Enhancing Power System Operational Resilience Against Wildfires

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***Abstract*—Catastrophic impacts of wildfires on the performance of power grids have increased in the recent years. Though various methods have been applied to enhance power grid resilience against severe weather events, only a few have focused on wildfires. Most previous operational-based resilience enhancement methods have focused on corrective or restorative strategies during and after extreme events without proactively preparing the system for forecasted potential failures. Also, the propagation behavior of wildfires among system components induces further complexities resulting in a mathematically involved problem accompanied with many modeling challenges. During sequential failures, operators need to make decisions in a fast-paced manner to maintain reliable operation and avoid cascading failures and blackouts. Thereby, the complexity of decision processes increases dramatically during extreme weather events. This article proposes a probabilistic proactive generation redispatch strategy to enhance the operational resilience of power grids during wildfires. A Markov decision process is used to model system state transitions and to provide generation redispatch strategies for each possible system state given component failure probabilities, wildfire spatiotemporal properties, and load variation. For a realistic system representation, dynamic system constraints are considered including ramping rates and minimum up/down times of generating units, load demand profile, and transmission constraints. The IBM ILOG CPLEX optimization studio is utilized to solve the optimization problem. The IEEE 30-bus system is used to validate the proposed strategy under various impact scenarios. The results demonstrate the effectiveness of the proposed method in enhancing the resilience level of power grids during wildfires.**

***Index Terms*—Extreme weather events, generation redispatch, Markov decision process (MDP), resilience, wildfires.**

NOMENCLATURE

Indices and Sets

C	Index of impacted system components
i, i'	Index of Markov states
i''	Index of all proceeding states from $S_{i,t}$
j	Index of generators
m	Index of system components
n, n'	Index of buses
t	Index of time instants
Ω^A	Set of all possible actions
Ω^G	Set of all generators
Ω^G_n	Set of generators connected to bus n
Ω^N	Set of all buses
Ω^N_n	Set of buses connected to bus n
Ω^T	Set of all time instants
$\Omega_{c,t}$	Set of all impacted components at t
$\Omega_{S,t}$	Set of all Markov states at t
$\Omega^S_{i,t+}$	Set of all possible transition states from $S_{i,t}$

Notation for Optimization Problem

a	An action
$A_{a,t}$	Possible actions at t
b	Linear fuel cost coefficient
$C_t(S_{i,t}, A_{a,t})$	Immediate cost of state $S_{i,t}$ given $A_{a,t}$
C_{cu}	Cost of curtailed loads
$Cu_{n,t,i}$	Load curtailment at bus n in state i at t
$C_f(P^G_{j,t,i})$	Operating cost of generator j in state i at t
$C_{su}(T^{ON}_{j,t,i})$	Startup cost of generator j in state i at t
$C_{sd}(T^{\text{OFF}}_{j,t,i})$	Shutdown cost of generator j in state i at t
$\lambda_{m,t}$	Failure probability of component m at t
$N_{C,t}$	Number of impacted components at t
$P(S_{i,t}, S_{i,'t+1})$	Transition probability from $S_{i,t}$ to $S_{i,'t+1}$
$P(o_{m,t}, o_{m,t+1})$	Transition probability due to change of status of component o_m from t to $t+1$
S_i	Markov state
$S_{i,t}$	Markov state at t
T	Number of decision periods
$v^*_t(S_{i,t})$	The optimal value of state $S_{i,t}$
$v_t(S_{i,t}, A_{a,t})$	Expected overall cost of state $S_{i,t}$ given $A_{a,t}$
W_1	Weighting factor of load curtailment cost
W_2	Weighting factor of operational cost

Notation for System Constraints

$B_{n,n'}$	Susceptance of line between bus n and bus n'
$L_{n,t,i}$	Amount of load in MW at bus n in state i at t
$o_{m,t}$	Status of component m at t
$P^G_{j,t,i}$	Supplied real power by generator j in state i at t
$P^{G,\text{Min}}_j, P^{G,\text{Max}}_j$	Minimum/maximum power rating of generator j

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$P^L_{n,n,'t,i}$	Real power flow between bus n and bus n' in state i at t
$P^{\text{Min}}_{n,n'}, P^{\text{Max}}_{n,n'}$	Real power flow limits between bus n and bus n'
R^{UP}_j, R^{DN}_j	Up/down ramping rate of generator j
$T^{ON}_{j,t,i}, T^{\text{OFF}}_{j,t,i}$	Turn ON/OFFsignal of generator j in state i at t
UT, DT	Up/down time
$u_{j,t,i}$	Status of generator j in state i at t
$\theta_{n,t,i}$	Voltage angle of bus n in state i at t

I. Introduction

EXTREME weather events have shown significant negative impacts on power system operations ranging from prolonged outages to catastrophic destruction of system components [1], [2]. Economic losses due to extreme weather-related outages is estimated to exceed $25 billion per year in the United States [3]. In 2018, a statistical analysis on wildfires over the period 2000–2016 has shown that wildfires cost utilities more than $700 million in parts of California's transmission and distribution systems [4]. The risk of severe wildfire has forced electric utilities to cut off power to 800 000 customers in California, USA, in 2019 [5]. The recent Dixie wildfire in the West Coast of the United States has lasted for more than 60 days, burned almost one million acres of land, and resulted in evacuation orders for thousands of families [6]. In California, it is estimated that more than 1.8 million acres will be impacted by wildfires in 2021 [7].

Various strategies have been proposed to improve the resilience of power systems against extreme weather events. Such strategies have focused mainly on restoration approaches such as mobile energy storage systems, network reconfiguration, and microgrid formation [8], [9]. Proactive and corrective resilience-based enhancement strategies have not been sufficiently explored, specifically against wildfires [10]. To reduce modeling complexities, some generation and transmission constraints are usually relaxed, yielding higher resilience levels [11], [12]. Impacts of load variations, system preparedness level, event attack time (i.e., the instant at which an extreme event hits the system), and future potential failures have been given less attention [1]. Since extreme weather events may create sequential failures of system components, other studies have considered the role of system operators in the decision-making process for improved resilience [11], [13]. The need of having a fast-acting decision tool to optimize system operations during extreme events has increased dramatically [14]. Thus, implementing resilience-based strategies that enhance the performance of power systems during wildfires, taking into account the aforementioned constraints, operational costs, and extreme weather spatiotemporal characteristics, has become more important than ever before.

Enhancement strategies for operational resilience focus on utilizing available system assets to provide an immediate solution due to severe impacts of adverse events. Resilience enhancement strategies can be classified according to the study period into: proactive, corrective, and restorative [15]. Proactive and corrective strategies tend to prepare the system in advance or instantly controlling the system due to severe impacts of extreme events, whereas restorative strategies provide solutions to retain failed components or curtailed loads in a stable and reliable manner [1].

Several operational resilience enhancement strategies have been proposed. Maintenance planning [16]–[18] and mobile energy storage allocation [19]–[21] strategies have been studied to prepare the system before an event. A decision-making framework based on an analytical hierarchy process has been proposed in [22] to evaluate possible locations of solar panels and battery energy storage systems for multiple contingencies to improve resilience of distribution systems and reduce operational costs. In [23], a graph theory-based approach integrated with Choquet integral has been used to quantify resilience enhancements and to maintain power supply to critical loads at the distribution level. In [24], a procurement plan of black start units has been studied assuring sufficient energy supply prior to events at minimal cost; however, the spatiotemporal characteristics of extreme weather events have not been considered. A proactive generation redispatch strategy has been proposed in [11] to reduce load curtailments during hurricanes where operational costs and load variations are not considered. An approach for generation redispatch during hurricanes has been proposed in [12] and [25], which takes into account event attack time, operational costs, and generation level prior to the event. Though several resilience enhancement strategies have been studied at the distribution level, developing resilience enhancement methods at the transmission level still requires further investigation [16]. The impacts of sequential probabilistic component failures create stressed operating conditions on the transmission system with the potential of cascading failures or blackouts. Also, preparing power systems for potential $N-k$ (i.e., $k>1$) contingencies is an important factor for enhancing power system resilience against extreme events—$N-1$ and $N-1-1$ criteria can be sufficient for normal outages.

Several studies have been conducted to assess the impacts of wildfires on power grids. In [10], a brief review of challenges and solutions to improve grid resilience during wildfires has been presented. A detailed review in [26] and [27] has presented causes of wildfires and prevention, detection, and management of wildfires. In [28], an analytical method has been proposed to quantify the impacts of wildfires on conductivity of transmission lines based on radiative heating. A simplified flame model has been provided in [29] to model a flame front behavior in wildfires. In [30], a convolutional neural network model has been trained for real-time fault localization for wildfire detection at distribution system levels. A proactive line outage prediction model due to wildfire progression has been proposed in [31].

A few studies have proposed resilience enhancement strategies against wildfires [32]–[35]. In [32], the impact of wildfires on the optimal power flow solution of transmission system has been studied based on propagation of flat fire surface toward one transmission line. In [33], a proactive dispatch algorithm of distributed generators at the distribution level has been proposed considering uncertainties of wildfire progression and accompanied impacts on transmission line ratings. A stochastic programming approach has been proposed in [34] to determine the optimal utilization of renewable energy resources on the main feeder of a distribution system during a wildfire given uncertainties of weather parameters. In [35], a resilience-based enhancement strategy has been proposed to avoid spurious trip of inverter-based resources and eliminate the risk of wildfires. A probabilistic decision process has been proposed in [36] to improve resilience of power systems against wildfires; however, the propagation rate of a wildfire has not been considered. Although several enhancement strategies against wildfires have been proposed, only a few have tested the applicability of proactive generation redispatch considering probabilistic behavior of component failures due to spatiotemporal characteristics of wildfires.

In this article, a generation redispatch strategy is proposed to enhance the operational resilience of power grids against wildfires. The Markov decision process (MDP) is used to determine the optimal generation dispatch decision at each time instant as a wildfire propagates across a power system. Due to uncertainties of component failures, the system topology, represented by a Markov state, varies based on available assets. The proposed algorithm aims to reduce the amount of load curtailments and operational costs during wildfire events. Several system dynamic constraints have been considered including transmission constraints (line capacity, line availability, etc.), generation constraints (ramping rates, minimum up/down times, start-up/shut-down generation costs, etc.), and other constraints such as load variation. A wildfire is assumed to spread across a power system during the peak load period to increase the severity level of the event. A mixed integer linear programming (MILP) optimization problem is formulated using the recursive MDP on MATLAB environment integrated with CPLEX solver to determine optimal generation redispatch strategies. The effectiveness of the proposed method is validated through simulation scenarios on the IEEE 30-bus transmission system. The impacts of generator ramping characteristics on resilience quantification are assessed.

The contribution of this article is summarized as follows.

1) Integrate the spatiotemporal characteristics of wildfires into probabilistic sequential failure behavior of power grid components.
2) Develop an MDP to determine optimal generation level at each time instant considering dynamic system constraints, spatiotemporal fragility model, and load variation.
3) Provide extensive simulation results via a standard test system to validate the capability and effectiveness of the proposed probabilistic proactive generation redispatch to improve operational resilience of power systems.
4) Assess the role of implementation time of the proposed strategy on resilience level for further improvements.
5) Evaluate the impact of generators' ramping characteristics on power system resilience level.

The rest of the article is organized as follows. Section II explains the concept of proactive generation redispatch. Section III describes the MDP algorithm for minimal overall operational and curtailment costs during extreme weather events. Section IV shows the implementation procedure on the IEEE 30-bus system and discusses the results. Section V concludes this article.

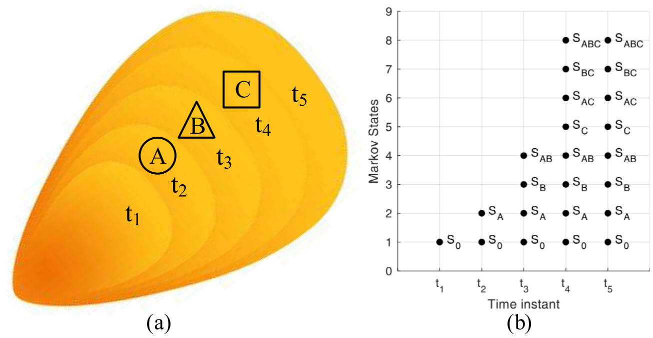

Fig. 1. (a) Components on the trajectory of a wildfire. (b) Potential Markov states at each time instant.

II. Proactive Generation Redispatch

This section describes the proposed resilience enhancement strategy for transmission systems against wildfires. First, it illustrates the impacts of propagation of a wildfire on power system components. Then, it explains the recursive decision process to formulate a probabilistic generation redispatch algorithm.

A. Impacts of Wildfire Progression

The propagation properties and spatiotemporal characteristics of each extreme event have unique impact on the performance of system components. For instance, the path of a hurricane can be predicted with a higher accuracy than the direction and behavior of a wildfire [28]. Probabilistic models have been proposed to model the propagation behavior of wildfires, identify the potential impacted components, and evaluate their probabilities of failure [10], [37]. Although fragility models have been used extensively in resilience-based studies [38], other studies have simulated actual events or forecasted failure scenarios [11], [12], [39]. As a wildfire propagates, system components can be impacted at sequential time intervals [10]. Wildfires are characterized by the possibility to change path, to be completely extinguished, or to have less intensity at any time instant [10]. Fig. 1(a) shows a scenario where three system components (A, B, and C) are on the potential trajectory of a wildfire at five time instants (t_1 to t_5). Also, the restoration time of failed components is usually high due to the significant damage and destruction caused by wildfires [34].

B. System States During Wildfires

Due to potential failures introduced by wildfires, the power grid might have different operating states at each time instant. In this work, a Markov state is defined to represent a unique system topology based on the available components. The total number of impacted components at time t is represented by $N_{C,t}$; and hence, $2^{N_{C,t}}$ is the total number of Markov states. Since failed components are assumed to withhold failure status during the event period, the set of impacted components at time t includes all current and previously impacted components. Fig. 1(b) provides an illustration of Markov states at each time instant due to progression of a wildfire, presented in Fig. 1(a)

S_o represents Markov state with no failures, whereas S_{ABC} denotes Markov state where all potential components are in failure states. Since at any time instant the power system can reside in one of several possible states, it is required to evaluate the transition probabilities from one state to consequential states. The transition probability, P, from state $S_{i,t}$ to $S_{i,'t+1}$ can be evaluated as follows:

$$P(S_{i,t}, S_{i,'t+1}) = \prod_{m \in \Omega_{c,t+1}} P(o_{m,t}, o_{m,t+1}) \text{ , } i \in \Omega_{S,t} \quad (1)$$

$$P(o_{m,t}, o_{m,t+1}) = \begin{cases} 1 & o_{m,t} = 0, o_{m,t+1} = 0 \\ 0 & o_{m,t} = 0, o_{m,t+1} = 1 \\ 1 - \lambda_{m,t+1} & o_{m,t} = 1, o_{m,t+1} = 1 \\ \lambda_{m,t+1} & o_{m,t} = 1, o_{m,t+1} = 0 \end{cases}. \quad (2)$$

C. Recursive Markov Process

The operational performance of the power grid varies significantly due to the sequential failure of power system components. For a resilient power grid, the priority is given to reducing the amount of load curtailments during extreme weather events rather than minimizing operational costs. In addition, the stochastic progression of wildfires across system components should be considered to obtain a feasible strategy that satisfies all system constraints such as ramping rates, minimum up and down times, and varying load demand. The proactive generation redispatch algorithm determines the optimal generation profile of each generator during the course of an extreme event given current and forecasted system states. To maintain resilient operation of the system, availability of nonimpacted assets must be assured during and after wildfires. Although the aforementioned constraints are difficult to fulfill during severe situations, it is recommended to have higher generation resources [25], [32]. For instance, multiple transmission line failures can result in islanding of the power grid into multiple grids where the generation level at each islanded grid should be sufficient to supply the required load; otherwise, curtailing loads will be a nonavoidable decision [25].

Since the status of each component might change during the progression of a wildfire, system operators should make decisions considering current and future states of the system. Each decision not only impacts the performance of the system at the current instant but also during upcoming instants. For example, turning off a reliable generator earlier in time may result in larger load curtailments in the following time instants. Also, maintaining full operation of a potentially impacted generator may lead to sudden power outages and cascading failures during the wildfire progression. Since generation dispatch usually takes place in terms of minutes, a discrete-time MDP can be used to model the whole process. Several methods have been used to solve the MDP such as the backward induction method and the value iteration method [40]. A proper solution of each state is obtained considering current system states as well as possible future states. In some cases, time-dependent constraints correlating Markov states at sequential time instants exhibit further complexities to the problem formulation. Therefore, the aforementioned solution techniques can be deemed infeasible. The linear scalarization method has proven to solve time-dependent MDPs via transforming the multiobjective optimization problem into a single objective optimization problem [11], [25].

Fig. 2 shows the progression behavior of a wildfire on system components. Prior to the event, no failure state is observed. All Markov states are encountered and their transition probabilities are calculated. At each time instant, the optimization model takes into account all possible observable states. An action is made and the system holds a new Markov state with a new set of observable states. An action represents the supplied real power by operating generators. This process is repeated for all time instants.

III. Markov Decision Process Formulation

This section provides a detailed formulation of the multiobjective optimization problem using MDP to minimize operational costs and load curtailment costs. A recursive model based on discrete-time MDP is developed based on variations of system topology as a result of sequential component failure. Various generation and transmission constraints are considered in the proposed algorithm.

A. Objective Function

Determining the minimal value function is necessary to hold a specific system state at a given time. In this work, the optimal generation redispatch value for a specific system state $S_{i,t}$ at a given time t is expressed as follows:

$$v_t^*(S_{i,t}) = \min\{v_t(S_{i,t}, A_{a,t}), a \in \Omega^A\}, i \in \Omega_{S,t}, t \in \Omega^T. \quad (3)$$

The value function of each state in MDP can be evaluated as follows:

$$v_t(S_{i,t}, A_{a,t}) = C_t(S_{i,t}, A_{a,t}) + \sum_{i' \in \Omega_{i,t+1}^S} \left[P(S_{i,t}, S_{i,'t+1}) \text{ . } v_{t+1}(S_{i,'t+1}, A_{a,'t+1}) \right]. \quad (4)$$

In (4), $\{a, a'\} \in \Omega^A$, $i \in \Omega_{S,t}$, and $\{t, t+1\} \in \Omega^T$.

The immediate cost of a Markov state can be evaluated as follows:

$$C_t(S_{i,t}, A_{a,t}) = W_1 \left[C_{cu} \text{ . } \sum_{n \in \Omega^N} Cu_{n,t,i} \right] + W_2 \left[\sum_{j \in \Omega^G} C_f(P_{j,t,i}^G) + C_{su}(T_{j,t,i}^{ON}) + C_{sd}(T_{j,t,i}^{\text{OFF}}) \right] \quad (5)$$

where W_1 and W_2 are weighting factors to prioritize each objective function [41]. Various methods can be used to determine their proper values such as the Pareto analysis method [42]. In this article, W_1 should have higher value compared to W_2 to assure that the algorithm prioritizes reducing load curtailments over operational costs.

B. Constraints

Transmission and generation constraints should be fulfilled to maintain reliable operation of power grids. In this article,

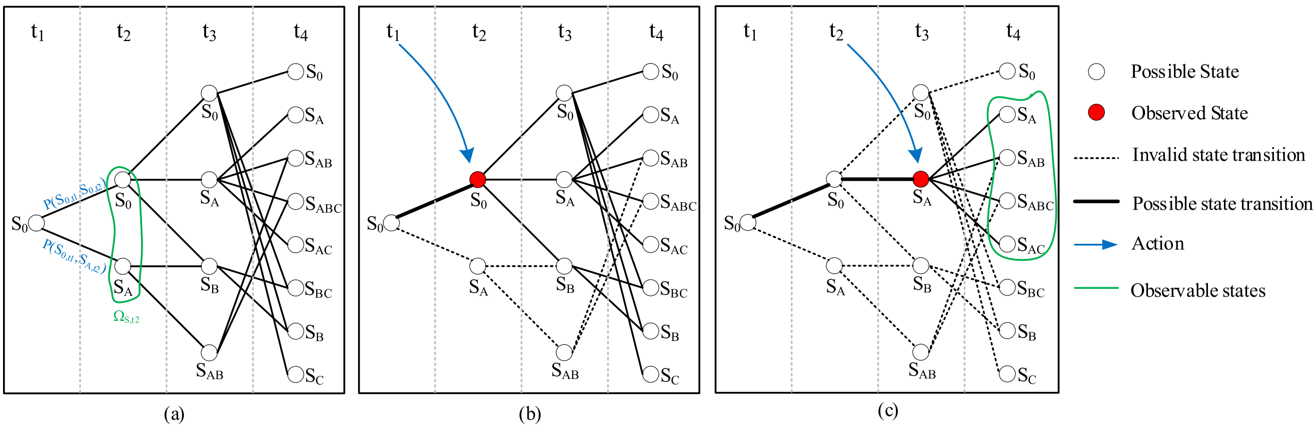

Fig. 2. (a) Markov states prior to the event. (b) Markov decision at t_1. (c) Markov decision at t_2.

dynamic generation constraints that govern the operation of generators during dispatching are considered. Also, transmission line constraints such as flow limits and their availability are considered. These constraints are explained as follows.

1) Power Balance: At any instant during normal operation conditions, the total amount of supplied power should be equal to the total load demand. If curtailing loads is necessary, the total supplied power should be equal to load demand after deducting the load curtailment. The power balance at system state $S_{i,t}$ at time t can be expressed as follows:

$$\sum_{j\in\Omega_n^G} P^G_{j,t,i} - (L_{n,t,i} - Cu_{n,t,i}) + \sum_{n'\in\Omega_n^N} P^L_{n,n,'t,i} = 0 \;\forall n \in \Omega^N. \tag{6}$$

2) Transmission Flow Limits: Power flow through a specific line connected at buses n and n' of system state $S_{i,t}$ must lie within the predefined line capacity limits as follows:

$$B_{n,n'}.(\theta_{n,t,i} - \theta_{n,'t,i}) - P^L_{n,n,'t,i} \leq P^{\text{Max}}_{n,n'} \tag{7}$$

$$B_{n,n'}.(\theta_{n,t,i} - \theta_{n,'t,i}) - P^L_{n,n,'t,i} \geq P^{\text{Min}}_{n,n'}$$
$$\forall n \in \Omega^N, n' \in \Omega_n^N. \tag{8}$$

3) Load Curtailment Limits: For each Markov state, $S_{i,t}$, the amount of load curtailment at each bus should be less than or equal to the total amount of load at the same bus as follows:

$$0 \leq Cu_{n,t,i} \leq L_{n,t,i} \;\;\forall n \in \Omega^N \;\forall t \in \Omega^T. \tag{9}$$

4) Generator Status: The status of each generator at state $S_{i,t}$ is represented by a binary number as follows:

$$u_{j,t,i} \in \{0, 1\} \;\;\forall j \in \Omega^G. \tag{10}$$

5) Generator Ramping Rates: The ramping behavior of each generator is governed by its status and generation level at the current instant and its expected status and generation level at the following instant. In (11), a generator should supply its minimum capacity when fired up or should not exceed the maximum ramp up rate if already running. A running generator can ramp down without exceeding its ramping down rate till it reaches its minimum capacity as provided in (12). The ramping constraints should be satisfied as follows:

$$P^G_{j,t+1,i'} - P^G_{j,t,i} \leq (2 - u_{j,t,i} - u_{j,t+1,i'}).P^{G,\text{Min}}_j$$
$$+(1 + u_{j,t,i} - u_{j,t+1,i'}).R^{UP}_j \;\;\forall i' \in \Omega^S_{i,t+1} \tag{11}$$

$$P^G_{j,t,i} - P^G_{j,t+1,i'} \leq (2 - u_{j,t,i} - u_{j,t+1,i'}).P^{G,\text{Min}}_j$$
$$+(1 - u_{j,t,i} + u_{j,t+1,i'}).R^{DN}_j \;\;\forall i' \in \Omega^S_{i,t+1}. \tag{12}$$

6) Generator Minimum Up/Down Time: Since the proactive redispatch is time-dependent, minimum up and down times for each generator should be satisfied as follows:

$$\sum_{t-UT+1}^{t} T^{ON}_{j,t,i} \leq u_{j,t,i''} \;\;\forall t \in \{UT, \ldots, T\} \tag{13}$$

$$\sum_{t-DT+1}^{t} T^{\text{OFF}}_{j,t,i} \leq 1 - u_{j,t,i''} \;\;\forall t \in \{DT, \ldots, T\}$$
$$\forall j \in \Omega^G \;\forall i'' \in \Omega^S_{i,t+}. \tag{14}$$

In (13), there should be at most one instant of turn ON signal for a duration of UT prior to T; whereas in (14), there should be at most one instant of turn OFF signal for a duration DT prior to T when the generator's status changes into 0.

7) Power Limits of Generating Units: The supplied real power of each generator can be expressed as follows:

$$P^{G,\text{Min}}_j.u_{j,t,i} \leq P^G_{j,t,i} \leq P^{G,\text{Max}}_j.u_{j,t,i} \;\;\forall j \in \Omega^G. \tag{15}$$

IV. Implementation and Results

The MDP is formulated as an MILP optimization problem and solved using the CPLEX solver to handle large number of variables and constraints.

A. Data Description

The proposed approach is applied to the IEEE 30-bus system for validation [43]. Generator data are provided in Table I. In this work, the wildfire is assumed to propagate across the system, as shown in Fig. 3. Due to the spatiotemporal characteristics of wildfires, system components may fail at each time instant.

TABLE I
GENERATOR PARAMETERS

Unit	Cost ($)			Time (min)		Power (MW)		Ramp
	b	C_{su}	C_{sd}	UT	DT	Min	Max	(MW/hour)
G_1	2.00	70	176	15	15	30	120	12.0
G_2	1.75	74	187	15	15	35	140	12.0
G_3	2.00	50	113	15	15	10	50	7.2
G_4	3.25	110	267	15	15	5	30	6.0
G_5	3.00	72	180	15	15	10	55	7.2
G_6	3.00	40	113	15	15	15	40	6.0

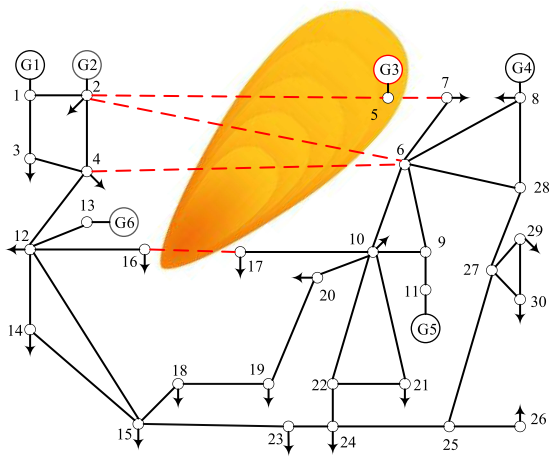

Fig. 3. Wildfire propagation on IEEE 30-bus system.

TABLE II
LIST OF IMPACTED COMPONENTS WITH THEIR PROBABILITY OF FAILURE

Time Instant	Component No.	Description	Failure Probability
t_1	–	–	–
t_2	C_1	Line 16-17	0.7
t_3	C_2	Line 4-6	0.4
t_4	C_3	Line 2-6	0.6
t_5	C_4	Line 2-5	0.3
t_6	C_5	G_3	0.7
	C_6	Line 5-7	0.3

Table II lists the set of impacted components and their failure probabilities. Although the propagation speed of a wildfire varies based on weather factors, fuel data (e.g., land type), and wildfire data, the scope of this work is resilience enhancement strategy under a given wildfire scenario. The impact of load variation is considered by scaling the system nominal load using load demand profile obtained from [44], as shown in Fig. 4.

B. Case Studies

The performance and effectiveness of the proposed method are tested and validated through several test cases. To induce more severe circumstances, the wildfire event is assumed to take place during the peak load period. The wildfire duration for crossing the indicated lines is assumed to be 25 min sampled at 5-min intervals for the recursive discrete decision epochs. As

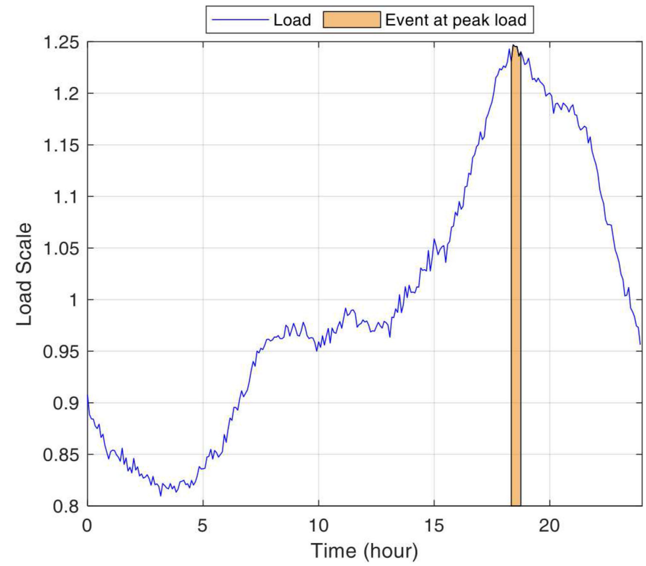

Fig. 4. Load scaling profile.

previously mentioned, to ensure that the algorithm prioritizes reducing load curtailments over operational costs, the scaling weight of W_1 is selected to be significantly higher than W_2. In this article, W_1 equals 100 and W_2 is 1. The performance of the proposed algorithm is tested through three simulation cases, which are: 1) Corrective strategy, 2) immediate proactive strategy, and 3) predictive proactive strategy. The impact of the propagation rate of a wildfire is assessed to validate the effectiveness of the proposed algorithm under diverse circumstances. Also, the impacts of different generator ramping rates are studied to assess their role in resilience enhancement. The optimal generation dispatch during normal operation (no wildfire) is computed and used for comparison.

1) Corrective Strategy: Since the system may experience component failures during a wildfire, the generation dispatch has to be readjusted to adapt to such failures and fulfill system generation and transmission constraints. In this case, no redispatch is applied prior to the event attack time; however, dispatching is applied at each time instant during the wildfire event to fulfill the current system constraints. In other words, the decisions are made to fulfill the current system constraints ignoring future impacts. This case is used for comparison and validation of the proactive generation redispatch algorithm and to highlight the importance of proactive resilience enhancement strategies.

Fig. 5(a) and (b) show the generation dispatch solution during normal operation and corrective strategy, respectively. For Fig. 5(b), the amount of load curtailment (dashed line) keeps growing throughout the wildfire duration for several reasons. First, G_3 (yellow line) ramps down to avoid any constraint violation starting at 18:45 due to sequential failures of transmission lines 2–5 and 5–7. Also, the failures of lines 2–5, 2–6, 4–6, and 16–17 impose stressful burden on the amount of transferable power from G_1, G_2, and G_6 to the load spots on the right side of the grid and results in ramping down of G_1 and G_2.

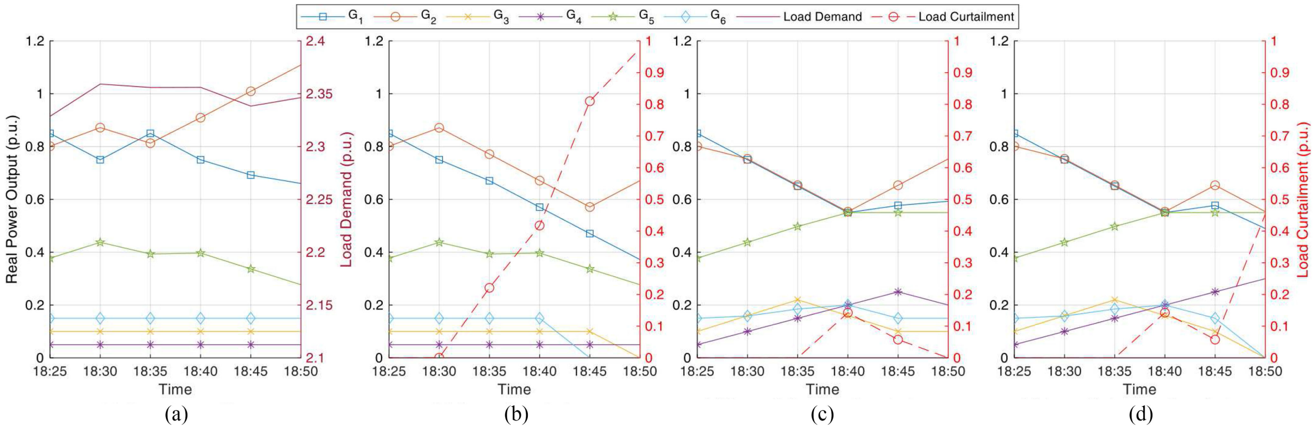

Fig. 5. Optimal generation dispatch under (a) normal operation, (b) corrective strategy, (c) immediate proactive strategy given no components fail during wildfire, and (d) immediate proactive strategy given all potential components fail during wildfire.

As a result, the generation profile of all units have changed significantly. It is obvious that proactive strategies are required to improve the system performance and reduce the amount of load curtailments. Also, the generation and transmission constraints impose further complexities which should be considered during the enhancement strategy.

2) Immediate Proactive Strategy: In this case, the MDP algorithm proactively dispatches generators *when* a wildfire *occurs* based on the predicted direction and speed of the wildfire and potential failures of system components. The formulated MDP considers all possible component failures due to the wildfire, which were ignored in case 1. The initial generation levels are obtained from the scheduled generation dispatch solution under normal operation and integrated into the MDP to ensure that the optimization problem is initialized with the proper system status prior to strategy implementation. Fig. 5(c) and (d) show the optimal generation dispatch for two scenarios: S_1—no components fail, and S_2—all potential components fail, respectively.

In this case, generation profiles for all generators have changed significantly, as shown in Fig. 5(c) and (d) compared to the corrective strategy case. Considering the results in Fig. 5(c), high reliance on the right-side generators (G_4 and G_5) compared to the left-side generators (G_1 and G_2) is observed during the first few instants to avoid violating the ramping constraints of large generation units, G_1 and G_2, which are highly utilized prior to the event due to their low operational costs. A very fast ramping up behavior of G_4 and G_5 is observed to compensate for the ramping down of G_1 and G_2 as well as increase in load demand. G_3 supplies high generation level at early instants utilizing its low operational costs; however, it ramps down at 18:35 to prepare for possible shutdown at 18:50. This highlights the capability of MDP to utilize low-operational cost generators. Since G_6 has high operational costs, it ramps down at 18:40 to reduce the operational costs during severe situations. Generators G_1 and G_2 ramp up at 18:40, while G_4 ramps down at 18:45 to reduce the overall operational costs since no failure takes place. On the other hand, G_1 and G_2 ramp up momentarily between 18:40 and 18:45 to utilize their low operational costs even with decreasing in load demand. As a result, MDP utilizes low operational cost generators as long as all generation and transmission constraints are not violated.

For scenario S_2 [Fig. 5(d)], the loss of G_3 and islanding of bus 5 result in nonavoidable curtailments at 18:50, yielding higher load curtailments compared to S_1. Although system components do not fail in S_1 [Fig. 5(b)], the load is curtailed at earlier time instants to avoid much larger curtailments in proceeding instants. From the results, the proposed MDP algorithm provides much less load curtailments compared to the corrective strategy.

Our work shows that MDP selects the optimal generation redispatch at each instant that ensures not only minimal load curtailments at the current instant but less negative impacts on the following time instants. In other words, the load curtailment profile for both scenarios is the same for all time instants till 18:45, which highlights the capability of MDP to consider future impacts and mitigate the worst case scenario earlier in time. The proposed algorithm is able to reduce the total amount of load curtailments more than 50%. Additionally, MDP prioritizes reducing amount of load curtailments over operational costs in present and future instants.

3) Predictive Proactive Strategy: Similar to case 2, the proposed strategy utilizes MDP to proactively dispatch generators given a predicted wildfire event. However, the optimal redispatch is determined *prior* to the *potential* wildfire. The MDP algorithm is used to determine the optimal initial generation level prior to the event so that if an event happens, further load curtailments will be avoided. Fig. 6 compares generation profile for S_2 under immediate and predictive proactive strategies.

The impact of the generation level prior to the event on the performance of the redispatch strategy is clearly noticed. The obtained generation dispatch profiles, shown in Fig. 6(b), are significantly different compared to Fig. 6(a). In this case, G_2, G_4, and G_5 have higher initial generation levels than G_1 compared to case 2. The full utilization of G_4 and G_5 earlier in time results in lower load curtailments at 18:40 and 18:45. MDP has prioritized G_5 over G_4 due to its lower operational costs. Also, MDP has selected a higher initial generation level for G_2 since it has the lowest operational costs and highest generation capacity. Although G_3 is expected to fail at 18:50, it is optimally utilized

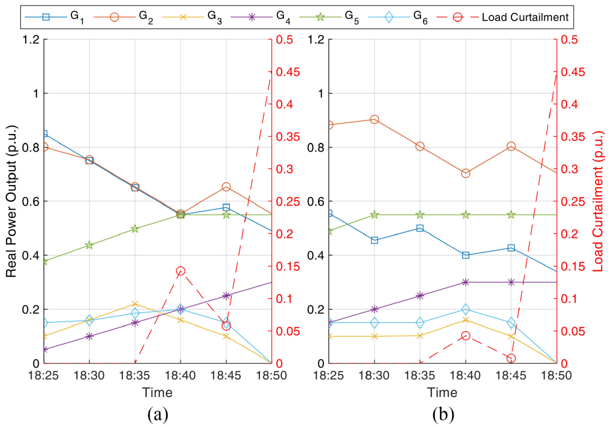

Fig. 6. Optimal generation dispatch for S_2 under (a) immediate proactive strategy and (b) predictive proactive strategy.

prior to that instant due to its low operational costs, which highlights the effectiveness of MDP to differentiate between low- and high-operational cost generators. MDP provides a proactive resilience enhancement approach to determine the proper allocation of sources prior to extreme weather events and avoid large curtailments.

The total amount of load curtailment during the event duration (18:30 to 18:50) is lower in Fig. 6(b) implying higher resilience level; however, both strategies show the same amount of load curtailments at 18:50. Deeper investigation shows that the shared spots of load curtailment at 18:50 for both strategies are buses 8, 12, 14, 15, 29, and 30. Such curtailments are deemed nonavoidable due to either insufficient generation supply or exceeding transmission capabilities. For instance, the load demand at bus 8 at 18:50 of almost 37 MW—calculated by scaling the base load using provided load profile—can be supplied through G_4 and transferable power through transmission lines connected to bus 8. If G_4 has a capacity lower than the load demand, the remaining load demand should be supplied through transferable power over transmission lines; however, that might not be feasible if these lines are fully occupied due to other load requirements. Regardless of the nonavoidable curtailments, case 3 provides better resilience level represented by fewer load curtailments. The obtained strategies reflect the effectiveness of the MDP algorithm to consider future potential generation outages and transmission failures. Also, MDP can be used to determine the most vulnerable spots due to extreme events and provide proper proactive planning.

To show the significance of the proposed algorithm on the overall costs, Table III describes the variation of cost values for S_2. The operational cost is higher in case 3 than in case 2. The curtailment cost is less in case 3 compared to case 2. This implies the capability of MDP to prioritize reducing load curtailment costs over operational costs. Also, relaxing the initial generation level constraint results in less total cost. The cost analysis can be used to determine optimal decisions taking into account the energy market regulations during extreme weather events.

4) Role of Wildfire Propagation Rate: Due to the large geographical distance between some components at the transmission level, the sequential failure behavior might take several hours instead of a few minutes [32]. In this case, the wildfire event is assumed to propagate across the system in 5 hours. The decisions are made at the start of each hour. To create more stressed operating conditions and show the importance of the proposed algorithm, a few extra constraints are imposed. First, the wildfire is assumed to ignite prior to peak load demand period. Each generator ramping rate (MW/hour) is assumed to be 25% of maximum power capacity [45]. Line 4–12 replaces line 16–17 in the list of potential components at t_2 (Table II) to create an islanding scenario and potential isolation of the two largest generators.

TABLE III
COST ANALYSIS

Cost ($)	Normal operation	Proactive strategy	
		Immediate (Case 2)	Predictive (Case 3)
Operational	2562	2711	2751
Curtailments	0	17454	13447
Total	2562	20165	16199

Fig. 7 compares the immediate proactive strategy and the corrective strategy with the normal operating conditions for a 5-h wildfire event. The total amount of load curtailment is reduced dramatically by applying the proactive redispatch strategy as noticed in Fig. 7(c) and (d). The islanding of buses 1, 2, 3, and 4 due to wildfire shows insufficient generation capability, yielding nonavoidable load curtailments. On the other hand, the MDP selects G_2 over G_1 in the proactive strategy compared to the corrective strategy revealing the effectiveness of MDP to consider low-cost generators. Figs. 5 and 7 confirm the capability of the proposed algorithm to provide feasible solution and better resilience for fast and slow-paced extreme weather events.

5) Impacts of Ramping Rates: The MDP solution relies on many factors including the dynamic characteristics of generators. Better resilience levels can be obtained through larger power capacity and faster ramping performance. In this case, the role of ramping rates is assessed. Three conditions are simulated: (a) Nominal ramping rates, (b) 20% increase in ramping rates, and (c) 50% increase in ramping rates. The generator capacity is assumed fixed as provided in Table II. For all simulated conditions, the initial generation levels are obtained from the scheduled generation dispatch solution under normal system operation, as shown in Fig. 5(a).

Fig. 8 shows the results for the two previously mentioned failure scenarios—S_1: No components fail, and S_2: all potential components fail. It is obvious that increasing the ramping rates results in a better performance represented in less load curtailments in both scenarios from 18:35 to 18:45. During the severe failure scenario (S_2), increasing the ramping rate by 50% enables the system to eliminate the avoidable curtailments of other cases and highlights the presence of nonavoidable load curtailments at 18:50. By comparing Fig. 8(c) and (e) with Fig. 8(a), it is noticeable that even with no failure occurrence, having a faster ramping provides the system with much faster response and proper immediate preparedness.

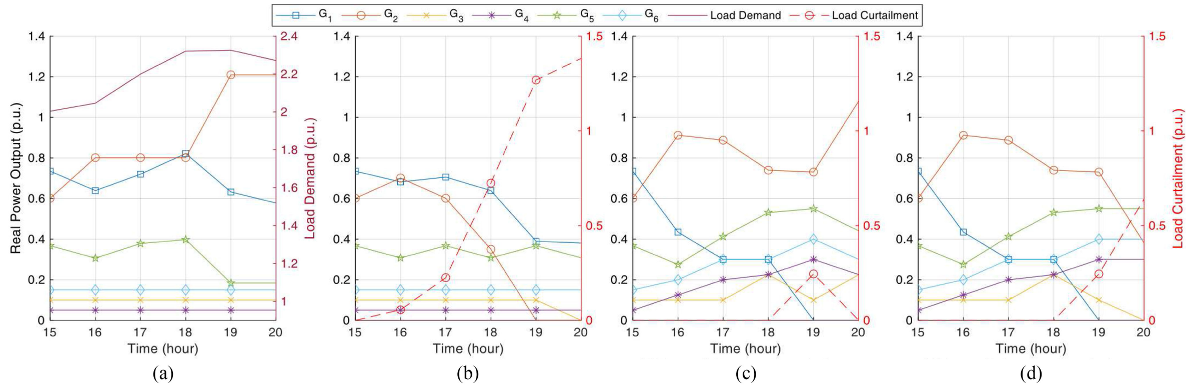

Fig. 7. Optimal generation dispatch for slow wildfire event under (a) normal operation, (b) corrective strategy, (c) immediate proactive strategy given no components fail during wildfire, and (d) immediate proactive strategy given all potential components fail during wildfire.

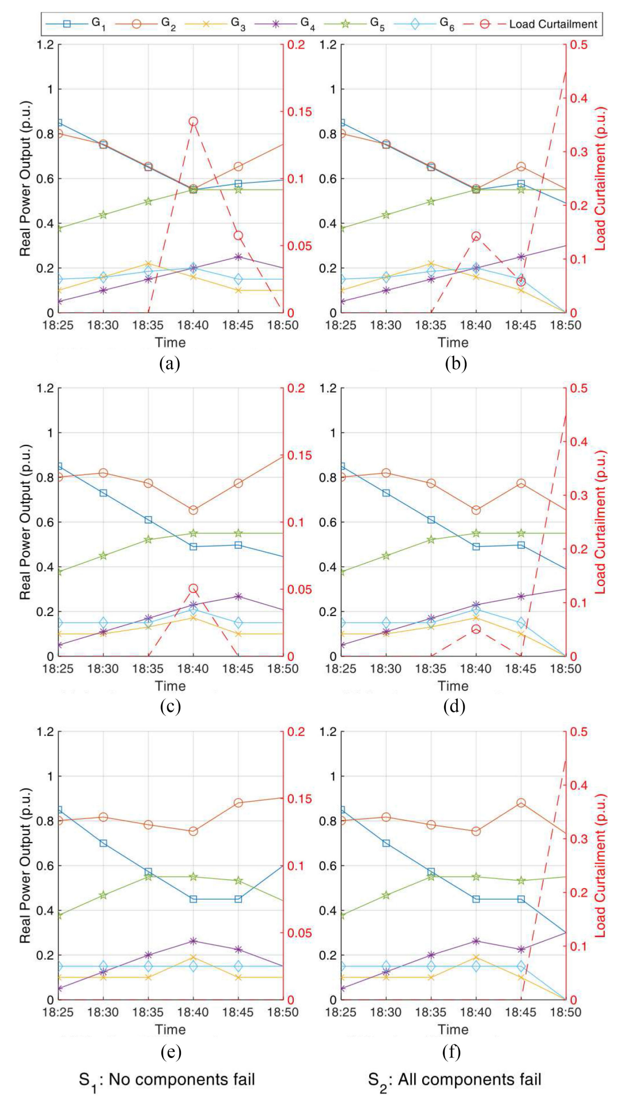

Fig. 8. Optimal generation dispatch under varying ramping rates for S_1: (a), (c), and (e) and S_2: (b), (d), and (f). (a) S_1 given Nominal ramp rates. (b) S_2 given Nominal ramp rates. (c) S_1 given 20% ramp increase. (d) S_2 given 20% ramp increase. (e) S_1 given 50% ramp increase. (f) S_2 given 50% ramp increase.

TABLE IV
COST ANALYSIS UNDER VARIOUS RAMPING RATES

Cost ($)	S_1			S_2		
	Nominal	20%	50%	Nominal	20%	50%
Operat.	2573	2597	2600	2711	2735	2741
Curtail.	5347	1352	0	17454	13459	12107
Total	7920	3949	2600	20165	16193	14847

The generation profile of all generators varies based on ramping rates. Reliance on generators with low operation cost such as G_2 is noticed when the ramping capabilities increase. In Fig. 8(c) and (d), the generation profiles of G_3, G_4, and G_5 increase due to the need of high generation supply on the right side of the grid. Fig. 8(e) and (f) shows that G_4 is utilized only when needed due to its high operational costs. In other words, G_4 ramps down at 18:40 to reduce operational costs. In most cases, G_1 ramps down due to its high cost compared to G_2—which is located in the same geographical vicinity—and transmission power limitation of line 4–12. In short, increasing the ramping rates creates more flexible system constraints achieving better resilient performance.

Table IV shows the effect of various ramping rates on operational costs and curtailment costs. In S_1, the total costs with 20% ramp increase is almost half the total costs for nominal case. The total costs in S_1 with 50% ramp increase is \$2600, which is very close to normal operation condition of \$2562. During severe situations, when all potential components fail, increasing the ramping rates reduces the curtailment costs dramatically but increases the operational costs slightly resulting in overall total costs reduction. In brief, increasing the ramping rates results in reducing the total costs between 25% to 67% among all scenarios.

V. Conclusion

This article has proposed a probabilistic proactive generation redispatch strategy to enhance the operation resilience of power grids during wildfires. The proposed method minimizes the cost of load curtailments as well as the operational costs under specified system modeling constraints. MDP is used to formulate the recursive decision optimization problem encountering the impact of potential failures and their failure probabilities. The proposed algorithm determines the optimal generation redispatch profile given uncertain future of system topology. The proposed method was demonstrated on the IEEE 30-bus system and various test cases were conducted to validate the accuracy and effectiveness of the proposed algorithm. The results showed that the generation redispatch strategy enhances the operational resilience of power grids. Proactive generation redispatch was able to reduce the total amount of load curtailment by 50% in some cases. The role of ramping rates was tested to quantify its impact on resilience of power systems. In some cases, increasing the ramping rates helped in reducing the overall costs by 65% and eliminating avoidable load curtailments. The proposed algorithm facilitates the decision-making process for system operators during extreme events by providing the operator with a shortened list of decisions at specific time instant considering all potential future impacts. This algorithm paves a framework for system operators that considers the uncertainty behavior of extreme weather events. Also, it helps system planners to determine proper system generation and transmission upgrades for more resilient power grids.

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