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Optimal resilient power grid operation during the course of a progressing wildfire

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ABSTRACT

We study a two-stage stochastic and nonlinear optimization model for operating a power grid exposed to a natural disaster. Although this approach can be generalized to any natural hazard of continuous (and not instantaneous) nature, our focus is on wildfires. We assume that an approaching wildfire impacts the power grid by reducing the transmission capacity of its overhead lines. At the time when proactive decisions have to be taken, the severity of the wildfire is not known. This introduces uncertainty. In this paper, we extend previous work by more realistically capturing this uncertainty and by strengthening the mathematical programming formulation through standard reformulation techniques. With these reformulation techniques, the resulting two-stage, convex mixed-integer quadratically constrained programming formulation can be efficiently solved using commercial quadratic programming solvers as demonstrated on a case study on a modified version of the IEEE 123-bus test system with 100 scenarios. We also quantify the uncertainties through a second case study using the following three standard metrics of two-stage stochastic optimization: the expected value of perfect information, the expected result of using the expected value solution and the value of the stochastic solution.

Introduction

Wildfires may get out of control and approach city limits, affecting also the power grid. The increased heat caused by the fire may limit power transmission capabilities of overhead lines. The reliable supply of power during such a disaster event is of foremost importance and may require a proactive transmission schedule. For instance, reserve requirements may have to be increased or loads may need to be adjusted via demand response. One may also have to activate additional generators distributed at different parts of the grid, or shed load as the last resort. When preparing for such a disaster event, uncertainty in the wildfire spread and severity needs to be taken into account accordingly. A resilient power grid is one that is able to withstand such a major disruption with limited degradation and can recover within a narrow timeframe with constricted costs [1]. Power grid resilience can be achieved in different ways based on the ultimate objective and the timeline of interest.

One way to achieve resilience is to use energy resources in addition to the main distribution substation. Using distributed energy resources such as distributed generation (DG), energy storage systems (ESS) and demand responsive (DR) loads as virtual generation can help improve the robustness of the power grid against contingencies [2,3]. At the same time, much effort has been made in the literature on ensuring that a power network is able to restore power to the outage areas following a large scale disturbance. This has often been addressed within the context of electric service restoration, and the problem has been solved either in a centralized fashion [4–6] or using a decentralized approach based on multi-agent theory [7,8]. Finally, some researchers have adopted security-constrained optimal power flow (SCOPF) approaches [9] to strengthen the power grid against forecasted contingencies. The objective here is to dispatch the generation resources in the power grid in such a way that all operational constraints are maintained not only for the normal operating condition, but also for all credible contingencies. More recent SCOPF approaches have incorporated the probabilities and severities of the contingencies into account, thus making them stochastic and risk-based in nature [10]. While the literature stands fairly comprehensive when it comes to preparing the grid for a natural disaster prior to the onset of the event (*i.e.*, through SCOPF approaches) or after it has run its course (*i.e.*, through electric service restoration), the management

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Notation

Wildfire modeling

The values provided in this section represent the numbers used in the two case studies.

Conductor parameters:

d_c	conductor diameter; $1.83 \cdot 10^{-2}$ [m]
h_c	conductor height from the ground; 6 [m]
$I_{c,\max}$	conductor rating; 530 [A]
R_c	conductor resistance; $1.9 \cdot 10^{-4}$ [Ω/m]
$T_{c,\max}$	maximum permissible conductor surface temperature; 373 [K]
ϵ_c	conductor emissivity; 0.5 [–]
μ_c	conductor absorption coefficient; 0.5 [–]

Fire parameters and variables:

L_f	fire flame length; 9 [m]
r_f	distance of fire to the object of interest; [m]
$r_f(0)$	initial distance of fire to the object of interest; 40 [m]
T_f	flame zone temperature; 1200 [K]
v_f	fire rate of spread; [m/s]
W_f	fire flame width; 15 [m]
γ_f	fire flame tilt angle; 45 [°]
ϵ_f	fire flame zone emissivity; 0.5 [–]
ρ_f	fuel bulk density; 40 [kg/m^3]

Atmospheric and weather parameters and variables:

T_α	ambient air temperature; 298 [K]
v_w	wind speed; [m/s]
Φ_s	solar irradiance; 1000 [W/m^2]
λ_α	atmospheric thermal conductivity; 0.0289 [W/m K]
μ_α	dynamic viscosity of air; $2.01 \cdot 10^{-5}$[Pa s]
θ_w	wind direction with respect to the conductor normal; [°]
ρ_α	air density; 1.0 [kg/m^3]
σ	Stefan–Boltzman constant; $5.67 \cdot 10^{-8}$ [W/m^{2}K^4]
τ_α	atmospheric transmissivity; 1.0 [–]

Heat flow variables:

Q_c	convective heat loss rate per unit length of conductor; [W/m]
Q_r	radiative heat loss rate per unit length of conductor; [W/m]
$Q_{r,f}$	radiative heat gain rate per unit length of conductor due to wildfire; [W/m]
Q_s	solar radiant heat gain rate per unit length of conductor; [W/m]

Mathematical programming problem

Function:

$\mathbb{I}_{\mathcal{A}}(a)$	indicator function: 1 if $a \in \mathcal{A}$, 0 o/w

Sets/indices:

$b \in \mathcal{B} = \{1, \ldots, B\}$	buses in the network
$r \in \mathcal{B}$	root node (location of substation)
$b \in \mathcal{B}_m \subset \mathcal{B}$	buses in microgrid m
$b, j \in \mathcal{J}_m \subseteq \mathcal{B}_m$	DG at bus j in Microgrid m
$b, k \in \mathcal{K}_m \subseteq \mathcal{B}_m$	DR (controllable) load at bus k in Microgrid m
$b, l \in \mathcal{L} \subseteq \mathcal{B}$	load buses
$m \in \mathcal{M} = \{1, \ldots, M\}$	Microgrid
$p \in \mathcal{P} = \{a, b, c\}$	phases
$p \in \mathcal{P}^{\mathrm{DG}}_{j,m} \subseteq \mathcal{P}$	phases served by DG at bus j in Microgrid m
$p \in \mathcal{P}^{\mathrm{DR}}_{k,m} \subseteq \mathcal{P}$	phases served by DR at bus k in Microgrid m
$q \in \mathcal{Q} \subset \mathcal{B} \times \mathcal{B}$	branches in the network
$s \in \mathcal{S} = \{1, \ldots, S\}$	wildfire scenarios
$t \in \mathcal{T} = \{1, \ldots, T\}$	periods, times or stages

Data/parameters (capital letters):

α_l	priority level of load bus; in [0,1]; [–]
$C^{\mathrm{DG,res}}_{j,m,t}$	reserve price for DG; [\$/kW h]
$C^{\mathrm{DR,res}}_{k,m,t}$	reserve price for DR; [\$/kW h]
$C^{\mathrm{DG,gen}}_{j,m,t}$	generation cost for DG; [\$/kW h]
$C^{\mathrm{DR,gen}}_{k,m,t}$	generation cost for DR (DR provides virtual generation through demand reduction); [\$/kW h]
C^{sub}_{t}	generation cost for distribution substation; [\$/kW h]
$C^{\mathrm{LR}}_{m,t}$	lost revenue due to load shedding; [\$/kW h]
$H^{\mathrm{DR}}_{k,m,p,t}$	conversion factor to connect active and reactive generation for DR; [–]
M^{d}	penalty for demand shedding; [\$/kW h]
$P_{l,p,t}$	active demand per load bus; [kW]
P_s	probability of scenario; [–]
$\overline{P}^{\mathrm{sub}}$	upper bound on substation generation; [kW]
$\overline{P}^{\mathrm{DG,gen}}_{j,m}$	upper bound on DG generation; [kW]
$\overline{P}^{\mathrm{DR,gen}}_{j,m,p,t}$	upper bound on DR virtual generation; [kW]
$Q_{l,p,t}$	reactive demand per load bus; [kVar]
$\overline{Q}^{\mathrm{sub}}$	upper bound on substation reactive generation; [kVar]
$\overline{Q}_{j,m}$	upper bound on reactive generation of DG; [kVar]
$\overline{S}_{q,s,t}$	line capacity; [kVA]

Further, we derive the total active demand per load bus

$$P_{l,t} := \sum_{p \in \mathcal{P}} P_{l,p,t},$$

and the total active demand per Microgrid

$$P_{m,t} := \sum_{l \in \mathcal{B}_m \cap \mathcal{L}} P_{l,t}.$$

Decision variables (small letters):

$f^{\mathrm{P}}_{p,q,s,t}$	active flow at branch q; [kW]; *free*
$f^{\mathrm{Q}}_{p,q,s,t}$	reactive flow at branch q; [kVar]; *free*
$p^{\mathrm{DG,res}}_{j,m,t}$	reserve quantity for DG; cumulative over all phases; [kW h]; *non-negative*
$p^{\mathrm{DR,res}}_{k,m,p,t}$	reserve quantity for DR; [kW h]; *non-positive*
$p^{\mathrm{DG,gen}}_{j,m,s,t}$	generation for DG; three-phase units will have the same generation for all phases; [kW h]; *non-negative*
$p^{\mathrm{DR,gen}}_{k,m,p,s,t}$	active generation for DR (virtual generation through active power demand reduction); [kW h]; *non-positive*
$p^{\mathrm{sub}}_{p,s,t}$	active generation of substation; [kW h]; *non-negative*