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Analysis of robust optimization for decentralized microgrid energy management under uncertainty

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ABSTRACT

The present paper provides an extended analysis of a microgrid energy management framework based on Robust Optimization (RO). Uncertainties in wind power generation and energy consumption are described in the form of Prediction Intervals (PIs), estimated by a Non-dominated Sorting Genetic Algorithm (NSGA-II) – trained Neural Network (NN). The framework is tested and exemplified in a microgrid formed by a middle-size train station (TS) with integrated photovoltaic power production system (PV), an urban wind power plant (WPP) and a surrounding residential district (D). The system is described by Agent-Based Modelling (ABM): each stakeholder is modeled as an individual agent, which aims at a specific goal, either of decreasing its expenses from power purchasing or increasing its revenues from power selling. The aim of this paper is to identify which is the uncertainty level associated to the "extreme" conditions upon which robust management decisions perform better than a microgrid management based on expected values. This work shows how the probability of occurrence of some specific uncertain events, e.g., failures of electrical lines and electricity demand and price peaks, highly conditions the reliability and performance indicators of the microgrid under the two optimization approaches: (i) RO based on the PIs of the uncertain parameters and (ii) optimization based on expected values.

1. Introduction

Renewable energies are promising solutions to the energetic and environmental challenges of the 21st century [1,2]. Their integration into the existing grids generates technical and social challenges related to their efficient and secure management.

From this point of view, a closer location of generation and consumption sources in decentralized microgrids is expected to increase service quality for the consumers by decreasing transmission losses and the time needed to manage fault restoration and congestions. However, energy management can become critical in the microgrid, due to possible conflicting requirements or poor communication between the different microgrids elements [3]. Therefore, there is a need of frameworks for efficient microgrid energy management.

A way to model microgrids and the related individual goal-oriented decision-making of the microgrid elements is that of Agent-Based Modeling (ABM) [4–6], which allows analyzing by simulating the interactions among individual intelligent decision makers (the agents). The most widespread application of this modeling approach concerns the bidding strategies among individual agents, who want to increase their immediate profits through mutual negotiations and by participating in a dynamic energy market [7–10]. Recent studies show the extension of the ABM approach to more complex interactions in the energy management of hybrid renewable energy generation systems [6,11,12]. In these works, the long-term goals are focused on the efficient use of electricity within microgrids, e.g., the planning of battery scheduling to locally store the electricity generated by renewable sources and reuse it during periods of high electricity demand [11]. However, the decision framework is commonly developed under deterministic conditions, e.g., those of a typical day in summer.

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Nomenclature

t	time step (h)
F_t^{pas}	passengers flow through TS at time t (number/h)
s_t	average solar irradiation at time t (W/m^2)
v_t	average wind speed at time t (m/s)
E_t^l	energy required for inside and outside lighting in the train station at time t (kW h)
E_t^{elev}	energy required for passengers lifting in the train station at time t (kW h)
E_t^{elec}	energy required for electronic equipment in the train station at time t (kW h)
E_t^{TS}	total hourly required energy in the train station at time t (kW h)
E_t^D	total hourly required energy in the district at time t (kW h)
P_t^{PV}	available energy output from the photovoltaic generators installed in the train station at time t (kW h)
P_t^{WPP}	available energy output from the wind power plant at time t (kW h)
S_t^{TS} and S_t^D	portions of energy purchased from the external grid by the TS and D, respectively (kW h)
L_t^{TS} and L_t^{WPP}	portions of energy sold to the external grid by the TS and WPP, respectively (kW h)
V_t^{PV} and V_t^{WPP}	portions of energy sold to the district and generated by the PV panels of the TS and WPP, respectively (kW h)
R_t^{TS} and R_{t-1}^{TS}	energy levels in the train station battery at time t and $t-1$, respectively (kW h)
R_t^D and R_{t-1}^D	energy levels in the district battery at time t and $t-1$, respectively (kW h)
$R^{TS,stor}$	energy portion that the train station battery is capable of charging or discharging during time t (kW h)
$R^{D,stor}$	energy portion that the district battery is capable of charging or discharging during time t (kW h)
$\delta_t^{TS,ch}$ and $\delta_t^{TS,dis}$	binary variables which model that the train station battery can either only be charged or discharged at time t
$\delta_t^{D,ch}$ and $\delta_t^{D,dis}$	binary variables which model that the district battery can either only be charged or discharged at time t
$R^{TS,max}$	the maximum train station battery charge (kW h)
$R^{D,max}$	the maximum district battery charge (kW h)
T	time horizon considered for the optimization (h)
α^{TS}	and α^D total costs for TS and D, respectively, for time period T (€)
α^{WPP}	total revenue for WPP in time period T (€)
c_t^p and c_t^s	average hourly costs of purchasing and selling 1 kW h from the external grid, respectively, at time t (€/kW h)
c_t^D	average hourly cost per kW h from the bilateral contract agreed with D at time t (€/kW h)
β and γ	coefficients defining the minimum amount of energy to be sold to D by TS and WPP, respectively
$\widetilde{E}t^D$	expected energy demand for D (for the moment, considered without uncertainty) at time step t, predicted by TS and WPP (kW h)
$\widetilde{V}_t^{PV}$ and $\widetilde{V}_t^{WPP}$	energy portions, which TS and WPP are ready to sell to D at time step t (kW h)
$\widehat{P}_t^{WPP}$	level of uncertainty quantified for the robust optimization at time t (kW h)
$P_t^{WPP,ub}$ and $P_t^{WPP,lb}$	upper and lower prediction bounds of WPP power output at time t, respectively (kW h)
τ	simulation time period composed of Ns time steps of one hour (h)
LOLE	Loss of Load Expectation, characterizing the probability of unsatisfied electricity demand during h/τ
LOEE	Loss of Expected Energy, quantifying the expected amount of energy losses during kW h /τ
P_t	available capacity in the microgrid at time step t (kW h)
E_t	energy demand in the microgrid at time step t (kW h)
$Pr_t(P_t < E_t)$	probability of loss of load at time step t
$E_t - P_t$	energy portion that the system is not able to supply at time step t (kW h)
$L_t^{WPP,c}$ and $V_t^{WPP,c}$	portions of energy contracted by the WPP to the external grid and microgrid, respectively (kW h)
$L_t^{WPP,*}$ and $V_t^{WPP,*}$	actual portions of energy provided by the WPP to the external grid and microgrid, respectively (kW h)
T_t^{WPP}	imbalance cost generated by wind power plant at time step t (€)
$d_t^{WPP,*}$	energy imbalance generated by wind power plant at time step t (kW h)
$c_t^{D,+}$ and $c_t^{D,-}$	prices for positive and negative imbalances, respectively, at time step t (€/kW h)
γ^C and γ^P	performance ratio calculated over a simulation period of Ns hours by normalizing the imbalance cost by the actual expenses/ revenues calculated in the case of perfect forecast (%)
T^{hw} and T^n	constants denoting the average annual duration of high and normal wind conditions, respectively, over the time period T^{tot} (h)
$\lambda^{wind}(v_t)$ and λ^{norm}	failure rates at high and normal wind conditions (occur./y), respectively
$f_t(v_t)$	weight factor caused by severe weather
f_t^d and f_t^h	weight factors for hourly and daily variations, respectively
r^{norm}	reference restoration time during normal weather conditions, modeled as a random variable with lognormal distribution

To account for the variability and randomness of the operational and environmental parameters of the energy systems, several optimization techniques have been progressively introduced for handling uncertainty [13]. Fuzzy mathematical programming models and their extensions have been developed for optimal management of hybrid energy systems [14,15]. Stochastic programming models, where the uncertain parameters are described by probability distributions, and interval programming models, where the uncertainty is described by intervals [16,17], have been used to deal with different sources of uncertainty in optimization problems, like economic-energy scenarios planning [18], design of renewable systems for community energy management [19], and water quality and waste management [20,21].

In this paper, we propose an analysis of a microgrid energy management framework based on Robust Optimization (RO) previously proposed by the authors [22]. The analysis is intended to