normal distribution with 5 hours as the mean and 1 hour as the standard deviation. Since outage prediction results contain probability of outages, a total of 20 outage scenarios are generated based on the outage predictions to account for prediction error.
- This feeder has a total PV capacity of 60% of its peak load (i.e., 2,100 kW), and 60% of the PV are randomly picked to be equipped with a BESS. Each BESS is assumed to be capable of supporting charging/discharging at PV-rated power for 3 hours.
- A simplified transportation network with 9 nodes is introduced for mobile DER dispatch. The network is shown in Fig. 3. Each line in Fig. 3 denotes a transportation route with its travel time listed. For example, a route with 4τ means the travel time is 4 time steps, which is 60 minutes.

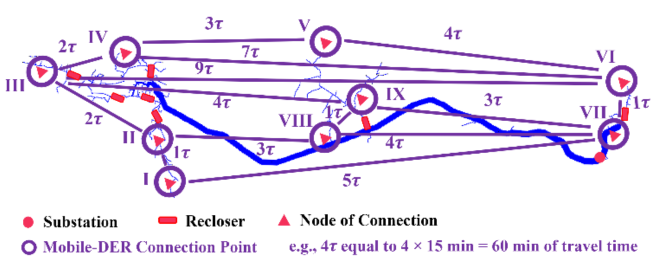

Fig. 3. Topology, mobile DER connection node, and the traffic routine of the real feeder in North Carolina

A. FPS without Mobile DER Deployment

In this section, we first disable mobile DER deployment and focus on validating the impacts of outage prediction. The following assumptions are made to initialize mobile DERs: i) a mobile diesel generator (rating power 200 kW) is deployed to the node III; ii) a mobile BESS (rating power 200 kW/600 kWh) is deployed to the node IX; iii) a mobile transformer (rating capacity 250 kVA) is deployed at the substation node .To validate the effectiveness and benefits of the proposed FPS model, two comparative cases are studied:

- Case 0: FPS without forecast information, all BESS will be discharging whenever the outage event starts;
- Case 1: FPS model using the proposed outage prediction results as input.

First, we run simulation on the 20 outage scenarios, each with a different outage prediction result. For the outage scenario #10, the resilience trapezoid and load shedding results generated by the proposed FPS model are shown in Fig. 4 below. The y-axis of upper and lower subplots are the uninterrupted system load supply (%) and system load shedding (kW), respectively. The resilience metric values and statistics are listed in Table III.

Fig. 4 and Table III clearly demonstrated that outage prediction has done a great job in anticipating most vulnerable areas and allocate resource accordingly. It is clearly shown in Fig. 4 that case 0 has very high load shedding and a longer outage duration, which is reasonable because the capability of DERs cannot be fully utilized without proper optimization and coordination. Based on the developed FPS scheme, case 1 can reduce the maximum load shedding by 115 kW, mitigate the interruption of energy supply by 14,764 kWh, and shorten the outage time by 2.75 hours. Hence, it is validated that outage predictions are important inputs for FPS models and key to improve distribution system resilience.

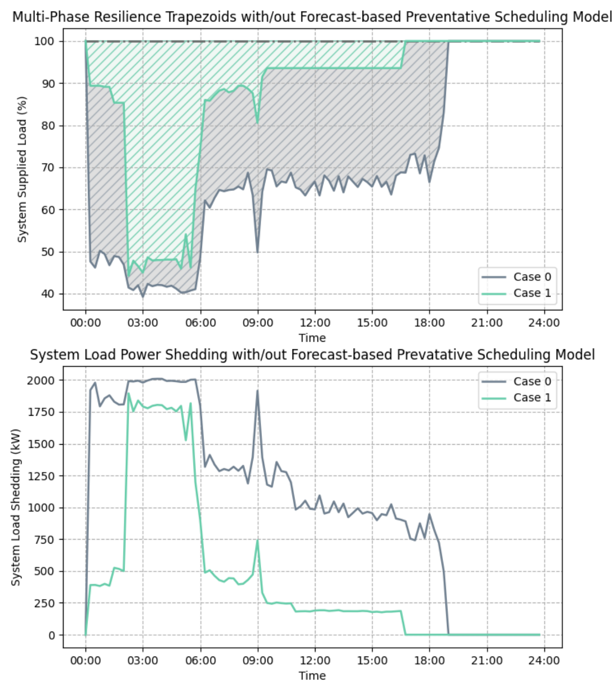

Fig. 4. Resilience trapezoids with the FPS model under event 10

TABLE III RESILIENCE METRICS WITH THE FPS MODEL UNDER EVENT 10

	Case 0	Case 1
Energy shortage (kWh)	25,311	10,547
Maximum load shedding (kW)	2,009	1,895
Resilience objective [11] (kWh)	55,446	36,603

B. FPS with Mobile DER Deployment

The following case will be simulated to validate the contributions from mobile DERs:

- Case 2: FPS model using the proposed outage prediction results and mobile DER dispatch approach.

Case 2 result is compared against case 1 where no mobile DERs are considered to validate whether the introduction of mobile DERs can improve system resilience performance. Outage scenario 10 is employed, and the simulation results are shown in Fig. 5. In Fig. 5, it is observed that introducing mobile DERs can further reduce the load shedding and energy shortage and accelerate service restoration by 267 kW, 1,105 kWh, and 1.25 hours, respectively. The resilience metric values and statistics are listed in Table IV. Fig. 5 and Table IV clearly validate that the deployment of mobile DERs can significantly improve distribution system resilience.

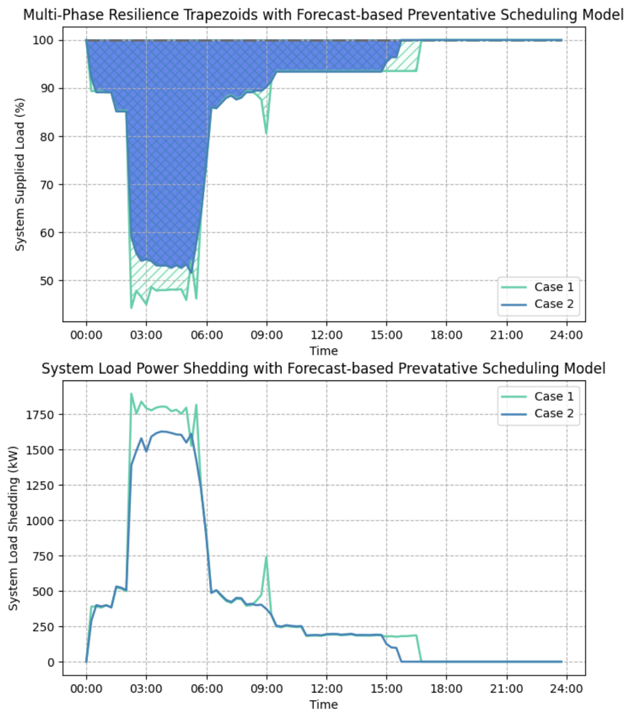

Fig. 5. Resilience trapezoids of Case 1 and Case 2 under event 10

TABLE IV Resilience metrics with and without Mobile DER

	Case 1	Case 2
Energy shortage (kWh)	10,547	9,442
Maximum load shedding (kW)	1,895	1,628
Resilience objective [11] (kWh)	36,603	28,571

TABLE V Mobile DER Dispatch Scheme in Case 2

Time slot	Mobile diesel generator	Mobile BESS	Mobile Transformer
1	II	IX	I
2	II → III	IX → IV	I
3	II → III	IX → IV	I
4	III	IX → IV	I
5	III	IX → IV	I
6	III	IX → IV	I
7	III	IX → IV	I
8	III	IV	I→ IX
9	III	IV	I→ IX
10	III	IV	I→ IX
11	III	IV	I→ IX
12	III	IV	I→ IX
13	III	IV	IX
14	III	IV	IX
15	III	IV	IX
16	III	IV	IX
17	III	IV→ V	IX
18	III	IV→ V	IX
19	III	IV→ V	IX
20	III→ I	V	IX
21	III→ I	V	IX
22	III→ I	V	IX→VII
23	I	V	IX→VII
24	I	V	IX→VII
25	I	V	VII
26	I	V	VII
27	I	V	VII
28	I	V→ IV	VII
29	I	V→ IV	VII
30	I	V→ IV	VII
31->END	I	IV	VII

Table V listed the detailed mobile DER dispatch and allocation scheme. Mobile diesel generator has the least frequent reallocation. After the diesel fuel is exhausted, mobile diesel generator can no longer provide generation. Mobile BESS, on the other hand, has the most frequent dispatch. This is because mobile BESS can travel to feeder segments with abundant power supply to charge its battery, and then travel to an outage area to discharge the battery to provide power supply. Mobile BESS has the highest flexibility, thus it will be dispatched most frequently. Mobile transformer will be dispatched to nodes with sufficient generation capacity but without proper connection to the power grid due to faults. The mobile transformer will be reallocated according to the prediction of outage events and the remaining generation capability at the node to which it is connected.

V. Conclusions

In this paper, we developed a preventative scheduling model for distribution systems to improve resilience performance against upcoming extreme events. Mobile DERs are considered as responsive resources in this scheduling model so that they are dispatched and allocated to locations where their capabilities are needed the most. A machine learning-based outage prediction module is integrated to estimate the possibility of substation and recloser outages based on historical data and extreme weather forecasts. A real feeder is used for simulation validation, simulation results confirmed that the proactive deployment of mobile DERs and consideration of outage predictions both help distribution systems to improve resilience performance.

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