Electrical Power and Energy Systems 56 (2014) 349–360

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

System modeling and optimization for islanded micro-grid using multi-cross learning-based chaotic differential evolution algorithm

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ARTICLE INFO

Article history:
Received 23 July 2013
Received in revised form 8 November 2013
Accepted 9 November 2013

Keywords:
Micro-grid
Differential evolution
Stochastic search
Optimal operation
Renewable energy
Chaotic search

ABSTRACT

This paper presents a comprehensive operation model for micro-grids (MG) operating in the islanded mode. Various energy sources of a MG including diesel engine generator, micro-turbine, wind turbine and photovoltaic cell as well as battery storage and AC/DC rectifier/inverter are modeled in the proposed framework. Fuel costs, emission costs, and operation and maintenance (O&M) costs of these sources as well as their operating limits and characteristics are considered in the model. Furthermore, a new multi-cross learning-based chaotic differential evolution (MLCDE) algorithm is presented to solve the optimization problem of MG operation. The numerical results obtained from the proposed solution approach for three MG test cases with real-world data are compared with the results of several other recently published optimization methods. These comparisons confirm the validity of the developed approach.

1. Introduction

The penetration of distributed and renewable generation at medium and low voltages into power systems is increasing in many countries worldwide. Micro-grid (MG) is an effective solution to incorporate distributed energy resources into power systems realizing environmental and economical network operation goals. One of the important applications of the MG generators is the utilization of small-modular residential or commercial generators for onsite service. The small scale of individual investments reduces capital extent and venture, by strictly matching capacity increase to demand growth. Composition of a variety of generator types and geographical situations lead to different configurations for MG [1]. MG generators can be managed so that they satisfy the customers' demand at minimum operation cost all the time. An adequate management framework is important for both better system efficiency and stability of hybrid systems [2]. The management of MG units requires an accurate economic model to describe the operating cost taking into account the output power production. This model is discrete and nonlinear in nature; hence effective optimization's tools are needed to reduce the operating costs to a minimum level. So far, many research works have been performed on the optimal operation scheduling of power systems and various optimization methods have been proposed to solve power dispatch problems [3–6]. However, we focus on the research works performed on the optimization of MG operation here. Some articles only minimize fuel cost of MG units [7,8], and some other ones minimize fuel cost and operation cost of MG units [9–13]. In [7,8], heat and electricity powers are balanced. In [8], the relation between the numerical weather information error and the operation results of the compound MG including a fuel cell, photovoltaic (PV) cells, a heat tank and batteries is described. In [11], annual energy cost of MG considering a fuel cell, a micro-turbine (MT) and reciprocating engine is minimized using Berkeley Lab's Distributed Energy Resources Customer Adoption Model. In [12], a smart energy management system (SEMS) is presented to optimize the operation cost of a MG, connected to main grid. The SEMS consists of power forecasting module, energy storage system management module and optimization module. The forecasting module uses neural network to predict the output power of the PV cells using the historical data. Compared to the model of the SEMS, wind turbine (WT) is added in the model of [13], but the forecasting module is not considered and it is assumed that accurate forecasts of spot market prices, solar irradiation and wind speed are available.

Emission cost of MG units is not taken into account in the optimization models of [7–13]. Minimization of pollutant gases is an important objective in the operation of a MG, given the sensitivity of community to control and decrease the greenhouses gases in recent years. Minimization of emission, fuel and operation costs are

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http://dx.doi.org/10.1016/j.ijepes.2013.11.015

considered in [14–19]. In [14], a framework is presented to optimally schedule the renewable power generators and energy storage in a grid-connected MG reducing the annual cost and emission of MG. In [15], a multi-scenario, multi-objective optimization method of a grid-parallel MG is presented, based on application scenarios' classification, minimizing the annual cost and emission of MG as well as maximizing the utilization of renewable energies. In [16,17], a mesh adaptive direct search algorithm is used to minimize the cost and emission of a grid-connected MG including a fuel cell, a MT, a diesel engine generator (DEG), a PV, a WT and batteries. Multi-objective optimizations of MG operation are transformed into single-objective using a weighted sum method in [14,15,19]. Similarly, in [16,18], emission cost for the units of MG is utilized in the optimization models using emission factor and cost of each emission type.

Despite the performed research works in the area, more accurate and comprehensive MG operation models are still demanded. For instance, mathematical models of some generators of the MGs are not presented in [7,8,10,14,15] and the optimization method is not clarified in [7,9,14,15]. Some generators like PV, WT, MT and DEG are not considered in the MG model of [8–13]. Binary variables (on/off status of MG units) are not considered or their handling procedure is not specified in the optimization model of [7–18]. Mapping between different types of emission and output power of DEG/MT is assumed to be linear in the optimization models of [14–19], while this assumption may lead to considerable approximation errors for the emission costs. In [19], the mapping between fuel cost and output power for DEG/MT is also assumed to be linear and all other generators have a same operation model.

Evolutionary algorithms (EAs) such as genetic algorithm (GA), differential evolution (DE), particle swarm optimization (PSO), Bat-inspired algorithm (BAT), gravitational search algorithm (GSA) and cuckoo search algorithm have been proposed for solving the optimization problems in recent years. EAs have been designed to only use the numerical values of the objective function and no knowledge about the internal structure of the problems is required. EAs can quickly adapt to nonlinear, non-convex, non-differentiable or discontinuous problems. Some of recently proposed EA approaches are reviewed in the following.

In [20], GSA as stochastic search method based on the Newtonian gravity rules is proposed to solve optimization problems. In PSOGSA [21], PSO is combined with GSA such that the local best particle of PSO is found by GSA. Also, PSO technique is combined with Newton–Raphson power flow in Hybrid PSO (HPSO) [22]. By increasing the iteration number, the inertia weight of the velocity vectors of HPSO is linearly decreased. GSA is a fast converging method due to its well-designed interacting forces and group movement. However, along GSA evolution, smaller masses are gradually attracted by larger ones. This characteristic decreases exploration capability of the algorithm to search different areas of the solution space. A similar problem may be seen in PSO, where the particles move gradually toward the global best of the swarm. Cuckoo search algorithm is inspired by the reproduction strategy of cuckoos. A local search based on exchanging the addition of information between best solutions is added to cuckoo search in modified cuckoo search (MCS) [23]. MCS can find all the optimal solutions simultaneously if the number of nests (population size) is much higher than the number of local optima, but it increases computational cost. Also, as a random walks search method, a fast convergence cannot be guaranteed. In [24], an improved harmony search (HIS) algorithm is proposed to solve the optimal capacitor placement problem. The control parameters of harmony search method are adjusted as a function of iteration number in the IHS. IHS does not discriminate the promising areas of the solution space from its other parts, while these areas deserve more careful search. BAT algorithm is based on the echolocation behavior of bats [25]. It tries to combine the characteristics of some existing EAs, but it leads to increase the number of control parameters. Also as reported in [25], the convergence rate of this algorithm is affected by the quality of its control parameters' adjustment. In GL25 [26], a global search is carried out for 25% of population and then a local search is implemented for whole population. The difference of the global and local search is in the different settings adopted for the control parameters. It increases the computational cost of GL25 and number of settings. In hybrid genetic algorithm (HGA) [27], a differential improvement and local Lamarckian-type optimization are added to a GA. It has been shown that the performance of HGA is dependent on the adjustment of the parameters, but no method is presented for this purpose. Some DE based EA techniques such as intersect mutation DE (IMDE) [28], effective and efficient DE (EEDE) [29], robust DE RDE [30], Janez DE (JDE) [31], self-adaptive neighborhood search DE (SANSDE) [32], self-adaptive DE (SADE) [33], ensemble of parameters and strategies DE (EPSDE) [34], and composite DE (CODE) [35] have recently been presented in the literature to solve complex optimization problems. Ranking and grouping the individuals as well as new intersected mutation and crossover operations are proposed within IMDE [28]. EEDE [29] is similar to basic DE, with the difference that the mutated vectors of basic DE is added to the population and then the half of population with better performance are only selected by the truncation selection of GA. RDE employs several crossover operators to enhance the search capability of the basic DE [30]. In JDE [31], the scaling factors and crossover parameters of DE are randomly adjusted within the ranges of $[0.1, 1.0]$ and $[0, 1]$, respectively. The control parameters of SANSDE [32] are adapted in specified stages of the evolution according to a statistical approach based on Gaussian and Cauchy distributions using the fitness of individuals. Similar to SANSDE, the control parameters of SADE [33] are adapted based on Gaussian distribution. However, in SADE, a pool of different mutation and crossover strategies is used based on the probability of their success in the previous stages. In EPSDE [34], a pool of control parameters is also used in addition to the pool of mutation and crossover strategies of SADE. The strategy and its associated control parameters for each individual of EPSDE are randomly selected from the pools. Similar to EPSDE, a pool of three strategies and a pool of three sets of control parameters are utilized in CODE [35]. However, in this method three trial vectors are concurrently generated for each individual using the three strategies and the best solution among the three trial vectors and their parent is considered for the next stage.

Some EA-based solution approaches have been used to solve the operation optimization problems of MG in recent years. GA-based optimizations are utilized for optimal operation of MG in [8,12,13,19]. In [36], an optimal power control strategy is presented for operation of an autonomous MG based on a real-time self-tuning PSO algorithm. A DE-based Algorithm is presented for optimal operation of a MG minimizing operation and emission costs in [18]. However, modeling and optimization of MG operation still demand further research.

The main purpose of this research work is minimizing the operation cost of MG in scheduling period considering fuel, operation and maintenance and emission costs. To aim this, MG components (including different generators, storage devices and loads) and their operation constraints are modeled in Section 2 of the paper. The connection between the introduced models of Section 2, including the power flow among MG components, is presented as the MG operation optimization problem in Section 3. Handling the various equality and inequality constraints, different integer and real variables and nonlinear nature of the model is a major challenge of the optimization problem. Thus, a new effective optimization approach for solving nonlinear mixed integer optimization problem, i.e. multi-cross learning-based chaotic differential