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A stochastic optimal power flow for scheduling flexible resources in microgrids operation

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HIGHLIGHTS

- Stochastic day-ahead microgrid management algorithm considering uncertainties in PV, load and temperature.
- Quantification of the effectiveness of demand side management by implementing thermal models and thermal comfort constraints.
- Comparison of comfort constraint violations and annual operational costs of a stochastically managed microgrid.
- Comparison of deterministic and stochastic day-ahead management strategies.

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ABSTRACT

Microgrid operations are challenging due to variability in loads and renewable energy generation. Advanced tools capable of taking uncertainty into account are essential to maximize microgrid benefits when operating microgrid owned DERs. This paper proposes a novel optimization model for day-ahead economic dispatch of flexible resources within a microgrid environment, considering uncertainty of PV and loads.This model is conceived to support the microgrid supervisory control layer, providing a security-constrained day-ahead strategy to operate three types of microgrid flexible resources: PV, electric storage and controllable loads. The work presented in this paper introduces a novelty in microgrid operations by presenting a stochastic version of the day ahead scheduling of microgrid DERs to deal with uncertainties associated with PV, load and temperature while considering microgrid network limits and end-user comfort as optimization constraints. An annual analysis quantifies the benefits of to the microgrid-owner of a stochastic formulation over a deterministic one both in terms of ensuring end-user comfort and decreasing operation costs.

1. Introduction

At the distribution grid level, uncertainties in renewable generation and load consumption represent a challenge to network operation, namely for day ahead planning of Distributed Energy Resources (DERs), such as grid connected storage, controllable loads or photovoltaic (PV) control strategies, implemented in real time by a distribution management system (DMS). These challenges are magnified in microgrids, where uncertainties are higher due to minimal aggregation and smoothing effects. Since microgrids are more easily perturbed by DERs, an accurate control is needed to manage multiple electric storage systems, load devices and generation units, while ensuring a stable and reliable operation of the microgrid network and minimizing costs [1,2].

Due to high uncertainties in load and renewable generation, microgrid control requires advanced forecasting tools and robust scheduling of controllable devices to guarantee power quality and security of supply. In particular, the control of individual loads, e.g. heating, ventilation and air-conditioning (HVAC) systems [3], brings new sources of uncertainty to the day ahead planning of DERs, such as ambient temperature, building occupancy and consumption habits. This uncertainty has a modest impact on grid operations when aggregated at the distribution level but it becomes relevant at the microgrid scale where a finer control is needed.

Optimization algorithms have been presented in the literature to

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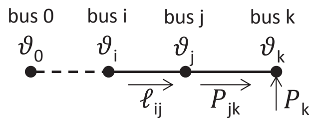
Nomenclature

Summary of notation:



A. Indices

t	period
ij	branch
j	node
pv	PV system association
ul	uncontrollable load
cl	controllable load
st	storage system association
hvac	heating, ventilation, and air-conditioning systems
ewh	electric water heater systems
$\overline{\Delta\theta}_{low}$	maximum degrees of under-heating tolerated (°C)
$\overline{\Delta\theta}_{high}$	maximum degrees of overheating tolerated (°C)
ext	external air temperature
int	internal air temperature of each house
w	property of water
d	controllable device
s	scenario-dependent variables
+	positive domain
c_w	water specific heat (J/g °C)
R_d	thermal resistance of device (°C/kW)
–	negative domain
0	substation node point of common coupling

B. Constants

c_e	cost of wholesale electricity (€/MWh)
c_c	cost of wholesale electricity plus distribution and transmission costs(€/MWh)
c_{cf}	cost of comfort constraint violation (€/°C h)
r_{ij}	resistance of a specific branch (Ω)
x_{ij}	reactance of a specific branch (Ω)
η	efficiency of a device
C_d	thermal capacity of a device (kWh/°C)
α	heat loss coefficient of building (kW/°C)
$\overline{P}$	maximum active power value allowable (MW)
$\overline{S}$	maximum apparent power value allowable (MVA)
$\underline{V}$	minimum voltage constraint of grid (V)
$\overline{V}$	maximum voltage constraint of grid (V)
$\overline{soc}$	maximum state of charge of battery (MWh)
$\underline{soc}$	minimum state of charge of battery (MWh)
$\underline{\theta}$	minimum temperature (°C)
$\overline{\theta}$	maximum temperature (°C)

C. Variables

P	active power (MW)
ℓ	squared current magnitude (A)
Q	reactive power (MW)
ϑ	squared voltage magnitude (V^2)
soc	state of charge of a battery system (MWh)
θ	temperature (°C)
$v_{d,t}$	electric hot water consumption (l)
θ_{in}	inlet water temperature (°C)
θ_{out}	desired outlet water temperature (°C)
$\Delta\theta_{low}$	degrees of under-heating (°C)
$\Delta\theta_{high}$	degrees of overheating (°C)

solve the problem of day ahead scheduling of microgrid dispatchable resources. Numerous examples of deterministic [4,5], stochastic [6,7] and hybrid [8,9] approaches to plan and operate renewable intensive microgrids are presented in the literature. Optimization methods include quadratic programming (QP) [10], as well as heuristic and metaheuristic techniques [4,11]. In the optimal scheduling of DERs in multinode microgrids, heuristics have the advantage of enabling exact network constraints [4], while QP requires a convex relaxation of power flow equations [9]. Due to the random aspect of search techniques in heuristic methods, calculation time can be high and the global optimal is not guaranteed. However, QP methods perform significantly better in terms of computational time. Thus, when combined with techniques that guarantee accuracy of the power flow calculations, e.g. linear cuts [12], they become a better solution.

Stochastic approaches have been used in optimal operation of microgrids to capture uncertainties of renewable sources [13]. Primarily, these strategies include either scenario trees [14,7] or statistical parameters of the stochastic variables [15,11,16] that are integrated into the optimization problem. Monte Carlo simulation along with the distribution functions for generators and load are used to generate scenarios in [15]. Scenarios are constructed by analyzing the mean, standard deviation and probability density functions of load and generation in [11]. Upper and lower bounds on generation and load are considered in [16]. A scenario tree is developed to represent stochastic variables such as temperature, electricity prices and consumer occupancy through the calculation of quantiles and consideration of the probability density function (PDF) of historical data [7].

The day ahead operation of microgrids includes optimal scheduling of multiple DER technologies. Besides the generation and storage control solutions, demand response (DR) has been a valuable resource to compensate the variability of the renewable sources, especially through the control of thermal loads, such as HVAC and Electric Water Heaters (EWH). In fact, as shown in [8], load control can significantly reduce microgrid operation costs as well as CO_2 emissions. Two primary modeling strategies are presented in the literature for DR consideration: an aggregated model or individual modeling of devices. Aggregated models make acceptable assumptions about individual devices [14] and improve aggregated controllability of the microgrid, but the comfort of individual end users is not modeled in detail. Thus, individual load models become more appropriate for small scale applications (e.g. buildings) where a detailed comfort representation is required. In [9], individual load models are used in optimization of building operations with DR. A deterministic approach that considers end-user comfort constraints and PV for a 3 building micro-grid is detailed in [5]. An algorithm proposing an economic penalty for violations in thermal comfort constraints is presented in [7] however, this paper does not consider the electric network and instead performs only an energy balance.

A majority of the mentioned citations take into account the losses in the electrical lines in a two-step process and do not integrate a full AC optimal power flow (AC-OPF) into the optimization problem [13,11,15].

This paper presents a novel method for day ahead scheduling of loads and DERs that has a low calculation burden while considering network constraints. To the authors knowledge, it is the first time that a full AC-OPF algorithm is used while considering thermal comfort constraints of end users. Moreover, the presented model adds on recent innovations in the field of stochastic AC-OPF [17], by expanding the