Electric Power Systems Research 104 (2013) 1–8

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Optimal allocation of distributed energy resources through simulation-based optimization[☆]

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ARTICLE INFO

Article history:
Received 7 October 2012
Received in revised form 15 May 2013
Accepted 29 May 2013
Available online 4 July 2013

Keywords:
Distributed energy resources
Dynamic optimal power flow
Hybrid power systems
Particle swarm optimization
Simulation-based optimization

ABSTRACT

In this study, a new two-layer simulation-based optimization (SBO) approach is proposed to determine the optimal allocation and capacity of distributed energy resources (DER) in a power distribution system with an imperfect grid connection. In the first layer, a dynamic optimal power flow (DOPF) routine is embedded in a simulation algorithm that is run for each system configuration based on a set of operational rules to calculate the cost and reliability level of the system over one year. In the second layer, a particle swarm optimization (PSO) algorithm uses the outputs of the first layer to optimize the location and capacity of wind turbines, PV panels, and grid-scale batteries, in order to minimize cost while meeting reliability requirements. The proposed approach is tested on a 16-bus U.K. generic distribution system (GDS) under different grid availability conditions, and the results are reported. The merits and limitations of the proposed approach are discussed, and the differences between it and rule-free constrained optimization approaches are highlighted.

1. Introduction

Motivated by global warming concerns, nations are trying to reduce the carbon emissions associated with electricity generation through using renewable energy sources such as solar and wind to generate power [1,2]. Intermittent and not fully predictable in nature, these sources cannot be solely utilized to satisfy the demand reliably. One way to overcome this problem is to combine several types of conventional and renewable power generation and energy storage technologies to form hybrid power systems (HPS). To ensure economic and reliable supply of energy, the configuration and operation strategies of HPS should be chosen properly, preferably meeting specified optimality criteria.

The optimal HPS design problem of finding the generation and storage mix that minimizes cost while satisfying reliability requirements and technical constraints is studied in [3–9]. A feasibility analysis of renewable energy supply for a stand-alone large hotel accommodation is presented in [3,4]. A multi-period optimization model for an interconnected micro-grid with hierarchical control that participates in wholesale energy market is formulated and solved using genetic algorithm (GA) in [5]. The optimal sizing of various energy sources in a stand-alone HPS is proposed and solved using particle swarm optimization in [6]. The optimal expansion plan for a system of autonomous power generation sources, including renewable energy units, is determined through dynamic optimization in [7], considering total operational and investment costs. A combined optimization procedure for determining the optimal system configuration, along with the operation strategy of a hybrid power system, is given in [8]. A mathematical model for minimizing the total cost of a wind-diesel system with hydrogen storage unit is given in [9]. In all these studies, the power system is represented as a single node having all generators and loads connected to it. Thus power flow limitations and losses are not considered in the formulation.

The more complex problem of selecting the optimal size and location of DER units, whereby a detailed representation of network configuration is considered, is studied in [10–16]. An analytical approach for determining optimal DER location by loss sensitivity factor in a radial distribution system is given in [10]. In [11], a model is formulated to determine the optimal DER capacity and location by minimizing the system planning cost, power losses, and DER investment and maintenance cost in the market environment. A multi-objective genetic algorithm (GA) is used to find the optimal location and size of DER units in a radial distribution system with

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[☆] This work was supported by the Masdar Institute, Abu Dhabi, UAE with project number 400060.

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http://dx.doi.org/10.1016/j.epsr.2013.05.019

δ_i	voltage angle at bus i
η_{bat}	battery discharging efficiency
ρ_g^t	electricity price at period t
θ_{ij}	phase angle of ijth element in the system Y-bus matrix
$\lvert V_i \rvert$	voltage magnitude at bus i
$\lvert Y_{ij} \rvert$	magnitude of ijth element in the system Y-bus matrix
Ch_{bat}^i	charging power for the battery at bus i
Dch_{bat}^i	power discharged by the battery at bus i
DOD_{max}	maximum allowable depth of discharge
DP^i	dumped real power at bus i
DR_t	ratio between hourly and peak power demand
EIR	energy index of reliability
GS	binary scalar denoting the grid status, 1 if available, and 0 if islanded
H	nominal storage capacity of battery units (kVAh per kW capacity)
IR	interest rate applicable on DER investment
P_D^i	real power demand at bus i
$P_{D,curt}^i$	real load curtailed at bus i
P_g	active power supplied by source g (a DER or the grid)
P_{SG}	power supplied by the grid
PD_{peak}	peak power demand
Q_D^i	reactive power demands at bus i
$Q_{D,curt}^i$	reactive load curtailed at bus i
Q_g	reactive power supplied by source g (a DER or the grid)
RC_{bat}^i	rated capacity of the battery at bus i
S_{ij}	MVA power flow from bus i to bus j
S_{ij}^{max}	maximum allowable limit of S_{ij}
SoC_t^i	battery state of charge at node i at the beginning of time period t
TAC	total annual cost
V_i^{max}	voltage upper limit at bus i
V_i^{min}	voltage lower limit at bus i
$\mathrm{I}C_{DER}$	expected operational life of each DER type
C_{DER}	initial cost per unit capacity of each DER type
P_{DER}^i	installed capacity of each DER type at bus i

different voltage dependant load types in [12]. The optimal size and location of DER units in a micro-grid for the minimization of deployment cost and heat compensation cost are determined using a simulated annealing (SA) approach in [13]. The optimal location of DER considering loss minimization with acceptable reliability and voltage profile is found using GA in [14]. A discrete particle swarm optimization algorithms hybridized with jumping frog optimization is used to find optimal DER location and capacity in a single period optimal power flow framework in [15]. The optimization methods applied to the above problems can be classified under three major categories: analytical methods [16], constrained optimization (CO) methods [12], and simulation-based optimization (SBO) methods [9]. Analytical methods can be used to solve simple cases, whereas realistic power system design problems usually require more sophisticated algorithms. The CO and the SBO methods are compared in detail in Section 2.

In this paper, a SBO approach combining the dynamic optimal power flow (DOPF) routine with the meta-heuristic particle swarm optimization (PSO) algorithm is used to determine the optimal allocation and capacity of non-dispatchable renewable DER and grid-scale energy storage units in a spatially dispersed HPS under imperfect grid connection and strict reliability requirements. In this two layer approach, PSO is used first in the upper layer to sample a set of HPS configurations. These configurations are then tested using a DOPF-based simulation algorithm that implements a set of operational rules in the lower layer to calculate their cost and reliability metrics. After each iteration, the results obtained from the lower layer algorithm are sent back to the PSO algorithm to search for better configurations for further testing. The process continues until no further improvement can be achieved.

2. Constrained vs. simulation-based optimization

In a typical constrained optimization (CO) approach, the entire model is formulated at the beginning and handed to a solver that manipulates all the variables simultaneously to find the feasible combination of values that optimizes the objective function. In the context of this problem of determining the optimal allocation and capacity of DER, using such an approach implies that the modeler has full prior knowledge about the problem parameters, including the future supply profiles of DER. This is obviously a non-valid assumption that might lead to inaccurate results. As an example of this situation, assume that the energy stored in the batteries is barely above the minimum level permitted at a certain time interval. Assume also that in this specific period the grid is connected, but that power interruption will occur in the next period. If the optimization routine has to supply loads in the next period, it must charge the batteries during the current period, so they can feed the loads when the grid is disconnected. If a CO approach is used to solve the problem, this is exactly what will happen based on the knowledge of this future information (*i.e.* the power interruption in the next period). However, in reality, the system operator does not know when the system is going to island, therefore, it will not be able to predict this event and subsequently will not charge the batteries. Clearly, without prior knowledge of this piece of information, the optimal configuration obtained through a CO approach will fail to satisfy the demand with the expected reliability. Despite the improvements in forecasting techniques for both power supply and demand, this concern will persist unless perfect predictability is achievable. Another issue of using classical CO approaches to solve this problem is their inability to handle operational rules. Practically, HPS systems are operated using a set of pre-defined static rules specifying the priority at which each source is utilized in case of supply demand mismatch. For example, a rule might state that, if the grid is disconnected, batteries will be used up to their maximum limits to feed the load demand before any load is curtailed. A typical CO approach does not follow such a rule, but instead finds the absolute optimal system configuration and operating plan.

Simulation-based optimization (SBO) refers to any stochastic optimization problem that can be solved using computer simulations [17]. When compared to the classical CO, SBO follow a quite different approach, which is to simulate the actual operation of the system using different system configurations and then choose the one that gives the best result. Simulations are usually done using certain rules mimicking the actual rules followed by the system operator; therefore, it is also referred to as “rule-based” optimization, in contrast to the “rule-free” orientation of the traditional CO approaches. Many large-scale optimization problems with inherent complexity can be solved using SBO approach. A nice comparison between the two approaches is given in [9].

3. Dynamic optimal power flow (DOPF)

In the context of this study, dynamic optimal power flow (DOPF) refers to a multi-period optimal power flow (OPF) routine in which the results obtained from one time interval are used as inputs for the next interval. It differs from the conventional multi-period OPF