Dynamic Distribution System Restoration Strategy for Resilience Enhancement

Preprint

Weijia Liu, Fei Ding, and Changhong Zhao

National Renewable Energy Laboratory

Presented at the 2020 IEEE Conference on Innovative Smart Grid Technologies (IEEE ISGT)
Washington, D.C.
February 17–20, 2020

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Conference Paper
NREL/CP-5D00-74735
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Contract No. DE-AC36-08GO28308

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Suggested Citation
Liu, Weijia, Fei Ding, and Changhong Zhao. 2020. *Dynamic Distribution System Restoration Strategy for Resilience Enhancement: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5D00-74735. https://www.nrel.gov/docs/fy20osti/74735.pdf.

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National Renewable Energy Laboratory
15013 Denver West Parkway
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This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by NREL's Laboratory Directed Research and Development Program.

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Dynamic Distribution System Restoration Strategy for Resilience Enhancement

Weijia Liu, Fei Ding, Changhong Zhao
National Renewable Energy Laboratory
Golden, CO, U.S.A.
{weijia.liu; fei.ding}@nrel.gov

Abstract — **In electric power distribution systems, distributed energy resources (DERs) can act as controllable power sources and support utility operators to minimize power outages after extreme weather events (e.g., hurricane, earthquake, wildfire) and thus help enhance the grid's resilience. Meanwhile, the influences of extreme events and the capabilities of DERs are dynamic and difficult to predict. Hence, the desired distribution system restoration strategy should be able to evolve according to real-time fault/disturbance information and the availability of DERs. In this paper, we propose a new dynamic distribution system restoration strategy to enhance system resilience against potential hazards. An efficient reconfiguration algorithm is developed to eliminate the use of integer variables to relieve the computational burden. Model predictive control is implemented to adjust the system topology and DER operation setpoints based on the updated fault information and DER forecasts. The effectiveness of the proposed restoration model in enhancing distribution system resilience is validated through an IEEE 123-bus test system. Simulation results also validate that the proposed restoration model can mitigate the occurrence of unexpected events and the fluctuations of DERs.**

Index Terms--**Distribution system reconfiguration, distribution system restoration, distributed energy resources (DERs), model predictive control (MPC), power system resilience, three-phase unbalanced distribution system**

I. INTRODUCTION

Modern power systems are operating in an increasingly efficient and reliable manner thanks to the enhancement of infrastructure and the development of advanced measurement and communications technologies. Power outages, however, especially those caused by natural hazard, still occur and result in enormous social and economic damages [1]. For example, the 2008 blackout in China and the 2017 blackouts in Puerto Rico were caused by a snowstorm and hurricane, respectively [2],[3]. In view of the impacts of natural hazard on power systems, the concept of power system resilience emerges to illustrate the capability of a power system to self-heal [4]. Resilience is becoming an important metric to evaluate the performance of power systems in delivering secure, sustainable and reliable power to customers under extreme conditions.

Compared to power outages in high-voltage transmission systems, distribution systems are more vulnerable to natural hazard because of the lack of flexible generating resources and redundant distribution feeders. The consumption of customers is directly affected by failures in the distribution systems as well. As such, effective distribution system restoration strategies are in urgent demand to recover power supply to distribution loads in a timely fashion and enhance system resilience [5].

Distribution system restoration has been extensively studied with emphasis on distribution system reconfiguration technique, where the power supply can be recovered through alternative paths created by operating tie switches. For example, the restoration strategy with multiple distribution system faults was proposed in [6]. The combination of a power system restoration algorithm and voltage control was studied in [7]. To obtain the optimal configuration of distribution systems, heuristic algorithms and mixed-integer programming techniques were extensively studied in [8] and [9], respectively. Meanwhile, the fast-growing capacity of distributed energy resources (DERs) in distribution systems has provided additional power sources and operational flexibility to recover from failures and outages. The potential contributions of DERs to distribution system restoration have been explored and integrated into traditional distribution system reconfiguration techniques to accelerate the restoration speed and enhance system resilience. The impacts of energy storage units were investigated by an agent-based framework in [10]. A distributed generation-based restoration strategy was studied in [11] considering cold-load pickup characteristics. And the microgrid concept and spanning tree search methodology were employed to formulate distribution restoration strategies in [12].

Although the implementation of DERs in distribution system restoration appears to be promising, two major concerns remain to be solved. The first is associated with the resilience of distribution systems against natural hazard. Hazards such as tornados are mobile and will occasionally reshape fault situations. Existing work generates reconfiguration plans based on stationary fault scenarios, which do not work when the power system is affected by natural hazard. The second is the uncertainty of DERs. The generation capabilities of renewable energy sources and the consumption behaviors of customers are difficult to predict, which makes conventional distribution system restoration strategies infeasible when forecast errors are large. In this context, this paper employs model predictive control (MPC) and proposes a dynamic distribution system restoration strategy. The proposed restoration strategy can adjust distribution network topologies through switch operations with respect to real-time fault information. The capabilities of DERs are also integrated into the restoration model, where the uncertainty of DERs is managed by MPC. In this way, the capabilities of DERs can be fully used, and the resilience of distribution systems will be enhanced.

The rest of this paper is organized as follows. Section II briefly introduces the self-evolving restoration framework for distribution systems. The distribution system reconfiguration algorithm and the MPC of DERs are discussed in Section III and Section IV, respectively. Section V demonstrates the simulation results based on the proposed method. Section VI concludes the paper.

II. Dynamic, Hierarchical Restoration Framework

Typically, distribution systems are operated and managed by distribution system operators (DSOs), whereas DERs are owned by dispersed customers. In this paper, every individual household is managed by a home energy management system (HEMS), which also serves as the entity to communicate with the DSO [13]. When a natural hazard occurs and damages the distribution system infrastructure, the DSO will collaborate with HEMS to assess the conditions of available infrastructure and DER resources to recover power supply to outage loads. Fig. 1 illustrates the proposed hierarchical framework for dynamic distribution system restoration against natural hazard (e.g., a tornado). The detailed responsibilities of the DSO and HEMS are as follows:

- The DSO monitors the influences of natural hazard and the faults in the distribution system concerned. Optimal reconfiguration strategies will be generated and updated based on the feasible power ranges of DERs submitted by the HEMS. The optimized DER setpoints will be sent to the HEMS to direct their consumption pattern. The restoration/reconfiguration strategy will be modified by the DSO when updated fault information or feasible power ranges are available.
- Each HEMS optimizes and updates its energy generation/consumption schedule based on its own preference and up-to-date forecasts, etc. The HEMS submits its feasible power range to the DSO and follows the received power setpoints during operation.

III. Distribution System Reconfiguration Algorithm

Distribution system reconfiguration modifies distribution system topology through switch operations, and thus it is normally formulated as a mixed-integer program. For large-scale three-phase unbalanced distribution systems, the number of integer variables significantly increases, making the mixed-integer models more difficult to solve in a timely fashion. To cope with this difficulty, this paper proposes a three-phase optimal power flow (OPF) model that solves the near-optimal system topology using a heuristic reconfiguration process [14]. The proposed OPF deals with only continuous variables and significantly reduces the computational burden.

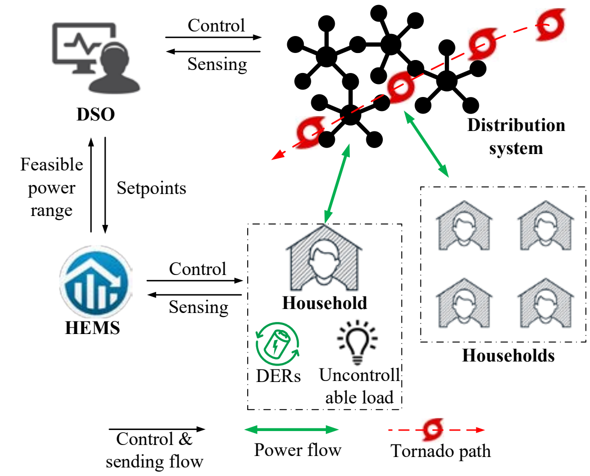

Fig. 1 The proposed dynamic distribution system restoration framework

A. Three-Phase OPF Model

Consider a three-phase unbalanced distribution network modeled by a connected directed graph $G(N,E)$, where N is the set of nodes (each node might have one, two, or three phases) and E is the set of all the lines regardless whether they are open or closed. A line connecting nodes $i,j \in N$ is denoted as $ij \in E$. Let $E_S \subset E$ be the set of lines with switches. Define E_D^t as the set of undamaged or repaired lines in time slot t.

Assuming all undamaged lines are closed, $G(N,E_D^t)$ might be divided into C connected subnetworks denoted as $G(N_1^t,E_{D,1}^t)$, $G(N_2^t,E_{D,2}^t)$,…, $G(N_C^t,E_{D,C}^t)$. For every $c \in [1,C]$, the switch states in subnetwork $G(N_c^t,E_{D,c}^t)$ are collected as $S_{D,c}^t := \{s_{ij}^t | ij \in E_S \cap E_{D,c}^t\}$. Moreover, we use $E\left(S_{D,c}^t\right)$ and $E(S_D^t)$ to denote the set of lines in $G(N_c^t,E_{D,c}^t)$ and $G(N,E)$ that are still connected after incorporating the switch states, respectively. Because different subnetworks are independent of each other, solving the OPF of the original network $G(N,E)$ is equivalent to solving the OPF of each subnetwork $G(N_c^t,E_{D,c}^t)$, $\forall c \in [1,C]$.

For subnetwork $G(N_c^t,E_{D,c}^t)$, the following quantities are introduced to describe the three-phase unbalanced OPF. Let Φ_i and Φ_{ij} denote the sets of phases at node $i \in N_c^t$ and line $ij \in E_{D,c}^t$, respectively. Let $\Lambda_{ij}^t \in \mathbb{C}^{|\Phi_{ij}|}$ and $s_i^t \in \mathbb{C}^{|\Phi_i|}$ be the column vector collecting complex power flows and net complex power injections on all the phases of line $ij \in E\left(S_{D,c}^t\right)$ and node $i \in N_c^t$, respectively. Let $\text{diag}(\Lambda_{ij}^t)$ denote the diagonal matrix whose diagonal is vector Λ_{ij}^t. Define matrix $v_i^t := V_i^t (V_i^t)^H \in \mathbb{C}^{|\Phi_i|\times|\Phi_i|}$, where $V_i^t \in \mathbb{C}^{|\Phi_i|}$ is the column vector collecting complex voltage phasors at all the phases of node $i \in N_c^t$, and $(V_i^t)^H$ denotes the transposed conjugate of V_i^t. The series impedance of line $ij \in E_{D,c}^t$ is a known constant matrix denoted by $z_{ij} \in \mathbb{C}^{|\Phi_{ij}|\times|\Phi_{ij}|}$. Superscript Φ_{ij} denotes the submatrix of a quantity that is restricted to rows and columns corresponding to Φ_{ij}. A constant phase-shift matrix Γ is defined as follows:

$$\Gamma := \begin{bmatrix} 1 & e^{j2\pi/3} & e^{-j2\pi/3} \\ e^{-j2\pi/3} & 1 & e^{j2\pi/3} \\ e^{j2\pi/3} & e^{-j2\pi/3} & 1 \end{bmatrix} \quad (1)$$

Based on these notations, three-phase unbalanced power flow in the connected subnetwork $G(N_c^t, E_{D,c}^t)$ can be modeled by the following equations ($\forall i \in N_c^t$, $ij \in E(S_{D,c}^t)$) [15]:

$$\textstyle\sum_{ki\in E(S_{D,c}^T)} \Lambda_{ki}^{t,\Phi_i} + s_i^t = \sum_{ij\in E(S_{D,c}^T)} \Lambda_{ij}^{t,\Phi_i} \quad (2)$$

$$v_j^{t,\Phi_{ij}} = v_i^{t,\Phi_{ij}} - \Gamma^{\Phi_{ij}} \cdot \mathrm{diag}(\Lambda_{ij}^t) \cdot z_{ij}^H - z_{ij} \cdot \mathrm{diag}(\Lambda_{ij}^t)^H \cdot (\Gamma^{\Phi_{ij}})^H \quad (3)$$

Because $(N_c^t, E_{D,c}^t)$ is not necessarily radial, (2) and (3) might not be exactly relaxed by semidefinite programming techniques [15]. Instead, this power flow model is simplified by deriving the real-number expression for the diagonal of v_i^t, i.e., the squared voltage magnitudes at all the phases of node i. Split the real (active) and imaginary (reactive) parts of $\Lambda_{ij}^t = P_{ij}^t + jQ_{ij}^t$ and $s_i^t = p_i^t + jq_i^t$, and split the real (resistance) and imaginary (reactance) parts of $z_{ij} = r_{ij} + jx_{ij}$. The simplified model can be written as ($\forall i \in N_c^t$, $ij \in E(S_{D,c}^t)$, $\phi \in \Phi_{ij}$):

$$\textstyle\sum_{ki\in E(S_{D,c}^t)} P_{ki}^{t,\Phi_i} + p_i^t + \xi_i^t = \sum_{ij\in E(S_{D,c}^t)} P_{ij}^{t,\Phi_i} \quad (4)$$

$$\textstyle\sum_{ki\in E(S_{D,c}^t)} Q_{ki}^{t,\Phi_i} + q_i^t + \zeta_i^t = \sum_{ij\in E(S_{D,c}^t)} Q_{ij}^{t,\Phi_i} \quad (5)$$

$$\begin{aligned} v_j^{\phi\phi,t} = {} & v_i^{\phi\phi,t} - 2(P_{ij}^{\phi,t} r_{ij}^{\phi\phi} + Q_{ij}^{\phi,t} x_{ij}^{\phi\phi}) \\ & + 2\alpha(P_{ij}^{\phi',t} r_{ij}^{\phi\phi'} + Q_{ij}^{\phi',t} x_{ij}^{\phi\phi'} + P_{ij}^{\phi'',t} r_{ij}^{\phi\phi''} + Q_{ij}^{\phi'',t} x_{ij}^{\phi\phi''}) \\ & + 2\beta(P_{ij}^{\phi',t} x_{ij}^{\phi\phi'} - Q_{ij}^{\phi',t} r_{ij}^{\phi\phi'} + Q_{ij}^{\phi'',t} r_{ij}^{\phi\phi''} - P_{ij}^{\phi'',t} x_{ij}^{\phi\phi''}) \end{aligned} \quad (6)$$

$$\Delta p_{ij}^{\phi\phi,t} \ge r_{ij}^{\phi\phi}\left[(P_{ij}^{\phi,t})^2 + (Q_{ij}^{\phi,t})^2\right] \quad (7)$$

In (4) and (5), ξ_i^t and ζ_i^t denote the amount of active and reactive load shedding. In (6), $v_i^{\phi\phi,t}$ is the ϕ-th diagonal term of matrix v_i^t. $P_{ij}^{\phi,t}$ and $Q_{ij}^{\phi,t}$ are the ϕ-th elements of vectors P_{ij}^t and Q_{ij}^t, respectively. $r_{ij}^{\phi\phi}$, $r_{ij}^{\phi\phi'}$, $r_{ij}^{\phi\phi''}$, and $x_{ij}^{\phi\phi}$, $x_{ij}^{\phi\phi'}$, $x_{ij}^{\phi\phi''}$ are the corresponding terms in the impedance matrix $z_{ij} = r_{ij} + jx_{ij}$ for line ij. For phase ϕ, ϕ' and ϕ'', respectively, denote the phase that leads and lags ϕ by $2\pi/3$. In (6), α and β, respectively, denote $\cos(2\pi/3)$ and $\sin(2\pi/3)$. In (7), the line losses are approximated ignoring the voltage magnitude v_i^t for convexity.

Based on the simplified three-phase power flow (4)–(7), the OPF model for subnetwork $G(N_c^t, E_{D,c}^t)$ can be described as:

$$\min \; \textstyle\sum_{t\in T}\left(\sum_{i\in N_c^t}\sum_{\phi\in\Phi_i} p_i^{\phi,t} + \sum_{ij\in E(S_{D,c}^t)}\sum_{\phi\in\Phi_{ij}} \Delta p_{ij}^{\phi\phi,t}\right) \quad (8)$$

subject to: (4) – (7)

$$\underline{p}_i^{\phi,t} \le p_i^{\phi,t} \le \overline{p}_i^{\phi,t}, \quad \underline{q}_i^{\phi,t} \le q_i^{\phi,t} \le \overline{q}_i^{\phi,t} \quad (9)$$

$$\underline{v}_i^{\phi} \le v_i^{\phi\phi,t} \le \overline{v}_i^{\phi} \quad (10)$$

$$0 \le \xi_i^{\phi,t} \le p_i^{\phi,t}, \; 0 \le \zeta_i^t \le q_i^{\phi,t} \quad (11)$$

$$G\left(N_c^t, E(S_{D,c}^t)\right) \text{ is a connected tree} \quad (12)$$

$$S_{D,c}^t = \{s_{ij}^t \in \{0,1\} | ij \in E_S \cap E_{D,c}^t\} \quad (13)$$

where T denotes the set of time slots. Nodal active and reactive power injections are constrained by (9), where $\underline{p}_i^{\phi,t}$, $\overline{p}_i^{\phi,t}$, $\underline{q}_i^{\phi,t}$, and $\overline{q}_i^{\phi,t}$ represent the feasible power ranges of DERs submitted by the HEMSs. The squared voltage magnitude $v_i^{\phi\phi,t}$ is constrained by its upper bound $\overline{v}_i^{\phi}$ and lower bound $\underline{v}_i^{\phi}$ in (10). Constraint (11) guarantees that the shedded load will not exceed its maximum consumption. Constraint (12) guarantees that the subnetwork should be connected. The switch status s_{ij}^t is a Boolean variable, as shown in (13).

B. Heuristic Reconfiguration Algorithm

The Boolean variables $S_{D,c}^t$ and the topology constraint (12) make the three-phase OPF model (4)–(13) difficult to solve. In light of the algorithm in [14], a computationally efficient heuristic algorithm is proposed to obtain a good approximate solution of the OPF model (4)–(13). The proposed heuristic algorithm, denoted as Algorithm 1, contains the following steps:

Algorithm 1

1: $c \leftarrow 1$
2: Identify the connected subnetworks $G(N_c^t, E_{D,c}^t)$. Set $s_{ij}^t \leftarrow 1$ for all $ij \in E_S \cap E_{D,c}^t$.
3: Solve the optimization model (4)–(11), i.e., solve the three-phase OPF model in Section III-A without topology constraint (12) and Boolean variables $S_{D,c}^t$.
4: From the optimal solution Step 3, identify the *openable* switch with minimum accumulative active power flow over time and mark this line as ij^*, i.e., $ij^* := \mathrm{argmin}_{ij\in E_S\cap E_{D,c}^t\, openable} \sum_{t\in T}\sum_{\phi\in\Phi_{ij}} P_{ij}^{\phi,t}$. An *openable* switch is a switch, by opening which, the subgraph remains connected.
5: $s_{ij^*}^t \leftarrow 0$
6: If the updated subnetwork $G\left(N_c^t, E(S_{D,c}^t)\right)$ becomes a tree, then go to Step 7; otherwise, return to Step 3.
7: Solve optimization model (4)–(11) to obtain the optimal dispatch. If all subnetworks have been optimized (i.e., $c = C$), end the algorithm; otherwise, return to Step 2 with $c \leftarrow c + 1$.

Note that the optimization model (4)-(11) in Algorithm 1 contains only continuous variables and convex quadratic constraints. Thus, computational efficiency can be guaranteed by using commercial solvers such as CPLEX. Moreover, subnetworks are independent of each other, so Algorithm 1 can be performed in parallel to reduce the computational time.

IV. Implementation of Model Predictive Control

Algorithm 1 discussed in Section III deals with the distribution system reconfiguration problem with stationary faults. Moreover, the reconfiguration model relies on the feasible power ranges from HEMS to optimize the topologies of subnetworks as shown in constraint (9). In this section, Algorithm 1 is extended to an MPC framework to address the uncertainty factors and the coordination between the DSO and HEMS.

A. Open-Loop MPC

Assuming that the time interval is t, and denote the time horizon of MPC as T, the MPC solves the optimal control based on the forecasts within $[t, t+T]$ [16]. In the studied problem, the h-th HEMS optimizes its energy schedule based on the forecasts of DERs and load throughout $[t, t+T]$.

In Algorithm 1, the DSO requires the upper and lower bounds of active and reactive power consumption to conduct optimal reconfiguration. Assuming that larger feasible bounds will be rewarded for contributing to the distribution system restoration, each HEMS will maximize the feasible power bounds while respecting its physical constraints and comfort settings. The HEMS model can be described as ($\forall \tau \in [t, t+T]$):

$$\max \ \sum_{\tau \in [t,t+T]} \gamma_{i,\tau} (\bar{s}_{i,h}^{\tau} - \underline{s}_{i,h}^{\tau}) \tag{14}$$

$$\text{subject to:} \quad l_{i,h}(x_\tau, \bar{s}_{i,h}^{\tau}) = 0\,, \ \ l_{i,h}(x_\tau, \underline{s}_{i,h}^{\tau}) = 0 \tag{15}$$

where $\gamma_{i,\tau}$ denotes the weights of power bounds at different nodes and time slots, $l_{i,h}$ denotes the control function of DERs (e.g., air-conditioning system), and x_t denotes the state variable, respectively. The real and imaginary parts can be obtained by splitting $\bar{s}_{i,h}^{\tau} = \bar{p}_{i,h}^{\tau} + \mathrm{j}\bar{q}_{i,h}^{\tau}$ and $\underline{s}_{i,h}^{\tau} = \underline{p}_{i,h}^{\tau} + \mathrm{j}\underline{q}_{i,h}^{\tau}$. Detailed HEMS model can refer to [13], [17] and will not be elaborated.

B. *MPC-Based Reconfiguration Algorithm*

According to the framework discussed in Section II, the MPC-based reconfiguration algorithm, denoted as Algorithm 2, contains the following steps:

Algorithm 2

1: $t \leftarrow 1$

2: Each HEMS solves its energy management model (14)–(15) to submit its feasible power bounds $\bar{s}_{i,h}^{\tau}$ and $\underline{s}_{i,h}^{\tau}$ throughout time horizon $[t, t+T]$ to the DSO.

3: DSO updates the set of undamaged/repaired lines E_D^t. The received feasible power bounds $\bar{s}_{i,h}^{\tau}$ and $\underline{s}_{i,h}^{\tau}$ are aggregated to their corresponding nodes and phases to obtain $\underline{p}_i^{\phi,\tau}$, $\bar{p}_i^{\phi,\tau}$, $\underline{q}_i^{\phi,\tau}$, and $\bar{q}_i^{\phi,\tau}$.

4: The DSO conducts reconfiguration based on Algorithm 1 and solves $S_{D,c}^{\tau}$, $p_i^{\phi,\tau}$, $q_i^{\phi,\tau}$.

5: The distribution network gets reconfigured using $S_{D,c}^{t}$, and dispatch results $p_i^{\phi,t}$ and $q_i^{\phi,t}$ are sent to the HEMS as power set points. Each HEMS modifies its energy schedule and dispatches all controllable devices at time slot t based on the set points.

6: Return to Step 1 with $t \leftarrow t+1$.

Similar to Algorithm 1, steps 2 and 5 of Algorithm 2 are managed by each HEMS and can also be performed in parallel.

V. Case Study

The IEEE 123-bus test feeder is employed to verify the proposed self-evolving distribution system restoration model [18]. The test feeder is slightly modified by adding several additional switches, as shown in Fig. 2. A total of 350 households are considered, 197 of which have flexible DERs, including photovoltaic (PV) panels, air-conditioning systems, and battery energy storage. A brief summary of the test system data is listed in Table I. The 24-hour generation forecasts of PV at Node 35 and the wind turbine at Node 48 are illustrated in Fig. 3 as examples. The proposed models are solved by GAMS/CPLEX on a laptop computer with a quad-core i7 processor and 16-GB RAM.

Table I Summary of IEEE-123 Test Feeder Data

Household load capacity			
	Households without DERs		Households with DERs
Phase A	610 kW+j195 kVar		790 kW+j567.5 kVar
Phase B	450 kW+j105 kVar		502 kW+j435 kVar
Phase C	485 kW+j125 kVar		652.5 kW+j492.5 kVar
Switches			
13-152	18-135	60-160	97-197
56-95	83-95	49-250	151-300
Substation and utility-owned distributed generation			
Type	Node		Capacity (MVA)
Substation	149		5.0
Diesel	21, 64, 108		0.5
Photovoltaic	35, 78		0.3
Wind	48, 95		0.4

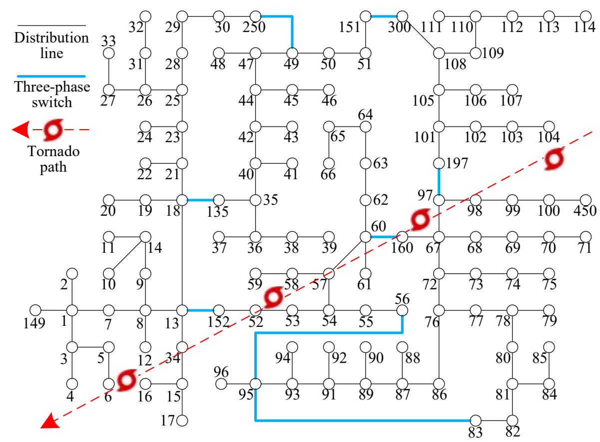

Fig. 2 IEEE 123-bus test system

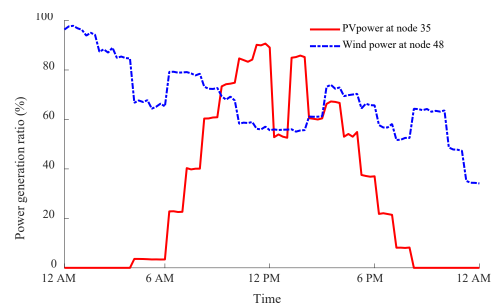

Fig. 3 Power generation forecasts of PV and wind power.

Table II System Line Outage Sequence

Timestamp (starting from t)	Line	Action
00:00	67-97, 67-72, 57-60	Tripped
00:45	52-152, 101-197	Tripped
01:45	57-60	Repaired
02:15	13-18	Tripped
03:30	97-98, 67-72	Repaired
05:15	52-152, 101-197	Repaired

To validate the proposed dynamic restoration strategy, a sequence of distribution line outages is generated to simulate the influences of a tornado, as described in Table II. The MPC horizon T is set to 6 hours, and the time interval is 15 minutes. Note that the load consumption and DER generation capacities are time-varying, as shown in Fig. 3. Thus, for the same outage sequence as shown in Table II, different restoration strategies might be optimized if the event occurs at different time stamps. The following two simulation cases are carried out: Case 1: The tornado hits the studied system at $t = 6$ am; Case 2: The tornado hits the studied system at $t = 6$ pm. The simulation results are summarized in Table III, and the operations of selected switches throughout the 6-hour horizon are illustrated in Fig. 4.

TABLE III SUMMARY OF DYNAMIC RESTORATION RESULTS OVER THE 6-HOUR HORIZON

	Case 1 Phase [A, B, C]	Case 2 Phase [A, B, C]
Total Load supply (MWh)	[2.57, 2.01, 2.04]	[2.33, 1.77, 1.84]
Minimum voltage (p.u.)	[0.994, 0.992, 0.996]	[0.993, 0.992, 0.997]
Average CPU time of solving one MPC time slot	14.5 s	16.2 s

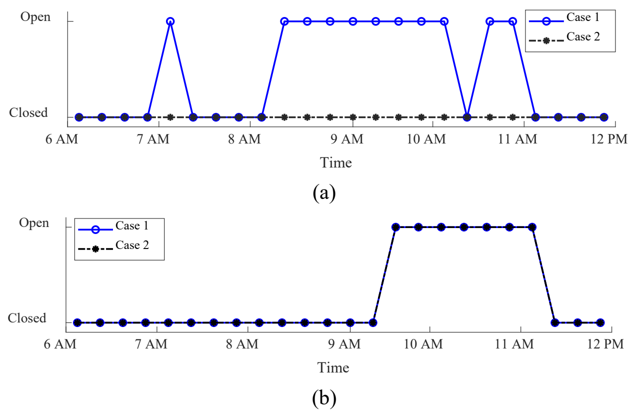

Fig. 4 Switch statuses: (a) switch 18–135; (b) switch 56–95.

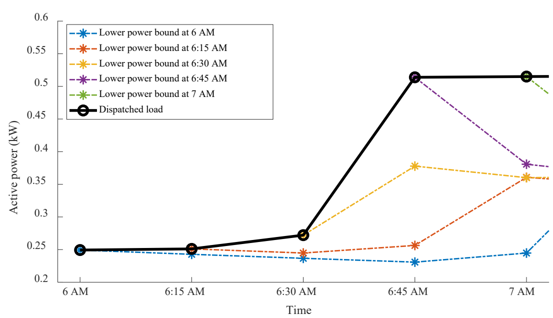

Fig. 5 Comparison of MPC-based lower power bound and dispatched load for a single household.

As shown in Table III and Fig. 4, because of time-varying conditions (e.g., load consumption and renewable generation), the DSO will make different restoration strategies to cope with the same outage sequence listed in Table II based on the proposed dynamic restoration framework. The major difference between Case 1 and Case 2 is the capabilities of utility-owned distributed generation and the capabilities of DERs that are derived from MPC. In both cases, the computer processing unit (CPU) times of the proposed MPC-based strategy for each time slot are significantly smaller than the time interval of 15 minutes.

A household at Node 11, Phase A, is selected as an example to illustrate the performances of DER energy dispatch and the MPC for home energy management. The desired lower power bound from the HEMS and actual dispatched load using the proposed approach in Case 1 are demonstrated in Fig. 5. With updated environmental information such as ambient temperature and solar radiation, a gradual increment in the lower bound estimation based on the MPC is observed in Fig. 5 because more power is needed to accommodate the comfort settings of the corresponding customer. And the solutions obtained from the proposed dynamic restoration approach can effectively meet the time-varying needs.

VI. CONCLUSIONS

This paper proposed a dynamic distribution system restoration strategy using DERs. A heuristic technique was introduced to solve the optimal reconfiguration problem in a timely fashion. The MPC framework was employed to continuously update the reconfiguration of islands based on real-time fault information, DER operating ranges, etc. The proposed strategy was validated to be able to evolve and adjust to the time-varying features of natural hazard and DERs that are difficult to predict. Hence, the proposed strategy is effective in using the capabilities of DERs to recover load power supply and enhance system resilience.

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