Electrical Power and Energy Systems 71 (2015) 1–14

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Economic analysis of unit commitment with distributed energy resources

Manisha Govardhan, Ranjit Roy *

Department of Electrical Engineering, S.V. National Institute of Technology, Surat 395007, Gujarat, India

ARTICLE INFO

Article history:
Received 29 January 2014
Received in revised form 13 January 2015
Accepted 31 January 2015
Available online 6 March 2015

Keywords:
Distributed energy resources (DERs)
Emergency demand response program (EDRP)
Plug-in electric vehicles (PEVs)
Teaching–learning based optimization (TLBO) algorithm
Unit commitment problem (UCP)

ABSTRACT

Classic unit commitment (UC) is an important and exciting task of distributing generated power among the committed units subject to several constraints over a scheduled time horizon to obtain the minimum generation cost. Large integration of distributed energy resources (DERs) in modern power system makes generation planning more complex. This paper presents the individual and collective impact of three distributed energy resources (DERs), namely, wind power generator as a renewable energy source, plug-in electric vehicles (PEVs) and emergency demand response program (EDRP) on unit commitment. In this paper, an inconsistent nature of wind speed and wind power is characterized by the Weibull probability distribution function considering overestimation and underestimation cost model of the stochastic wind power. The extensive economic analysis of UC with DERs is carried out to attain the least total cost of the entire system. To obtain the optimum solution, Teaching–learning based optimization (TLBO) algorithm is employed to solve the unit commitment problem considering IEEE standard 10 unit test system in this study. It is found that the combined effect of wind power generator, plug-in electric vehicles and emergency demand response program on UC significantly lessen the total cost of the system.

Introduction

The invention in the smart grid is accelerated in the direction of the greater reliance upon DERs with new changes and challenges in the century-old electric utility industry as the need for a more economical, ecological and reliable power system. DERs incorporate several customer-side technologies such as energy efficiency, demand response program, distributed generation, electric storage and smart electric vehicle charging which motivates the world-wide energy generation authorities to reduce the power system difficulties of limited generation resources, growing energy demand and fuel price. Unit commitment (UC) is a critical combinatorial optimization problem for daily economic planning and operation of the modern power system which collectively performs suitable on/off decision of generating units and distributes generated power among the committed units to achieve minimum generation cost while satisfying power demand, reserve and other basic constraints over a scheduled time horizon. The integration of DREs into UC has become a challenging task due to its nonlinear and random nature involving definite constraints, nonlinear objective function and enormous dimensions. This paper has incorporated three types of DERs such as wind power generator, emergency demand response program (EDRP) and plug-in electric vehicle (PEV) in conventional UC and their impact on generation scheduling and total cost of the system have been critically investigated.

Wind power source is considered as one of the most popular renewable energy source due to its clean, free and continuous source of energy but its volatile and uncertain nature introduces many challenges in power system such as transient and voltage stability, incompatibility between load demand and wind power generation, response during contingency and its influence on distribution networks [1]. In many countries, additional resources such as PEVs and demand response programs are introduced to deal with the erratic nature of wind power generation and to obtain reliable and secure power system. In recent years, PEVs have been evolved as the recent technological development in the automotive sector which have a great potential of emission reduction and peak load saving. PEVs can be charged from the grid and can feed power to the grid by discharging their battery. But, if the charging/discharging profile of PEVs is not suitably planned then large penetration of PEVs in power system may adversely result in amplified system losses, poor load profile and increase in investment cost [2]. Demand response is one of the significant load shaping programs against continuous electricity price varia-

* Corresponding author. Tel.: +91 9904402937; fax: +91 261 2227334.
E-mail address: rr@eed.svnit.ac.in (R. Roy).

http://dx.doi.org/10.1016/j.ijepes.2015.01.028
0142-0615/© 2015 Published by Elsevier Ltd.

Nomenclature

Decision variables

$A_{(i,h)}$ binary variable of *i*th charging vehicle at hour *h*
$B_{(i,h)}$ binary variable of *i*th discharging vehicle at hour *h*
$P_{G(i,h)}$ generated power output of *i*th unit at hour *h*
$P_{W(i,h)}$ wind power output of *i*th wind power generator at hour *h*
$u_{(i,h)}$ on/off status of unit *i* at hour *h*
$x_{(i,h)}$ start-up indicator of unit *i* at hour *h*
$y_{(i,h)}$ shut down indicator unit *i* at hour *h*

Parameters

a_i, b_i, c_i fuel cost coefficients of unit *i*
c scale factor of a particular location
C_{edrp} revenue cost of participating customer in EDRP
C_{vehi} charging/discharging cost of vehicles connected to a grid
C_{wd} direct cost of wind power generator
C_{wo} overestimation cost of wind power generator
C_{wu} underestimation cost of wind power generator
CSC cold start-up cost
CSH cold start hour
d_w direct cost coefficient of wind power generator
E price elasticity
HSC hot start-up cost
h hour index
i thermal unit, wind power generator and vehicle index
I incentive offered to the customer
$I_{\min}/I_{\max}$ minimum/maximum limit of an incentive offered by ISO
IS initial status
k shape factor of a particular location
k_p penalty cost coefficient
k_r reserve cost coefficient
MD minimum down time of a unit
MU minimum up time of a unit
N_G number of thermal units
N_{Vch}/N_{Vdish} number of charging/discharging vehicles
$N_{V\max}$ maximum number of vehicles that can connect to grid per hour
N_V^{total} total number of vehicles
N_W number of wind power generator
PEM price elasticity matrix
P_G generated power output of a thermal unit
$P_G{}^{\max}$ maximum generation capacity of a unit
$P_G{}^{\min}$ minimum generation capacity of a unit
P_L initial load demand
P_{Lnew} load demand after implementing EDRP
P_{Vch}/P_{Vdish} charging/discharging power of vehicles
$P_{VdishLimit}/P_{VchLimit}$ PEV's discharging/charging limit
$P_{W,avl}$ available or generated wind power from wind power generator
P_{Wr} rated power of wind power generator
$P_{W,sch}$ scheduled or predicted wind power
p_v power capacity of a vehicle
RD/RU ramp down/up limit
SD shut down cost
SP initial spot electricity price
$\mathrm{SP}_{\mathrm{new}}$ spot electricity price after implementing DRPs
SR spinning reserve
SU start-up cost
T total schedule period
T_B total benefit of the customer
TC total cost of the system
T_f teaching factor
U^{off} continuous OFF duration of a unit
U^{on} continuous ON duration of a unit
v wind speed in m/s
v_r, v_{ci}, v_{co} rated, cut-in and cut out speed of wind turbine respectively (m/s)
α customer participation rate in EDRP (in %)
η_{Vch}/η_{Vdish} charging/discharging efficiency of a vehicle
Ψ_{dep}/Ψ_{pre} depleted/present state of charge of a battery
$\Psi_{\min}/\Psi_{\max}$ minimum/maximum limit of state of charge

Functions

$INC(\Delta P_{L(h)})$ total incentive given to the participating customer for load demand reduction
$C_i(P_{G(i,h)})$ fuel cost of unit *i* at hour *h*
$B(P_{L(h)})$ customer's income during hour *h*
$E_{(h,j)}$ price elasticity of *h*th hour with respect to *j*th period
$f_v(v)$ Weibull probability distribution function
$F_V(v)$ cumulative distribution function
$f_{PW}(P_W)$ wind power cumulative distribution function

tion during low load, off-peak and peak period of the day in deregulated market. According to Federal energy regulatory commission (FERC), demand response program (DRP) is basically categorized into two types, namely, incentive based program (IBP) and time-based program (TBP) [3]. DRPs encourage the consumers to reduce their energy consumption during peak hours or to shift their load demand from peak hours to off-peak hours and get financial pay back for reducing their electricity consumption in terms of cash or discount in bill. The summary of DRP is given in [4]. Implementation of DRP results in enhanced load profile and reduction in total cost of the system.

Even though wind power generator and PEVs have a significant potential of reducing total generation cost and emission pollution, they have their own above mentioned challenges in power system. Their integration into unit commitment turns into more complexity in generation scheduling. Moreover, DRP has been proven as an organized approach of reshaping the inconsistent load curve by reducing the load demand during peak period of a day. Hence, the main objective of this study is to investigate the individual and combined effect of different DERs, namely, wind power generator, PEVs and DRP on generation scheduling and total cost of the system.

Recently, many research papers on generation scheduling considering wind uncertainty are published in [5–7]. The uncertainty of wind power in the unit commitment problem (UCP) can be formulated by using deterministic and stochastic approaches. In deterministic approach, wind power is considered in a similar way as the transmission and generation contingencies. Deterministic approach can be characterized mainly by two methods [8]. In first method, three-sigma approach is used to provide short-term security by scheduling adequate spinning reserve. In second method, security constrained unit commitment is solved considering large number of scenarios generated [8,9]. In stochastic approach, some probability distribution based strategies [10–13] are developed to deal with the wind power forecast error. In [14], the method to estimate the impact of wind power to the load