

# Coordinating Transactive Demand Response and Rolling Outage Management of Diverse Loads to Enhance Resilience of Distribution Systems

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**Abstract**—The dispatch of demand-side resources is becoming increasingly essential for enhancing the resilience of distribution systems against extreme weather events. Traditional studies rely primarily on direct load curtailment to mitigate power shortages, thereby neglecting the power demand of different customers. To bridge this gap, a novel coordination method of transactive demand response (DR) and rolling outage management of diverse loads is proposed. First, the DR program is designed to incentivize voluntary load adjustments by coordinating participation of private consumers. Considering the diversity and characteristics of customers during DR, detailed models of diverse loads are established, including an energy-material flow model of industrial loads (ILs), an adjustable load model of commercial loads (CLs), and an outage-sensitive model of residential loads (RLs). When the supply-demand imbalance exceeds the adjustment capacity of DR, rolling outage measures are integrated into the proposed method to reduce losses incurred by load shedding. The coordination of transactive DR and rolling outage management is formulated as a bilevel optimization problem from system operators and responsive load, which is solved by the Stackelberg game-theoretic approach. Finally, the proposed method is tested on the modified IEEE 33-node distribution system. The results show that the proposed method can effectively ensure customer profit and reduce load interruption loss by dispatching demand-side resources during restoration.

**Index Terms**—Extreme weather, resilience, distribution system, demand response, rolling outage, resilience.

## I. INTRODUCTION

**E**XTREME weather events, referred to as high-impact low-probability (HILP) events such as hurricanes, snowstorms, and floods have significantly affected power systems

over the past few decades [1], [2]. Distribution systems, in particular, are highly vulnerable to these extreme weather events and often suffer the most severe consequences [3]. Reports indicate a 67% increase in weather-related power outages since 2000, with 80%-90% of these outages attributed to failures in distribution systems [4], [5]. For example, in 2021, extreme winter storms triggered massive power outages in Texas, USA, affecting over 4 million residents and crippling critical infrastructure [6]. Thus, it is urgent to enhance the resilience of distribution systems in the face of HILP events.

During HILP events, faults typically result in the de-energization of downstream nodes within a radial distribution system. By effectively coordinating the routing of repair crews, the affected outage areas can be re-connected to the power system [7], [8]. However, the repair process for faulty components can be time-consuming, often lasting for several hours or even days. To mitigate critical load loss during such events, the distribution system can be partitioned into multiple islanded microgrids (MGs), which sustain a power supply through distributed generators (DGs). Recent studies [9]–[12] have developed MG formation models that facilitate the division of outage areas into self-sufficient MGs, thereby ensuring that the load demand is met by the output of DGs. In addition, some studies have further considered frequency stability constraints in the MG formation process, developing secure scheduling strategies to ensure reliable operation during service restoration [13]. Nonetheless, the demand within these DG-assisted MGs tends to increase during HILP events, particularly when temperature-sensitive loads are heavily operating during extreme heat or cold waves. This surge in demand can worsen the imbalance between load and demand, highlighting the importance of demand-side management.

Previous studies on MG formation have primarily focused on the dispatch of DG units; nevertheless, the demand response (DR) has also gained attention for enhancing the resilience of distribution systems, which can change the energy usage of end-users to better match the demand with the available supply [14]. Within certain load variation ranges, the DR program offers flexibility to adjust demand patterns according to the required control actions. Shiftable loads can alter the time and amount of power consumed, whereas inter-

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ruptible loads can be curtailed to prioritize other critical loads [15]. A two-stage service restoration method is proposed in [16], which involves determining MG formation in the first stage and the output of responsive load in the second stage. Additionally, responsive load control is suggested in [17], accounting for the comfort of customers and load priorities. While the DR studies mentioned above rely on direct load control to modify load patterns, direct coordination may be impractical in many cases due to the private ownership of most loads. Consequently, an urgent need exists to design a mechanism for emergency power exchanges between the distribution system and privately owned loads.

To enable the participation of non-dispatchable loads in DR, transactive DR is a promising solution to mitigating the power shortage during restoration. Motivated by price signals and incentives, certain private loads can be flexibly managed to participate in DR programs [18]. In [19], a transactive real-time load demand management scheme is proposed to address power deviations caused by renewable generation variability. Notably, industrial loads (ILs) represent a significant potential resource for DR programs, accounting for approximately 54% of global energy consumption [20]. In [21], the optimal scheduling of IL aggregators for DR market participation is explored. The adjustment range to quantify the participation rate of diverse loads is modeled, facilitating the interaction between the distribution system operator (DSO) and volunteer consumers [19]. However, the current transactive DR methods primarily focus on normal operation conditions, with limited applications during HILP events. Currently, incentive-based methods facilitate emergency energy trading between DSOs and private MGs [22], as well as with distributed energy resources [23], enabling the supply of surplus energy in exchange for financial compensation. Consequently, the potential and impact of transactive DRs could be further exploited to enhance the resilience of distribution systems.

Despite this, load participants are typically profit-driven and risk-averse, which can reduce their willingness to respond to market signals, especially when facing sustained load reductions and power shortages under extreme weather events. For example, electricity prices in Texas, USA increased by a factor of 360 during the cold wave in 2021 [24], and less than 10% of the total load was engaged in DR during extreme heat events in Sichuan, China in 2022 [25]. While transactive DR contributes to a reduction in the imbalance between demand and supply, it cannot fully prevent load shedding when the power is insufficient. Sudden and extended power outages can lead to equipment damage for ILs and several adverse health impacts for the general public [26]. For example, 65% of deaths were caused by hypothermia during the cold wave in Texas, USA in 2021 [27]. It is emphasized that the power outage should not last for more than two hours during heat waves to avoid overheating risks [28]. To avoid leaving some areas in continuous blackouts, an effective method is to rotate limited power across affected areas. Each zone receives intermittent power access through the strategic and selective operation of sectionalizers and smart switches [29]. Thus, when DR measures are inadequate

for addressing power shortages, rolling outage measures become essential for minimizing the losses associated with load interruption.

In previous studies, traditional restoration method mainly focuses on the dispatch of the typology structure and generation output, and does not fully exploit the potential of private load by transactive DR. A detailed model of the responsive load is rarely studied to represent the operation adjustment during the DR process. Furthermore, the exploration of the intermittent power ratio remains inadequate in terms of mitigating losses due to power outages.

In this paper, a novel coordination method of transactive DR and rolling outage management of diverse loads is proposed to reduce the load interruption loss during service restoration and enhance the resilience of distribution systems. The main contributions of this paper are summarized as follows.

1) The transactive DR program is exploited to incentivize private load adjustment, alleviating the imbalance between load demand and limited generation output under extreme weather events. In particular, rolling outage management is innovatively coordinated with transactive DR to reduce load interruption loss through direct control.

2) To capture customer characteristics during DRs and rolling outages, the detailed models of diverse loads (responsive and nonresponsive) are developed. These include an energy-material flow model of ILs, an adjustable load model of commercial loads (CLs), and an outage-sensitive model of residential loads (RLs).

3) The coordination of transactive DR and rolling outage is established as a bilevel optimization problem from DSOs and the load side, and then solved by the Stackelberg game-theoretic approach.

The remainder of this paper is organized as follows. In Section II, the framework of the proposed method is presented. Section III describes the detailed models of diverse loads. The bilevel optimization problem and solution are introduced in Section IV. Numerical simulation is presented in Section V, followed by conclusion in Section VI.

## II. FRAMEWORK OF PROPOSED METHOD

### A. Coordination of Transactive DR and Rolling Outage

The impacts of extreme heat waves on distribution systems are specifically addressed in this paper. Their impacts can be categorized into three main aspects.

1) Reduction in the upstream power supply: during the restoration process, the available upstream power gradually decreases due to insufficient hydropower output caused by drought conditions.

2) Occurrence of line faults: extreme heat waves accelerate the insulation aging of distribution lines and increase the risk of transformer overload, which can lead to multiple line faults and subsequent power interruptions during restoration.

3) Adverse health impacts on residents: prolonged outages expose residential customers to extreme thermal stress, potentially causing severe health risks. The longer the duration of the outage lasts, the more significant the adverse health

consequences will become.

To enhance the resilience of the distribution system, the potential and impact of diverse loads are exploited. The coordination of transactive DR and rolling outage are depicted in Fig. 1. The main grid supply is represented by arrows, indicating a progressive power decrease from the upper grid as the disaster persists. When the power supply is sufficient at time  $T_1$ , all the load demands can be met, as shown in Fig. 1(a). However, under the prolonged impact of extreme disasters, the power supply from the main grid to the distribution system gradually decreases at time  $T_2$ . To mitigate power shortages, some responsive loads initiate DR to reduce power consumption, as depicted in Fig. 1(b).

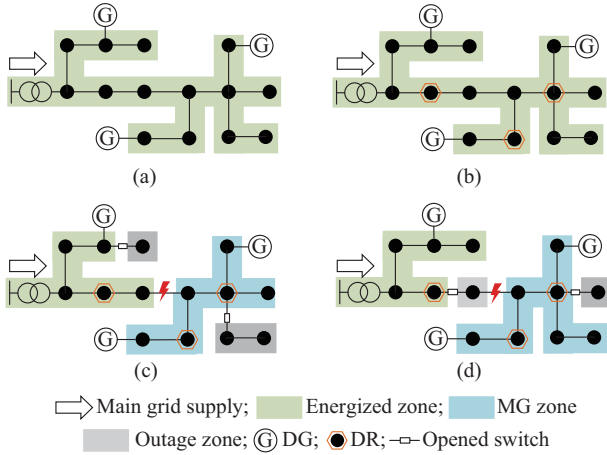


Fig. 1. Illustration of coordination of transactive DR and rolling outage. (a) Time  $T_1$ . (b) Time  $T_2$ . (c) Time  $T_3$ . (d) Time  $T_4$ .

After line faults occur in the distribution system, MGs can be formed by DGs to support critical loads. Due to the limited availability of local power generation resources, the extent of DR deepens to further reduce the demand. However, as the power supply continues to decline, DR measures alone become insufficient to address the imbalance between demand and supply. Active load shedding is required to prevent the collapse of the distribution system. To minimize the impact of power outages, rolling outages are implemented through line switches at time  $T_3$  and time  $T_4$ , as illustrated in Fig. 1(c) and (d).

### B. Bilevel Optimization Problem

To alter the power consumption behavior of responsive loads, a transactive market is established between the DSO and responsive customers. This market is associated with emergency DR programs triggered by load loss risk during extreme heat waves. The DSO aims to mitigate the imbalance between demand and supply, whereas customers with responsive loads seek to maximize their profits. As power shortages intensify, rolling outage is being increasingly utilized, with direct control over switches to minimize load loss. The bilevel optimization problem to coordinate the transactive DR and rolling outage during service restoration is illustrated in Fig. 2. At the upper level, based on the imbalance between the demand and supply from the main grid and DG, DSO formulates the DR strategies. In response to

incentive signals, each responsive customer makes operational decisions. At the lower level, industrial customers allocate limited power among different processes, while the loads of commercial customers are divided into adjustable and baseline loads. Customers also update their power demand information to the DSO to maximize their profits. Once the power shortage exceeds the adjustment capacity of the DR, rolling outage measures are implemented by operating sectionalizers and load breakers. MG formation and rolling outage decisions are enforced to directly adjust power consumption. By coordinating the DR program and rolling outage, the DSO seeks to minimize the load loss.

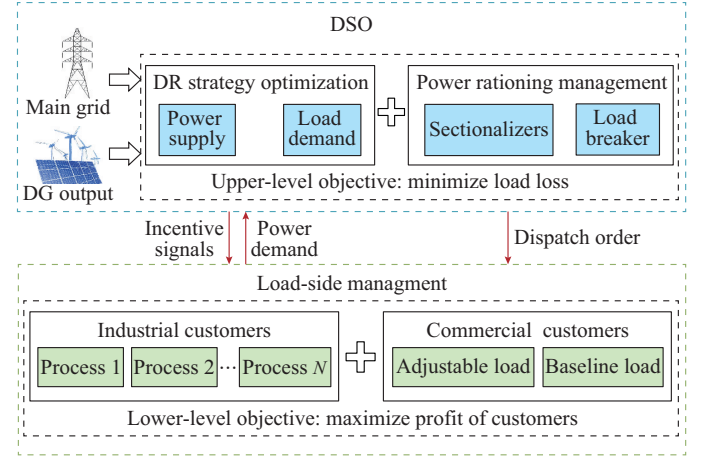


Fig. 2. Bilevel optimization problem.

### III. DETAILED MODELS OF DIVERSE LOADS

In this section, detailed models of diverse loads are presented that include an energy-material flow model of ILs, an adjustable load model of CLs, and an outage-sensitive model of RLs.

#### A. Energy-material Flow Model of ILs

Industrial customers always include factories such as steel plants, which contain different types of equipment closely related to industrial output. Considering the continuity of electrical characteristics, the loads of industrial customers can be divided into continuous and discrete loads.

##### 1) Multi-process Coupling of ILs

The operations of industrial customers across different processes are affected by both the power supply and material consumption, which is illustrated in Fig. 3, where R1-R5 are the material inventories. To represent the constraints, the energy-material flow with multi-process coupling of ILs is captured as:

$$z_{k,t}^{dis} \leq \frac{1}{RT_k} \sum_{\tau=t-RT_k-1}^t v_{k,\tau}^{dis} - \sum_{\tau=t-RT_k-1}^{t-1} z_{k,\tau}^{dis} \quad \forall k \in K^{dis}, \forall t \quad (1)$$

$$L_{k,t}^{dis} = v_{k,t}^{dis} \cdot PD_{k,t}^{dis} \quad \forall k \in K^{dis}, \forall t \quad (2)$$

$$L_{k,t}^{con} = v_{k,t}^{con} \cdot PD_{k,t}^{con} \quad \forall k \in K^{con}, \forall t \quad (3)$$

$$v_{k,t}^{con} \cdot PD_k^{min} \leq PD_{k,t}^{con} \leq v_{k,t}^{con} \cdot PD_k^{max} \quad \forall k \in K^{con}, \forall t \quad (4)$$

$$R_{k,t} = R_{k,t-1} + k_k^P L_{k,t}^{con} - k_{k+1}^P \cdot PD_{k,t}^{\xi} \quad \xi \in \{dis, con\}, \forall k \in K^{con}, \forall t \quad (5)$$

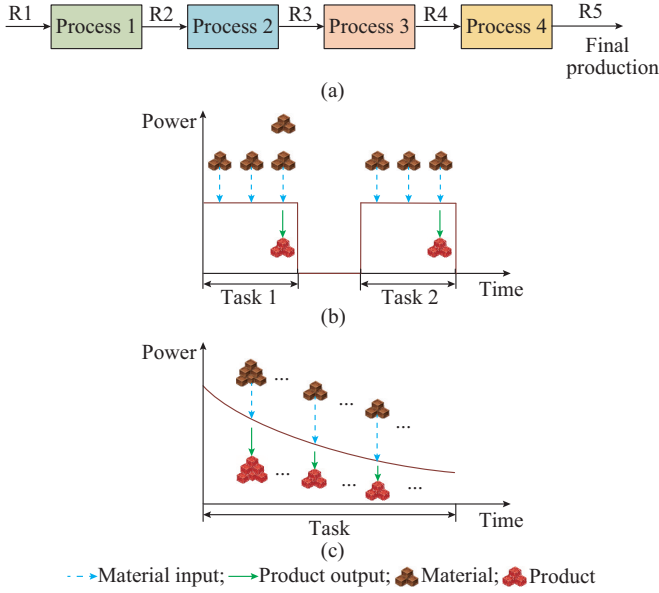


Fig. 3. Energy-material flow of ILs. (a) Different processes. (b) Discrete process. (c) Continuous process.

$$R_{k,t} = R_{k,t-1} + k_k^P z_{k,t}^{dis} - k_{k+1}^P \cdot PD_{k,t}^{\zeta} \quad \zeta \in \{dis, con\}, \forall k \in K^{dis}, \forall t \quad (6)$$

$$R_{k,t} \geq 0 \quad \forall k, \forall t \quad (7)$$

$$B_i^{ind,P} = c_i R_{K,T} \quad (8)$$

$$B_i^{ind,DR} = \sum_t \sum_k \lambda_t (PD_{k,t}^{dis} - L_{k,t}^{dis} + PD_k^{max} - L_{k,t}^{con}) \quad (9)$$

where  $v_{k,t}^{dis}$  and  $v_{k,t}^{con}$  are the binary variables indicating whether discrete process  $k$  and continuous process  $k$  are energized, respectively;  $z_{k,t}^{dis}$  is the production status of discrete process  $k$ ;  $RT_k$  is the required time for a single task of discrete process  $k$ ;  $L_{k,t}^{dis}$  and  $PD_{k,t}^{dis}$  are the dispatched and rated power of discrete process  $k$ , respectively;  $RT_k$  is the required time for single task of discrete process  $k$ ;  $PD_{k,t}^{con}$ ,  $PD_k^{max}$ , and  $PD_k^{min}$  are the dispatched, upper-limited, and lower-limited power of continuous process  $k$ , respectively;  $c_i$  is the revenue coefficient of the final product about IL  $i$ ;  $R_{k,t}$  is the material inventory of continuous or discrete process  $k$ ;  $k_k^P$  is the conversion coefficient between power and material output of continuous or discrete process  $k$ ;  $B_i^{ind,P}$  and  $B_i^{ind,DR}$  are the production profit and interactive benefit of industrial customer  $i$ , respectively;  $\lambda_t$  is the incentive price;  $K^{con}$  and  $K^{dis}$  are the sets of continuous and discrete processes, respectively; and  $K$  and  $T$  are the final process and the last time step during production, respectively.

Equation (1) represents the discrete processes that can only produce output after  $RT$ . Equation (2) represents the power of discrete processes. Since the operating state of this type of equipment is limited to on/off modes, it cannot achieve continuous changes in power consumption. Equation (3) indicates that the energy consumption behavior of a continuous load can change in continuous and controllable increments. Equation (4) specifies the range of power variation for continuous loads. Equations (5)-(7) indicate the material changes between the different processes with respect to the

continuous or discrete load. Equations (5) and (6) indicate the material production and consumption of continuous and discrete processes, respectively. Equation (7) ensures that the inventory of materials cannot be negative. Equation (8) describes the product profit of the ILs, since it benefits from the final production. Equation (9) is used to determine the benefits from participating in DR.

## 2) Cold Load Pick-up

Power shortages may cause both continuous and discrete loads in the factory to experience power interruptions. For ILs, continuous loads typically involve equipment such as boilers, which require a gradual restoration of power and a careful startup process to return to normal operation during cold load pick-up, as shown in Fig. 4. Additionally, frequent start-stop cycles can lead to higher repair and maintenance costs. To mitigate this, a cold load pick-up model is developed to capture the power consumption and startup cost associated with continuous load operation.

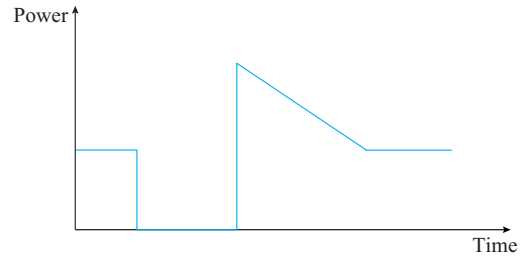


Fig. 4. Cold load pick-up for continuous load of ILs.

$$u_{k,t}^{(1)} + u_{k,t}^{(2)} + u_{k,t}^{(3)} = 1 \quad \forall k \in K^{con}, \forall t \quad (10)$$

$$u_{k,t}^{(2)} = 1 - v_{k,t}^{con} \quad \forall k \in K^{con}, \forall t \quad (11)$$

$$u_{k,t}^{(2)} + u_{k,t}^{(3)} = v_{k,t}^{con} \quad \forall k \in K^{con}, \forall t \quad (12)$$

$$\begin{cases} SO_{k,t}^{con} \leq 0.5 + (v_{k,t-1}^{con} - v_{k,t}^{con})/2 \\ SO_{k,t}^{con} \geq -0.4 + (v_{k,t-1}^{con} - v_{k,t}^{con})/2 \end{cases} \quad \forall k \in K^{con}, \forall t \quad (13)$$

$$\sum_{\tau=t}^{t+CT_k} u_{k,\tau}^{(1)} = (1 - u_{k,t}^{(2)}) \cdot CT_k \quad \forall k \in K^{con}, \forall t \quad (14)$$

$$\begin{cases} LD_{k,t}^{con} \leq L_{k,t}^{con} + (1 - u_{k,t}^{(1)})M \\ LD_{k,t}^{con} \geq L_{k,t}^{con} - (1 - u_{k,t}^{(1)})M \end{cases} \quad \forall k \in K^{con}, \forall t \quad (15)$$

$$\begin{cases} LD_{k,t}^{con} \leq (1 - u_{k,t}^{(2)})M \\ LD_{k,t}^{con} \geq -(1 - u_{k,t}^{(2)})M \end{cases} \quad \forall k \in K^{con}, \forall t \quad (16)$$

$$\begin{cases} LD_{k,t}^{con} \leq PD_k^C - \Delta P_k^C \left( \sum_{\tau=t}^{t+CT_k} u_{k,\tau}^{(3)} - 1 \right) + (1 - u_{k,t}^{(3)})M \\ LD_{k,t}^{con} \geq PD_k^C - \Delta P_k^C \left( \sum_{\tau=t}^{t+CT_k} u_{k,\tau}^{(3)} - 1 \right) - (1 - u_{k,t}^{(3)})M \end{cases} \quad \forall k \in K^{con}, \forall t \quad (17)$$

$$PD_{i,t} = \sum_k LD_{k,t}^{con} + \sum_k L_{k,t}^{dis} \quad \forall k \in K, \forall t \quad (18)$$

$$C_i^O = \sum_k \sum_t c_k \cdot SO_{k,t}^{con} \quad (19)$$

where  $u_{k,t}^{(1)}$ ,  $u_{k,t}^{(2)}$ , and  $u_{k,t}^{(3)}$  are the indicator variables of continuous process  $k$ , corresponding to normal operation, shutdown, and ramping (cold load pick-up) states, respectively;  $SO_{k,t}^{con}$  is the shutdown occurrence variable of continuous process  $k$ ;  $CT_k$  is the duration of the cold load pick-up interval of continuous process  $k$ ;  $LD_{k,t}^{con}$  is the load demand under several states of continuous process  $k$ ;  $PD_k^C$  is the rated power of continuous process  $k$ ;  $\Delta P_k^C$  is the power increment during ramping of continuous process  $k$ ;  $C_i^O$  is the total shutdown cost;  $c_k$  is the coefficient of shutdown cost of continuous process  $k$ ; and  $M$  is a sufficiently large positive number used for linearization.

Equation (10) ensures that the continuous load can only be in one of the three operation states at any time. Equation (11) and (12) describe the logical relationships between the energized status  $v_{k,t}^{con}$  and the three operation states. Equation (13) determines the start time of shutdown, which is updated according to the change of the energized status. Equation (14) defines the recovery time constant. Equations (15)-(17) express the power consumption behavior of continuous load in different operation states. Equation (18) ensures that the total power demand of ILs equals the sum of all discrete and continuous load consumptions. Finally, (19) expresses the shutdown cost of industrial customer  $i$ , which is related to the unit shutdown cost and the shutdown occurrence.

### B. Adjustable Load Model of CLs

CLs are divided into adjustable and baseline loads. The adjustable load can be shed or shifted to reduce power shortages, and the baseline load is the basic load demand of commercial customers, whose reduction affects business activities and causes economic losses.

The adjustable load contains the interruptible and transferable loads, and the adjustable load model of CLs can be given as:

$$PD_{i,t}^{shift} = PD_{i,t}^{TL} + PD_{i,t}^{IL} \quad \forall i, \forall t \quad (20)$$

$$0 \leq PD_{i,t}^{IL} \leq \overline{PD}_{i,t}^{IL} \quad \forall i, \forall t \quad (21)$$

$$0 \leq PD_{i,t}^{TL} \leq \overline{PD}_{i,t}^{TL} \quad \forall i, \forall t \quad (22)$$

$$\sum_i PD_{i,t}^{TL} \leq PL_i^{TL} \quad \forall i \quad (23)$$

where  $PD_{i,t}^{shift}$  is the total adjustable load of commercial customer  $i$ , which consists of interruptible and transferable parts;  $PD_{i,t}^{IL}$  is the interruptible load of commercial customer  $i$  that can be curtailed to reduce power shortage;  $PD_{i,t}^{TL}$  is the transferable load of commercial customer  $i$  that can be shifted across different time periods;  $\overline{PD}_{i,t}^{IL}$  and  $\overline{PD}_{i,t}^{TL}$  are the corresponding upper bounds of  $PD_{i,t}^{IL}$  and  $PD_{i,t}^{TL}$ , respectively; and  $PL_i^{TL}$  is the maximum amount of transferable energy of commercial customer  $i$ .

Equation (20) defines the total amount of adjustable load as the sum of interruptible and transferable loads. Equations (21) and (22) specify the permissible adjustment ranges for interruptible and transferable loads, respectively. Equation (23) ensures that the total transferable load over all time

steps does not exceed the maximum transferable energy  $PL_i^{TL}$ , which represents the total amount of energy that can be shifted within the scheduling horizon.

$$0 \leq PD_{i,t}^{shedding} \leq u_{i,t}^{IL} P_{i,t}^{BS,max} \quad \forall i, \forall t \quad (24)$$

$$C_i^{com,P} = \sum_k \sum_t \alpha_i (P_{i,t}^{BS,max} - PD_{i,t}^{shedding}) (1 + \gamma_t) + c_i^{TL} \left( PL_i^{TL} - \sum_i PD_{i,t}^{TL} \right) + \sum_t c_i^{IL} (\overline{PD}_{i,t}^{IL} - PD_{i,t}^{IL}) \quad (25)$$

$$B_i^{com,DR} = \sum_t \lambda_t \left[ \sum_i PD_{i,t}^{shedding} + \sum_i (\overline{PD}_{i,t}^{IL} - PD_{i,t}^{IL}) \right] \quad (26)$$

where  $PD_{i,t}^{shedding}$  is the baseline load shedding of commercial customer  $i$ ;  $\alpha_i$  is the loss coefficient of the baseline load of commercial customer  $i$ ;  $\gamma_t$  is the customer attrition rate that varies with time;  $c_i^{TL}$  and  $c_i^{IL}$  are the unit loss coefficients of transferable and interruptible loads of commercial customer  $i$ , respectively; and  $PL_i^{TL}$  is the total transferable load capacity of commercial customer  $i$ ;  $P_{i,t}^{BS,max}$  is the upper limit of shedding of commercial customer  $i$ ;  $C_i^{com,P}$  is the economic loss of commercial customer  $i$ ; and  $B_i^{com,DR}$  is the benefit obtained by commercial customer  $i$  during DR.

Equation (24) constrains the shedding range. Equation (25) defines  $C_i^{com,P}$ , which consists of three parts: the loss caused by baseline load shedding, the loss associated with transferable load shortage, and the loss due to interruptible load curtailment. Equation (26) defines  $B_i^{com,DR}$ , which consists of the incentive payment corresponding to the reduced baseline and interruptible load determined by  $\lambda_t$ .

### C. Outage-sensitive Model of RLs

With respect to RLs, exposure to extreme weather events during a power outage can lead to several adverse health impacts for residents. Thus, damage functions related to interruption cost based on outage duration are developed as:

$$OD_{i,t}^{res} = v_{i,t} (OD_{i,t-1}^{res} + 1) \quad (27)$$

$$C_{i,t}^{res} = c_i^{res} \cdot OD_{i,t}^{res} \quad (28)$$

where  $OD_{i,t}^{res}$  is the outage duration of residential customer  $i$ , which depends on the restoration status variable  $v_{i,t}$ ;  $C_{i,t}^{res}$  is the medical cost of residential customer  $i$ ; and  $c_i^{res}$  is the unit medical cost coefficient.

Equation (27) updates the outage duration based on the previous time step, such that if a customer remains unenergized ( $v_{i,t} = 1$ ), the outage duration increases by one; otherwise, it resets to zero when the power is restored. For instance, if  $v_{i,t} = [1, 1, 0]$ , the outage duration  $OD_{i,t}^{res}$  can be  $[0, 0, 1, 2, 0, 0, 1, 2, 3]$ . Equation (28) defines  $C_{i,t}^{res}$ , which is linearly related to the outage duration through  $c_i^{res}$ . This model captures the health and safety impacts of prolonged power interruptions on residents during extreme weather events.

## IV. BILEVEL OPTIMIZATION PROBLEM AND SOLUTION

In response to the power reduction from main grid and line faults during extreme weather events, a coordination method is proposed to enhance the resilience of distribution systems. This method integrates transactive DR and rolling

outage management and is established as a bilevel optimization problem that includes DSO and the load side.

### A. Upper-level Optimization of DSOs

In the bilevel optimization problem, DSOs integrate line switches, DGs, responsive loads, and other non-dispatchable loads to reduce load loss during extreme weather events.

#### 1) Objective Function

The objective of the bilevel optimization model is to minimize the total operation costs, as well as the load shedding cost during the restoration:

$$F = \min(C^{SH} + C^{EX} + C^{DR} + C^{DG} + C^{MC}) \quad (29)$$

$$\begin{cases} C^{SH} = \sum_i \sum_t \rho_i^{SH} (PL_{i,t}^D - PD_{i,t}^D) \quad \forall t, \forall i \\ C^{EX} = \sum_i \sum_t \rho_i^D \cdot PS_{i,t}^D \quad \forall t, \forall i \in \Omega_{Sub} \\ C^{DR} = \sum_i (B_i^{ind,DR} + B_i^{com,DR}) \quad \forall t, \forall i \in \Omega_{IL} \cup \Omega_{CL} \\ C^{DG} = \sum_i \sum_t \rho_i^{DG} \cdot PG_{i,t}^D \quad \forall t, \forall i \in \Omega_{DG} \\ C^{MC} = \sum_i \sum_t C_{i,t}^{res} \quad \forall t, \forall i \in \Omega_{RL} \end{cases} \quad (30)$$

where  $F$  is the total objective function of DSOs, aiming to minimize the overall operation cost and load shedding losses during the restoration process;  $C^{SH}$  is the cost of unserved load calculated based on the difference between the demand  $PL_{i,t}^D$  and supplied power  $PD_{i,t}^D$  of customer  $i$  weighted by the unit load shedding cost coefficient  $\rho_i^{SH}$ ;  $C^{EX}$  is the electricity purchasing cost from the upper-level grid;  $PS_{i,t}^D$  is the purchased power of customer  $i$ ;  $\rho_i^D$  is the unit electricity price of the substation of customer  $i$ ;  $C^{DR}$  is the incentive cost paid to responsive customers for participating in transactive DR, including both industrial and commercial customers, denoted by  $B_i^{ind,DR}$  and  $B_i^{com,DR}$ , respectively;  $C^{DG}$  is the total generation cost of DGs;  $PG_{i,t}^D$  is the DG output;  $\rho_i^{DG}$  is the unit generation cost of customer  $i$ ;  $C^{MC}$  is the total medical cost of residential customers during power outages;  $C_{i,t}^{res}$  is the medical cost of residential customer  $i$ ;  $\Omega_{Sub}$  and  $\Omega_{DG}$  are the sets of nodes connected to the substation and DGs, respectively; and  $\Omega_{IL}$ ,  $\Omega_{CL}$ , and  $\Omega_{RL}$  are the load nodes categorized as ILs, CLs and RLs, respectively.

#### 2) MG Formation and Rolling Outage Management

Considering the reduction of continuous power supply and the line faults, it is insufficient to only use the DR measures to enhance resilience of distribution systems. MG formation and rolling outage management are employed to supplement DR, providing emergency power support and maintaining power balance through the operation of sectionalizers and load switches.

$$x_{i,i,t} = 1 \quad i \in \Omega_{Sub}, \forall t \quad (31)$$

$$x_{i,i,t} \leq 1 \quad i \in \Omega_{BDG}, \forall t \quad (32)$$

$$x_{i,i,t} = 0 \quad i \notin \Omega_{BDG} \cup \Omega_{Sub} \quad (33)$$

$$x_{i,j,t} + x_{j,i,t} \leq \beta_{i,j,t} - F_{i,j,t} \quad \forall (i,j), \forall k \quad (34)$$

$$\sum_j x_{i,j,t} \leq N_{node} \sum_j x_{j,i,t} \quad \forall i, \forall t \quad (35)$$

$$\sum_{i \in V} x_{i,j,t} \leq 1 \quad \forall j, \forall k \quad (36)$$

$$s_{i,t} = \sum_j x_{j,i,t} \quad \forall i, \forall t \quad (37)$$

$$v_{i,t} \leq s_{i,t} \quad \forall i, \forall t \quad (38)$$

$$\sum_t |v_{i,t+1} - v_{i,t}| \leq K \quad \forall i \quad (39)$$

where  $x_{i,j,t}$  is the energization path in the DS of line  $ij$ , which indicates the rolling outage management [30];  $\beta_{i,j,t}$  and  $F_{i,j,t}$  are the switch and fault statuses of line  $ij$ , respectively;  $v_{i,t}$  is the restored status of customer  $i$ ;  $N_{node}$  is the total number of nodes;  $\Omega_{BDG}$  is the set of black-start DG nodes; and  $s_{i,t}$  is the energized status of customer  $i$ .

Equations (31) - (33) indicate that the energization path must originate from a substation or DG with black-start capability. Equation (34) demonstrates that the energization path is determined by the status of the feeder switches and faults, excluding lines with open switches or faults. In (35), a child node can be energized once its parent node is energized. Equation (36) ensures radiality by limiting each node to have at most one parent node. Equation (37) specifies that the energized status  $s_{i,t}$  equals 1 after being visited by the energization paths. Equation (38) represents the rolling outage of various loads through load switch operations. Equation (39) limits the maximum number of load switch operations during a rolling outage.

#### 3) Distribution System Operation

Based on the coordination of transactive DR and rolling outage, the power flow of distribution system is calculated to determine the load restoration performance as:

$$0 \leq PS_{i,t} \leq PS_{i,t}^{sub} \quad \forall t, \forall i \in \Omega_{Sub} \quad (40)$$

$$0 \leq QS_{i,t} \leq QS_{i,t}^{sub} \quad \forall t, \forall i \in \Omega_{Sub} \quad (41)$$

$$0 \leq PD_{i,t}^D \leq v_{i,t} \cdot PL_i^D \quad \forall t, \forall i \quad (42)$$

$$0 \leq PG_{i,t} \leq u_{i,t} \cdot PG_i^{\max} \quad \forall t, \forall i \in \Omega_{DG} \quad (43)$$

$$0 \leq QG_{i,t} \leq u_{i,t} \cdot QG_i^{\max} \quad \forall t, \forall i \in \Omega_{DG} \quad (44)$$

$$-Mx_{i,j,t} \leq P_{i,j,t} \leq Mx_{i,j,t} \quad \forall (i,j), \forall t \quad (45)$$

$$-Mx_{i,j,t} \leq Q_{i,j,t} \leq Mx_{i,j,t} \quad \forall (i,j), \forall t \quad (46)$$

$$\sum_j P_{j,i,t} + PS_{i,t} + PG_{i,t} = PD_{i,t}^D + \sum_j P_{i,j,t} \quad \forall i, \forall t \quad (47)$$

$$\sum_j Q_{j,i,t} + QS_{i,t} + QG_{i,t} = k_i^D \cdot PD_{i,t}^D + \sum_j Q_{i,j,t} \quad \forall i, \forall t \quad (48)$$

$$U_{i,t} - U_{j,t} \leq 2(R_{i,j}P_{i,j,t} + X_{i,j}Q_{i,j,t}) + M(1 - x_{i,j,t}) \quad \forall i, \forall j, \forall t \quad (49)$$

$$U_{i,t} - U_{j,t} \geq 2(R_{i,j}P_{i,j,t} + X_{i,j}Q_{i,j,t}) - M(1 - x_{i,j,t}) \quad \forall i, \forall j, \forall t \quad (50)$$

$$v_{i,t} \underline{U}_i \leq U_{i,t} \leq v_{i,t} \bar{U}_i \quad \forall i, \forall t \quad (51)$$

where  $PS_{i,t}$  and  $QS_{i,t}$  are the active and reactive power purchased from customer  $i$ , respectively;  $PS_{i,t}^{sub}$  and  $QS_{i,t}^{sub}$  are the capacity limits of  $PS_{i,t}$  and  $QS_{i,t}$ , respectively;  $PL_i^D$  and  $PD_{i,t}^D$  are the restored load and the total load demand of customer  $i$ , respectively;  $PG_{i,t}$  and  $QG_{i,t}$  are the active and reactive power outputs of DGs of customer  $i$ , respectively;  $PG_i^{\max}$  and

$QG_i^{\max}$  are the maximum ratings of  $PG_{i,t}$  and  $QG_{i,p}$  respectively;  $P_{i,j,t}$  and  $Q_{i,j,t}$  are the active and reactive power flows of line  $ij$ , respectively;  $R_{i,j}$  and  $X_{i,j}$  are the resistance and reactance of line  $ij$ , respectively;  $U_{i,t}$  is the voltage magnitude of customer  $i$ ; and  $\underline{U}_i$  and  $\bar{U}_i$  are the lower and upper limits of  $U_{i,t}$ , respectively.

Equations (40) and (41) indicate that the purchased power is limited by the maximum obtainable power of the substation, which is used to model the power supply decrease from the main grid. Equation (42) indicates the amount of restored load, and constrains the total restored load according to the energized status  $v_{i,t}$ . Equations (43) and (44) show the active and reactive output limits of the DGs, respectively. Equations (45) and (46) apply linearized flow limits on the active and reactive power through line, bounded by a large positive constant  $M$  used for the big- $M$  linearization. A linearized DistFlow model [31], [32] is shown in (47)–(51). The active and reactive power balances are shown in (47) and (48), respectively. The node voltage is calculated using (49) and (50). The allowable range of voltage deviation is shown in (51).

### B. Lower-level Optimization of Responsive Load

On the responsive load side, different loads such as ILs and CLs respond to market signals, which aim to maximize profits while coordinating DR and production. The objective of the lower-level optimization is to maximize the production profits and interactive benefits.

$$F = \max(B^{pro} + B^{DR}) \quad (52)$$

$$\begin{cases} B^{pro} = \sum_i B_i^{ind,P} - \sum_i C_i^{com,P} & \forall t, \forall i \in \Omega_{IL} \cup \Omega_{CL} \\ B^{DR} = \sum_i B_i^{ind,DR} + \sum_i B_i^{com,DR} & \forall t, \forall i \in \Omega_{IL} \cup \Omega_{CL} \end{cases} \quad (53)$$

where  $B^{pro}$  and  $B^{DR}$  are the production profits and interactive benefits of ILs and CLs, respectively. Notably, the maximum production profits of CLs are defined as the minimum economic loss caused by DR.

### C. Solution of Bilevel Optimization Problem

During restoration, responsive customers adjust the power reduction amount based on the incentives provided by the DSO to maximize the benefits. The DSO adjusts the incentive price and rolling outage decisions based on power reduction for responsive customers to minimize the load loss, and this incentive price and rolling outage further affect the decision-making of responsive customers. Thus, DSO is the leader and responsive customers are the followers, and DSO engages in a master-slave game with responsive customers. The bilevel optimization problem coordinating the DR program and rolling outage can be formulated as a master-slave game model from DSOs and responsive customers.

The Karush-Kuhn-Tucker method is effective for solving the bilevel optimization problem, which replaces the lower level and recasts the original bilevel optimization problem into a single level [33]. However, many binary variables of load operation are involved in the lower level, and the strong duality of the transformation cannot be ensured. After being processed through linearization methods such as the

big- $M$  linearization, the upper and lower models can be directly solved by the CPLEX solver, and the bilevel optimization problem can be iteratively solved until convergence. Thus, the iterative solution process of bilevel optimization problem is shown in Fig. 5.

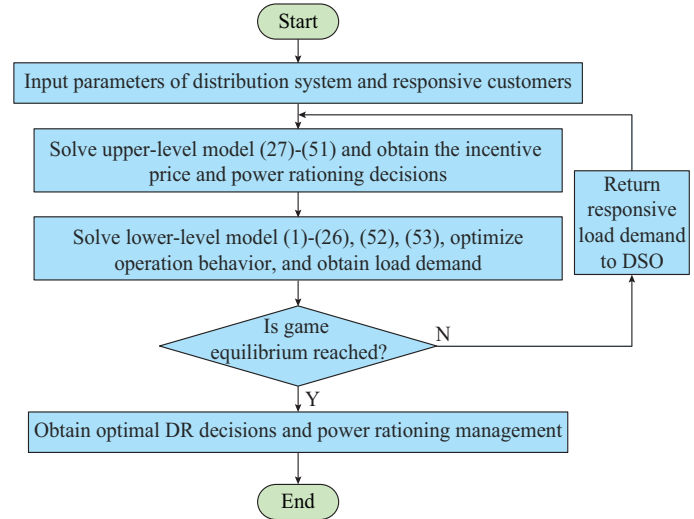


Fig. 5. Iterative solution process of bilevel optimization problem.

## V. NUMERICAL SIMULATIONS

### A. Test System

In this subsection, the proposed method is tested on a modified IEEE 33-node system to validate its efficiency. The topology of the test system is illustrated in Fig. 6, where WT represents the wind turbine, ESS represents the energy storage system, and F1 and F2 represent two line faults. Three ILs are assumed to be located at nodes 5, 16, and 30. Depending on the type of industry, each industrial model can be simplified as a combination of several discrete and continuous processes. Additionally, the other three CLs are located at nodes 15, 20, and 32. The detailed parameters of the ILs and CLs are presented in Tables I and II, respectively, where C and D represent continuous and discrete process loads, respectively.

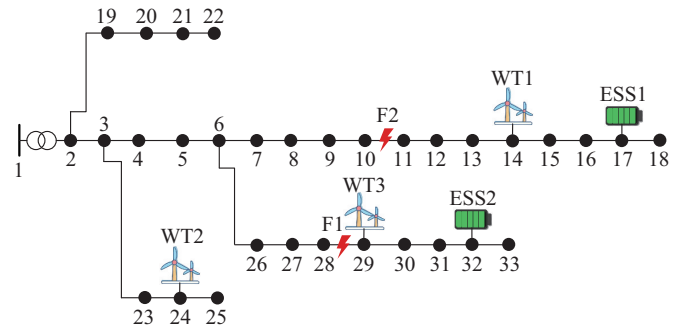


Fig. 6. Topology of test system.

The service restoration process is assumed to last for 6 hours, divided into 12 time steps of 30 min each. Owing to an extreme weather event, F1 and F2 occur at time steps 3 and 6. Moreover, the power supply from the main grid grad-

ually decreases, resulting in a more severe imbalance of demand and supply.

TABLE I  
DETAILED PARAMETERS OF ILS

| Number | Location | Type         | Process and power (kW)                |
|--------|----------|--------------|---------------------------------------|
| IL1    | 5        | Steel plant  | D1: 50, C1: 100, C2: 250, and D2: 100 |
| IL2    | 16       | Copper plant | D1: 70, C1: 120, and C2: 200          |
| IL3    | 30       | Cement plant | D1: 70, C1: 150, and D2: 100          |

TABLE II  
DETAILED PARAMETERS OF CLS

| Number | Location | Load demand (kW) |                    |                    |
|--------|----------|------------------|--------------------|--------------------|
|        |          | Baseline load    | Interruptible load | Transferrable load |
| CL1    | 15       | 80               | 40                 | 125                |
| CL2    | 20       | 200              | 100                | 250                |
| CL3    | 32       | 100              | 50                 | 150                |

### B. Optimization Results of Restoration Decisions

To address the severe imbalance between demand and supply during extreme weather events, the proposed method is optimized to achieve a coordination of transactive DR and rolling outage management.

#### 1) Optimized MG Formation and Rolling Outage

To address line faults during extreme weather events, two MGs are formed by ESSs with dynamic capabilities, in which two wind farms can provide a continuous power supply. Responsive loads are dispatched by market signals, which can mitigate power shortages by changing power consumption behavior. As the power shortage intensifies beyond the adjustment range of DR, rolling outage management is implemented to mandatorily allocate power to avoid significant losses by prolonged outages. The MG formation and rolling outage of the test system are illustrated in Fig. 7.

At time steps 1-3, the power supply from the substation begins to decline as the upstream grid is also affected, resulting in limited generation output. In the initial stages of power reduction of main grid, loads at node 20 initiate the DR actions, reducing the power consumption to accommodate the needs of other users. After the occurrence of line fault F1 at time step 3, MG1 is formed with support from ESS2 and WT3 to restore power for loads at nodes 29-33. With sufficient generation capacity from WT3, all load demands in MG1 can be met, although the DR intensity must be increased in the energized zone of substation.

After line fault F2 occurs at time step 5, MG2 is formed with support from ESS1 and WT1. However, the power output of MG2 is insufficient to meet the load demand due to its disconnection from the upstream grid. The IL and CL at nodes 15 and 16 further adjust their power consumption patterns to minimize the loss of other critical loads. As the output of WT1 fluctuates and decreases, the imbalance between demand and supply exceeds the DR capacity. Consequently, rolling outages are implemented to prevent a prolonged blackout, even when the IL at node 16 is included, with a low pick-up cost. As the power of main grid decreases and

the two wind power sources become disconnected due to line faults, the DR intensity progressively increases. Ultimately, rolling outages are necessary to manage the situation.

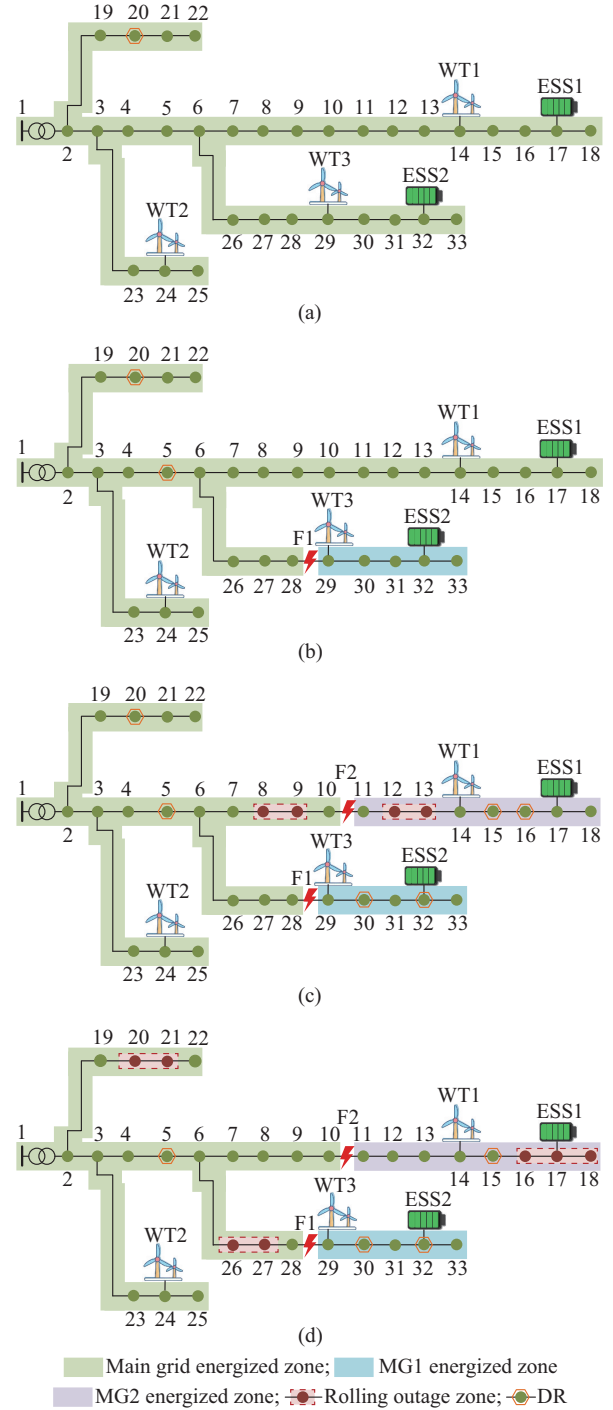


Fig. 7. MG formation and rolling outage of test system. (a) Time step 2. (b) Time step 5. (c) Time step 9. (d) Time step 11.

#### 2) Transactive DR Measures

Considering the power shortage during service restoration, the coordination of transactive DR and rolling outage management is utilized to reduce critical load loss. To indicate the supply and demand during the service restoration, the power demand and output in the three zones are shown in Fig. 8(a)-(c), respectively.

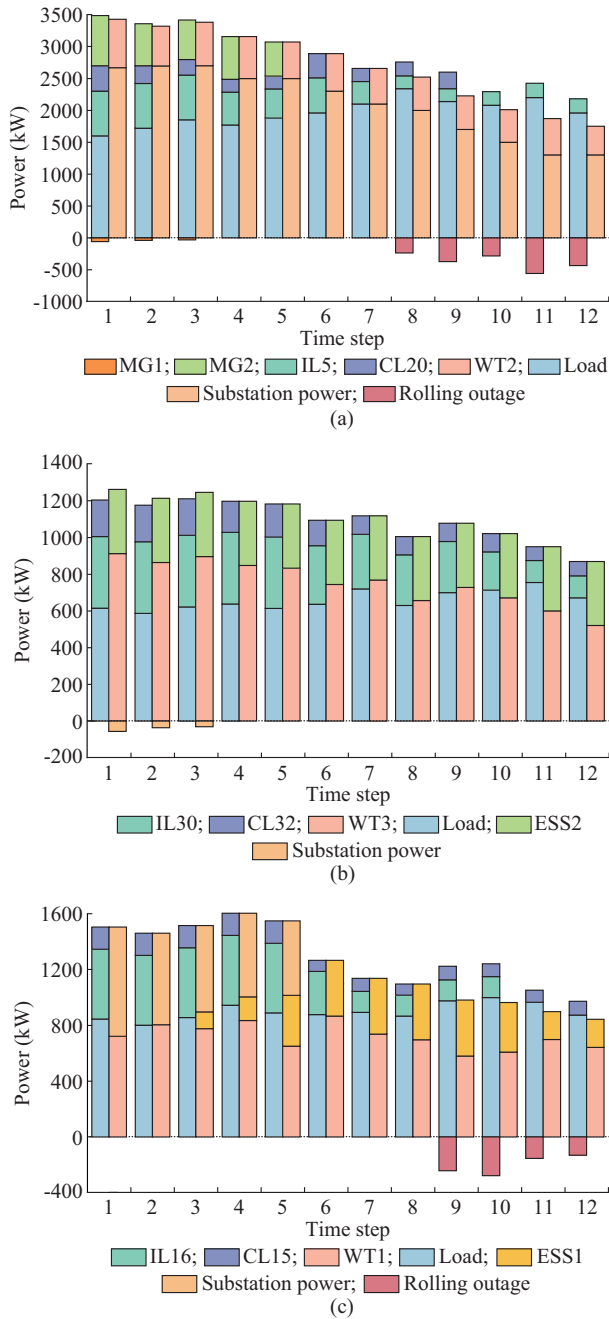


Fig. 8. Power demand and output in three zones energized by substation, MG1, and MG2. (a) Zone energized by substation. (b) Zone energized by MG1. (c) Zone energized by MG2.

Due to the sufficient generation outputs of WT3 and ESS2, the load can be supported in MG2. Even if the output of WT3 fluctuates downward, the slight DR of CL32 and IL30 can balance the output and demand without the need for alternating power outages to actively reduce the load.

With the load demand in MG2 larger than the DG output, a power gap is caused after F2, which makes it unable to obtain the power of main grid. The loads of CL15 and IL16 sharply decrease in response to the signal of a power shortage. As the output of WT1 further decreases, the power gap exceeds the DR adjustment range, and rolling outages of several non-critical loads are implemented, such as IL16 with a

low shutdown cost.

### 3) Energy-material Flow of ILs

The energy-material flow of ILs is proposed to model the load demand and production output across different processes. The energy-material flows of three ILs are shown in Fig. 9, illustrating the operational decisions made in response to the interactive needs of the distribution system, while maximizing the production revenue.

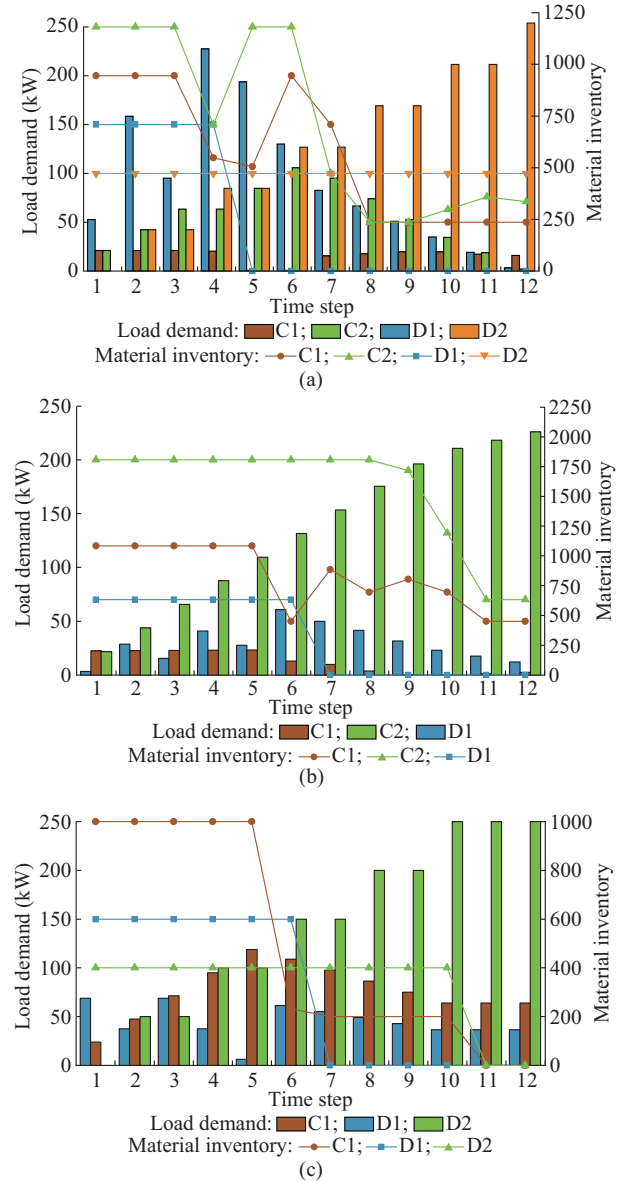


Fig. 9. Energy-material flows of three ILs. (a) IL5. (b) IL30. (c) IL16.

For IL5, which is located in the zone energized by the substation, the industrial customer consists of two discrete processes and two continuous processes, with the production flow following the sequence “D1→C1→C2→D2”. Due to the high profitability of the final product produced by D2, this discrete process maintains a constant load demand. The inventory of the final product increases every two time steps, corresponding to the time interval required for discrete process D2. Discrete process D1 operates normally and

shuts down after time step 5 to reduce power consumption, having produced enough primary products during its operational period. The continuous processes C1 and C2 gradually decrease their load demand as the power shortage worsens, and the power between C1 and C2 is distributed based on the energy-material flow and material inventory under a limited power supply. Eventually, C1 and C2 operate in the minimum power mode to avoid interruption due to high shut-down costs.

For IL30, which is located in the zone energized by MG1, the industrial customer consists of one discrete process and two continuous processes, with the production flow following the sequence “D1→C1→C2”. After F1 occurs at time step 4, the operation turns to the islanded mode in the formed MG1. Due to the relatively sufficient DG output, the imbalance between demand and supply can be solved by the DR of IL30. Discrete process D1 shuts down after sufficient primary products are available. Continuous processes C1 and C2 decrease the demand to mitigate power shortages, and still operate to earn a profit.

For IL16, which is located in the zone energized by MG2, the industrial customer consists of two discrete processes and one continuous process, with the production flow following the sequence “D1→C1→D2”. After F2 occurs at time step 6, causing a severe imbalance between demand and supply, the industrial customer quickly reduces its power consumption, with D1 shutting down and C1 operating in the minimum power mode. As the power of WT1 declines and the SOC of ESS1 becomes insufficient, IL16 is classified as a load subject to rotating power outages. It experiences power interruptions at time steps 11 and 12 due to its low-cost product and the minimal cost of starting and stopping the continuous loads.

### C. Optimization Results

To illustrate the superiority of the proposed method in terms of coordinating transactive DR and rolling outage management, three other methods are established for comparison. The results such as load loss cost, production profit of IL, and DR profit are listed in Table III.

TABLE III  
DETAILED PARAMETERS OF IL

| Method | Load loss cost (\$) | Production profit of IL (\$) | DR profit (\$) |
|--------|---------------------|------------------------------|----------------|
| 1      | 91000               | 7290                         | 5620           |
| 2      | 335000              |                              | 3840           |
| 3      | 7430000             | 762                          | 1150           |
| 4      | 838000              | 10500                        |                |

1) Method 1: the proposed method with a detailed model of ILs.

2) Method 2: the method for coordinating DR and rolling outage with the load adjustment range of IL.

3) Method 3: the method considering DR with the detailed model of ILs without rolling outage management.

4) Method 4: the method considering rolling outage management with the detailed model of ILs but without DR.

In terms of the load interruption loss, the results of Meth-

od 1 demonstrate that compared with alternative methods, it significantly reduces the load loss. Without rolling outage management, part of the load experiences a prolonged outage, leading to a significant increase in loss in Method 3. Without the DR considered in Method 4, the flexibility of the demand side cannot be exploited to address the power shortage. With only the adjustment range considered in Method 2, a limited scheduling potential can be utilized.

In terms of production and DR profits, the customers do not participate in the DR program, and the ILs can operate normally when provided with a power supply in Method 4. Thus, this method has the highest production profit and zero DR profit. In contrast, the rolling outage is not considered in Method 3. Although ILs can respond to the incentive signal, the responsive loads are always curtailed to prioritize power for critical loads. In Method 2, the lack of a detailed energy-material model of ILs and the mere provision of a power adjustment range hinder the full exploration of the DR potential of the ILs, resulting in decreased DR profit. In Method 1, the proposed method participates in the DR program while adjusting the power based on the energy-material flow model, which can increase the DR performance and production revenue. Thus, the maximum customer benefit, including production and DR profit, can be achieved in Method 1.

## VI. CONCLUSION

In this paper, a novel coordination method of transactive DR and rolling outage management of diverse loads is proposed during service restoration of distribution systems. This paper also establishes detailed models of diverse loads that include an energy-material flow model of ILs, an adjustable load model of CLs, and an outage-sensitive model of RLs. Afterward, the bilevel optimization problem is iteratively solved by the Stackelberg game-theoretic approach. The effectiveness of the proposed method is validated on a modified IEEE 33-node system, and the load interruption loss of the distribution system can be effectively reduced by DR and rolling outage strategies. The profit of customers can be improved by adjusting the power distribution between different processes.

In future studies, the participation willingness factor will be incorporated to capture the behavioral tendencies of customers. Additionally, multiple uncertainties such as renewable energy variability and more efficient solution algorithms will be integrated into coordination to ensure the security constraints during the service restoration process.

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