



Stochastic scheduling of renewable micro-grids considering photovoltaic source uncertainties



Fatemeh Najibi, Taher Niknam*

Department of Electronic and Electrical Engineering, Shiraz University of Technology, Shiraz, Iran

ARTICLE INFO

Article history:

Received 1 November 2014

Accepted 11 March 2015

Available online 18 April 2015

Keywords:

Uncertainty

PV model

Scenario Based Method

Modified Dolphin Echolocation

Optimization (M-DEO)

Renewable micro-grid

Storage device

Dolphin

Dolphin echolocation

ABSTRACT

This paper introduces a new electrical model of a PV array by simulating and tests it on one typical Micro-Grid (MG) to see its performance with regards of optimal energy management of Micro-Grids (MGS). In addition, it introduces a probabilistic framework based on a scenario-based method to overcome all the uncertainties in the optimal energy management of MGs with different renewable power sources, such as Photovoltaic (PV), Wind Turbine (WT), Micro Turbine (MT), and storage devices. Therefore, the uncertainty is considered for WT and PV output power variations, load demand forecasting error and grid bid changes at the same time. It is hard to solve MG problem with all its uncertainty for 24-h time intervals, and consider several equality and inequality at the same time. In fact, in order to resolve this issue, the problem needs one powerful technique that although it converges very fast, it escapes from the local optima. As a result, one modern Dolphin echolocation optimization algorithm (DEOA) is defined to explore all the search space globally. The DEO algorithm uses the ability of echolocation of the dolphins to find the best location. Additionally, the proposed modification method will be introduced in this paper. This method makes the algorithm work better and finds the locations faster. The proposed method is implemented on a test grid-connected MG and satisfying results can be seen after implementation.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

In recent years, most companies and countries have concerns about global warming and consumption of fossil energy sources. Therefore, studying renewable energy sources, such as solar energy, and wind energy becomes popular and crucial. Many countries have started examining renewable energy solutions in order to use renewable energies optimally. Moreover, increased fossil energy prices along with technological advances have made companies consider utilizing distributed energy resources (DER) [1–5].

Renewable Energy Resources (RESs) in different forms such as Wind Turbines (WT), Photovoltaic (PV), Fuel Cells (FC), and Micro Turbines (MT), have significant role in renewable energy, yielding better power quality and flexibility results in distribution systems [6–9]. By definition, distributed energy resources (DERs) include natural gas, wind power, solar photovoltaic cells, fuel cells, combine heat and power (CHP) systems, microturbines and their utility in distribution network [10]. Management of distributed generations (DGS), however, faces some problems such as Volt/Var

control, aggression of DGs, distributing energy among the DGs, and the problem with electrical loads [11,12].

In [13] a methodology has been used to control the load in islanded micro-grids. One MG has been simulated in [14] by Khodr et al. to explain a method for deterministic optimal management. In [15] a simulation is implemented based on an optimal design and planning of a hybrid renewable energy with the goal of minimizing the cost. The total cost of a hybrid solar wind MG is optimized by using linear programming method [16]. One model of supply reliability is presented in [17] for micro-grids including wind power and PV. One typical MATLAB-Simulink PV module is simulated in [18] by considering non-uniform irradiance. [19] Represents one PV/wind MG for rural housing, in which the MG has been optimized by using iterative genetic algorithm. One PV model is implemented in [20] to validate a system design as MG system and an algorithm based on particle swarm optimization (PSO) is used to determine the unknown parameters in PV module. One model with the goal of minimizing cost and emission, by taking account of all uncertainties of forecasting load demand, the output power of wind and PV units, and market prices is studied in [21] and it is worthy to note that the uncertainties is simulated by a scenario-based stochastic method. One PV module is simulated in [22] by using the meteorological module data and taking

* Corresponding author.

E-mail address: niknam@sutech.ac.ir (T. Niknam).

Nomenclature

| | | | |
|--------------------------------|--|------------------------------|--|
| I | PV current | $\Delta P_{PV,t,s}$ | photovoltaic forecasted power output error |
| I_{ph} | photo-generated current | $\Delta P_{D,ld,t}$ | ld th forecasted load demand error |
| V | PV voltage | $\Delta Price_{utility,t,s}$ | forecasted market price (€ct) error |
| I_0 | dark saturation current | N_{WT} | numbers of WT units |
| n_s | number of cells in module | N_{PV} | number of PV units |
| V_t | junction thermal voltage | NDt | number of time intervals |
| R_{sh} | parallel values of resistances | N_s | number of scenarios |
| R_s | series values of resistances | T | time intervals |
| k | Boltzmann's constant | σ | standard deviation error |
| T | junction temperature | π_s | a normalized probability of each scenario |
| q | electronic charge | β | the probability of intervals |
| A | diode quality factor | PP | predefined probability |
| I_{sc} | short-circuit current | PP_1 | the convergence factor of first loop |
| V_{oc} | open-circuit voltage | $Loop_i$ | the number of the current loop |
| V_{mpp} | voltage at MPP | Power | the degree of the curve |
| I_{mpp} | current at MPP | CF | convergence factor |
| G | desired irradiance | R_e | the effective radius |
| G_{stc} | standard irradiance | $AF_{(A+k)j}$ | the accumulative fitness of the $(A + k)$ th alternative |
| T | desired temperature | NL | number of locations |
| T_{stc} | standard temperature | NV | number of variables |
| K_i | temperature coefficient of current | P_{ij} | the probability of choosing alternative |
| K_v | temperature coefficient of voltage | X_{gbest} | the best location |
| $B_{Gi}(t)$ | the bid of i th DG at time t | X_i | each location |
| X | state variables vector | N | length of the control vector |
| $B_{Sj}(t)$ | the j th storage device bid at time t | | |
| $S_{Sj}(t)$ | start-up/shut down cost of j th storage device at time t | | |
| $S_{Gi}(t)$ | start-up/shut down cost of i th DG at time t | | |
| $P_{Grid}(t)$ | active power bought (sold) from (to) the utility at time t | | |
| $B_{Grid}(t)$ | utility bid at time t | | |
| $u_i(t)$ | state of the i th unit denoting ON/OFF statuses | | |
| n | number of the state variables | | |
| N_g | number of generating units | | |
| N_s | number of storage devices | | |
| π | the absorption coefficient | | |
| $P_{WT,t,s}$ | wind power output of unit WT | | |
| $P_{PV,t,s}$ | photovoltaic power output of unit PV | | |
| $P_{D,ld,t,s}$ | ld th load demand | | |
| $Price_{utility,t,s}$ | market price | | |
| $P_{WT,t,s}^{forecast}$ | forecasted wind power output of WT | | |
| $P_{PV,t,s}^{forecast}$ | forecasted power output of PV unit | | |
| $P_{D,ld,t,s}^{forecast}$ | ld th forecasted load demand | | |
| $Price_{utility,t}^{forecast}$ | forecasted market price | | |
| $\Delta P_{WT,t,s}$ | forecasted wind power output error | | |

List of abbreviations

| | |
|--------------|-----------------------------------|
| FC | Fuel Cell |
| WT | Wind Turbine |
| PV | Photovoltaic |
| NiMH-Battery | Nickel-Metal-Hydride Battery |
| PEM | Point Estimate Method |
| DG | distributed generation |
| PV | Photovoltaic |
| STC | standard test condition |
| DNI | direct normal irradiance |
| MG | micro-grid |
| MT | Micro Turbine |
| RES | renewable energy source |
| M-DEO | Modified DEO |
| DEO | Dolphin Echolocation Optimization |
| MPP | Maximum Power Point |
| RES | Renewable Energy Recourses |
| GHI | Global HZ Irradiance |
| Diff | Diffusion Irradiance |

account of the temperature and irradiance. As stated previously, management of MGs is faced with many complicating considerations. One of the most important considerations is not to ignore the uncertainties as they influence the optimal operating point. In fact, optimal management of MG should be done in a way that all the uncertainties are accounted for, as to finally accomplish the best results. The role of RESs in the new power utility also makes changes in operation of power systems. In order to reach the goal of optimizing MGs, one solution is using a stochastic framework. One of the RESs, which can have an important influence on power system operation, is photovoltaic (PVs). Stochastic analysis needs some assessment, which is possible by using simulation in random environment. In order to fulfill this requirement, we can use methods such as scenario-based methodology. So far, the research conducted on micro grid operating management the shortcoming of not simulating one operative PV model for the MG and then testing it to see its effect on the problem. Hence, in this paper one PV module is modeled and then examined on the

test MG. We have observed the output of PV module for four different days in one year in addition to taking note of the influence of different irradiances in different seasons on PV performance, output power and total price of MG. We have a micro grid with different types of RESs such as WT, PV, FC, Bat and MT. The output power of PV is varying and one of the uncertainty variables is PV output power that is different from the real value. One scenario for four different days of different seasons for both deterministic and stochastic analysis is discussed. In this scenario the battery charge has limitation and its initial charge is set to be zero while all the other DGs can switch between ON/OFF state and the two PV and WT units are working on their maximum power. By using this probabilistic method, the uncertainty of load forecast error, WT and PV output power variations and the market cost will be monitored and modeled. By taking account all of these, a need for a powerful optimization tool to find the best solution for our problem is sensed. Dolphin echolocation optimization algorithm (DEOA), which is a powerful tool to optimize the solution, is

Download English Version:

<https://daneshyari.com/en/article/763747>

Download Persian Version:

<https://daneshyari.com/article/763747>

[Daneshyari.com](https://daneshyari.com)