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Accurate modeling of uncertainties based on their dynamics analysis in microgrid planning

Masoud Salehi Borujeni, Asghar Akbari Foroud *, Abas Dideban

Electrical & Computer Engineering Faculty, Semnan University, Semnan, Iran

A R T I C L E I N F O

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A B S T R A C T

The accurate modeling of uncertainties is one important issue in planning of microgrids. The more accurate modeling of the uncertainties results in answers of the stochastic optimization methods which are close to the actual optimal values. This paper utilized a scenario-based stochastic optimization method, considering photovoltaic (PV) and wind turbine power output and load as the uncertain variables in determining the capacity of distributed generation resources in an autonomous microgrid. Costs were considered as the objective function while the grid reliability was the constraint. To generate the scenarios of variables with uncertainty in microgrid, the dynamics of variables was first characterized by the Recurrence Plot nonlinear analysis, followed by the study of their seasonal behaviors. Based on this analysis, a method for classifying data was presented according to their seasonal behavior and the appropriate method to generate the scenarios for each of the uncertain variables was determined. The results showed that generating the scenarios based on the analysis of the uncertain variables results to an increase in the optimization accuracy.

1. Introduction

Determination of the optimal capacity of energy resources in a microgrid improves its reliability and reduces the costs. In the planning of autonomous microgrids, in addition to the optimization of the costs and pollution rate, it is necessary to take into account the system reliability (Bahramirad et al., 2012).

Different methods have been proposed in literature for sizing of energy resources in microgrids. A straightforward method is the deterministic optimization that considers the historical meteorological data and the load profile for a year. Optimization can be done as a single-objective (cost optimization) or multi-objective with regard to cost, pollution rate and unmet load (Maleki and Pourfayaz, 2015; Nasiraghdam and Jadid, 2012).

Due to the high uncertainty in the historical solar radiation, wind speed and the load data, and the effect of these variables on sizing the microgrid, ignoring these uncertainties can cause a deviation from the optimal plan. A method that considers uncertainty of parameters is scenario-based stochastic programming method. In this method, uncertainties are modeled as a set of possible scenarios. Higher accuracy of scenario generation results in the stochastic programming method answers close to the actual optimal values (Bornapour and Hooshmand, 2015). In previous research, various methods were used to generate scenarios of uncertain variables of microgrids. One of these methods is generating scenarios using probability distribution function. In this method, based on Monte Carlo method, several scenarios are generated. In planning microgrids, scenarios for solar radiation, wind speed, and load were generated using univariate distribution function (Hajipour et al. 2015; Zhou et al. 2013).

Another method which was used to generate the scenarios of uncertain variables is Autoregressive Integrated Moving Average (ARIMA) model. This method was utilized for generating the scenarios of load and wind data in microgrid planning problems (Conejo et al. 2010; Abd-el-Motaleb and Kazem Bekdach, 2016). Clustering method is another method that has been used to generate the scenarios. This method has also been used for scenario generation of wind speed, solar radiation, and load (Wang et al. 2014; Jiao et al., 2014).

It is essential to note that the dynamic behaviors of solar radiation, wind speed, and load may be different to each other, and the appropriate method should be determined based on the dynamic behavior of the variable. For uncertain variables with deterministic dynamics (periodic and chaotic), a deterministic generating scenario method such as clustering is appropriate (Casdagli 1992). To model the stochastic variables in which there is no

* Corresponding author.
E-mail addresses: m.salehi.b@semnan.ac.ir (M. Salehi Borujeni), aakbari@semnan.ac.ir (A. Akbari Foroud), adideban@semnan.ac.ir (A. Dideban).

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Nomenclature

A_W swept area (m^2)
CAP_{pv}, CAP_{WT}, CAP_{dg}, CAP_{batt} optimal capacities of the PV, wind turbine, diesel generator and battery
CC_{pv}, CC_{WT}, CC_{dg}, CC_{batt} initial costs of the PV, wind turbine, diesel generator and battery
CRF capital recovery factor
$E_{batt}(t)$ energy in the battery at time t
$E_{batt,min}$, $E_{batt,max}$ the minimum and maximum amounts of allowed energy in the battery
F fuel consumption of diesel generator
FC_{dg} fuel cost of diesel generator
H_{dg} operation hours of the diesel generator
I_t total solar radiation (kW/m^2)
ir discount rate
K *Present value factor*
OMC_{pv}, OMC_{WT}, OMC_{dg}, OMC_{batt} operations and maintenance costs of the PV, wind turbine, diesel generator and battery
$P_{batt}(t)$ power supplied to or discharged from the battery at time t_{th}
$P_{batt,min}$, $P_{batt,max}$ the minimum and maximum amounts of allowed power supplied to or discharged from the battery
P_{dg} output power of diesel generator
P_{load} total energy demand
P_{PV} output power of PV
P_r rated power
P_{WT} output power of wind turbine
R project life time
RC_{DG}, RC_{batt} replacement costs of the diesel generator and battery
v_c cut-in speed of wind
v wind speed
v_r rated wind speed
v_o cut-out speed of wind

Greece letters
λ *eigenvalues*
Δ overall efficiency of PV
Δ_c, Δ_d battery charge and discharge efficiencies
Δ_w overall efficiency of wind turbine
ΔM, ΔV maximum changes in the monthly mean and variance

dependency among the data, generating the scenarios based on the univariate distribution function is more appropriate (Niknam et al. 2012a). ARIMA and multivariate distribution function methods are appropriate for the stochastic data which are serially dependent (Box and Jenkins, 1976)

On the other hand, in the majority of previous studies for scenario generation, the seasonal behavior of uncertain variables has not been taken into account. Seasonal behavior significantly changes mean, variance, or different dynamic behaviors over time. When the data have seasonal behavior, it can be divided into several seasons, and generation of the scenarios is done separately in each season. This prevents scenario generations from being influenced by the other seasons which have different behaviors, thus increases the modeling accuracy. In the studies that seasonal behavior is considered, a suitable method for season classification is not provided. In some papers, season is classified according to the year's months (12 months of the year), whereby scenarios has been generated individually for each month (Bornapour and Hooshmand, 2015). As the variable's behavior might be the same across several months, this increases the burden of calculations. In some other papers, season is classified according to the year's seasons (spring, summer, fall, and winter) (Hajipour et al. 2015). This method does not have sufficient accuracy as well. Accordingly, an appropriate method for season classification of the uncertain variables of microgrids is required.

In this paper, the main focus is on increasing the accuracy of scenario generation by considering the dynamic and seasonal behavior of uncertain variables. For analyzing the dynamics of uncertain variables, Recurrence Plot (RP) nonlinear analysis is used. Recurrence Plot analysis can specify periodic, chaotic or stochastic behavior of the uncertain variables. RP can also specify the changes in the behavior of uncertain variables. This paper tries to present a method based on RP analysis for data season classification. In this method, the seasonal behaviors including the variations in the dynamic behavior and in the mean and variance of the variables over time are considered. Following data season classification and scenario generation by the appropriate method with their dynamic behavior, considering the reliability of the system, the optimal capacity of distributed generation (DG) resources in an autonomous microgrid is determined by scenario-based stochastic programming method. The results of this paper indicate that generation of the scenarios of uncertain variables based on their dynamic and seasonal behavior leads to increase of modeling accuracy, and microgrid planning becomes much optimized.

The paper is organized as follows: The second section presents the mathematical modeling of microgrid components and DGs control strategy. The third section explains the optimization problem and how to generate scenarios of parameters with uncertainties based on time series analysis in a microgrid. The fourth section examines the calculated results of the optimal capacity of DGs via stochastic method. Fifth section concludes the paper.

2. Modeling of the system

The intended grid consists of PV, wind turbines, diesel generator and battery. The load is normally supplied by PV resources and wind turbines, but during the hours of peak demand, the battery is used. Also if the grid needs some more power, the diesel generator is applied. At all hours, the excess energy is stored in batteries in order to be used in the times of need.

2.1. Wind turbine model

The mathematical model which presents the wind turbine power output in terms of wind speed is as follows (Mohammadi et al. 2012):

$$p_W = \begin{cases} 0 & v \leqslant v_c \\ av^3 - bP_r & v_c < v < v_r \\ P_r & v_r \leqslant v \leqslant v_o \\ 0 & v > v_o \end{cases}, \tag{1}$$

where v is the wind speed, v_c is the cut in speed, v_r is the rated speed, v_o is cut-out speed, P_r is rated power of wind turbine and the parameters "a" and "b" calculated as:

$$a = \frac{P_r}{v_r^3 - v_c^3}, b = \frac{v_c^3}{v_r^3 - v_c^3}$$