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A new algorithm for combined heat and power dynamic economic dispatch considering valve-point effects

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ABSTRACT

In this study, combined heat and power units are incorporated in the practical reserve constrained dynamic economic dispatch, which minimizes total production costs considering realistic constraints such as ramp rate limits and valve-point effects over a short time span. The integration of combined heat and power units and considering power ramp constraints for these units necessitate an efficient tool to cope with joint characteristics of electricity power-heat. Unlike pervious approaches, the system spinning reserve requirements are clearly formulated in the problem and a novel charged system search algorithm is proposed to solve it. In the proposed algorithm a novel self-adaptive learning framework, adaptive selection operation and repelling force modeling are used in order to increase the population diversity and amend the convergence criteria. The proposed framework is applied for three small, medium and large test systems in order to evaluate its efficiency and feasibility.

1. Introduction

Combined Heat and Power (CHP) known as cogeneration has the ability of creating simultaneous generation of two types of energy: useful heat and electricity. It improves efficiency and therefore, is more environmental friendly [1]. It also reduces the generation cost between 10 and 40% [2]. In Thermal Units (TUs), all the thermal energy is not converted into electricity and large quantities of energy are wasted in the form of heat [3]. CHP uses the heat and can potentially achieve the energy conversion efficiency of up to 80% [4,5]. This means that less fuel needs to be consumed to produce the same amount of useful energy.

The objective of the CHP Dynamic Economic Dispatch (CHPDED) is to find the optimal dispatching of power and heat with minimum total operation cost while satisfying both heat and electricity load demands and other various practical constraints over a short time span. Thus, the CHP units operate in a bounded electricity power versus heat plane. However, the model of the CHPDED problem must consider the Spinning Reserve Requirements (SRRs) at the top of time interval coupling to compensate for the error in largest generation output and unexpected electric load deviations [6]. In practice, the change in unit power outputs from one time to another one is restricted due to the up and down ramp rate constraints [6]. Furthermore, opening steam valves of the large steam turbine for increasing the power output of the TUs leads to a non-convex fuel cost function. It should be noted that the mutual dependency of the heat production capacity and electricity generation for CHP units must be considered in the problem [7]. Consequently, a practical CHPDED problem should include valve-point effects, ramp rate limits, SRRs and joint characteristic of electricity power-heat which makes finding the optimal dispatching a challenging problem. Three approaches have been proposed in the literature: (i) addressing multi-period economic dispatch, also called DED [8], or (ii) considering SRRs in DED known as Reserve Constrained DED (RCDED) [9], and (iii) solving economic dispatch of CHP units [7]. However, no economic dispatch approach incorporating CHP units in a multi-period optimization framework i.e. RCCHPDED is currently available in the technical literature.

Currently, the available methods and algorithms for solving the DED problem can be generally classified into two categories: 1) optimization-based methods [10] and 2) meta-heuristic-based methods [11–26]. The optimization-based methods impose no restriction on the non-smooth and non-convex characteristics of the

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Nomenclature

Indices

h	heat-only (H) unit index
i	thermal unit (TU) index
ii, jj	electricity power generating unit index
j	Combined Heat and Power (CHP) unit index
j'	linear inequality constraint index
k	iteration index
m, n	charged particle index
t	time index

Constants

a_i, b_i, c_i, d_i, e_i	cost coefficients of thermal unit i
$B_{ii,jj,t}$	loss coefficient relating the productions of electricity power generating units ii and jj at time t (MW^{-1})
$B_{0,ii,t}$	loss coefficient associated with the production of electricity power generating unit ii at time t
$B_{00,t}$	loss coefficient parameter at time t (MW)
$\mathrm{DR}_i^{\mathrm{TU}}$	ramp-down rate of thermal unit i (MW/h)
$\mathrm{DR}_j^{\mathrm{CHP}}$	ramp-down rate of CHP unit j (MW/h)
DR_{ii}	ramp-down rate of electricity power generating unit ii (MW/h)
$H_{D,t}$	heat load demand at time t (MWth)
$H_{h,\max}^{\mathrm{H}}$	heat capacity of heat-only unit h (MWth)
$H_{h,\min}^{\mathrm{H}}$	minimum heat output of heat-only unit h (MWth)
$H_{j,\max}^{\mathrm{CHP}}$	heat capacity of CHP unit j (MWth)
$H_{j,\min}^{\mathrm{CHP}}$	minimum heat output of CHP unit j (MWth)
$k_{\max}$	maximum iteration
N_{CHP}	number of CHP units
N_{CP}	number of charged particles
NG	number of electricity power generating units
N_{H}	number of heat-only units
N_{lin}	number of linear inequality constraints
NT	number of time intervals
N_{TU}	number of thermal units
$P_{\mathrm{D},t}$	electricity load demand at time t (MW)
$P_{j,\max}^{\mathrm{CHP}}$	power capacity of CHP unit j (MW)
$P_{j,\min}^{\mathrm{CHP}}$	minimum power output of CHP unit j (MW)
$P_{i,\max}^{\mathrm{TU}}$	power Capacity of thermal unit i (MW)
$P_{i,\min}^{\mathrm{TU}}$	minimum power output of Thermal unit i (MW)
$P_{ii,\max}$	power capacity of electricity power generating unit ii, respectively (MW)
$\mathrm{rand}(\cdot)$ and $\mathrm{rand}_Q(\cdot)$ $Q = 1,\ldots,3$	random function generator in the range [0,1]
SR_t	10 min spinning reserve requirements at time t (MW)
UR_{ii}	ramp-up rate of electricity power generating unit ii (MW/h)
$\mathrm{UR}_j^{\mathrm{CHP}}$	ramp-up rate of CHP unit j (MW/h)
$\mathrm{UR}_i^{\mathrm{TU}}$	ramp-up rate of thermal unit i (MW/h)
$\alpha_j,\beta_j,\zeta_j,\gamma_j,\lambda_j,\phi_j$	cost coefficients of CHP unit j
σ_h,μ_h,ρ_h	cost coefficients of heat-only unit h

Variables

$\mathbf{Best}^k$	best position among all charged particles in iteration k
$F(\mathbf{PH}_G)$	total operational costs at time span NT ($)
$G_1(\mathbf{P}_t^{\mathrm{TU}})$	total thermal units costs at time t ($)
$G_2(\mathbf{P}_t^{\mathrm{CHP}},\mathbf{H}_t^{\mathrm{CHP}})$	total CHP units costs at time t ($)
$G_3(\mathbf{H}_t^{\mathrm{CHP}})$	total heat-only costs at time t ($)
$H_{h,t}^{\mathrm{H}}$	heat generation output of heat-only unit h at time t (MWth)
$H_{j,t}^{\mathrm{CHP}}$	heat generation output of CHP unit j at time t (MWth)
$\underline{H}_{j,t}^{\mathrm{CHP}}$	lower limit of the jth CHP unit output heat at time t (MWth)
$\overline{H}_{j,t}^{\mathrm{CHP}}$	upper limit of the jth CHP unit output heat at time t (MWth)
$H_{\mathrm{Loss},t}$	total heat losses at time t (MWth)
H_violate$t$	heat mismatch at time t (MWth)
$\mathbf{Mean}^k$	mean position of all charged particles in iteration k
$\mathbf{PH}_G$	generating unit vector
$P_{ii,t}$	power generation output of electricity power generating unit ii at time t (MW)
$P_{\mathrm{Loss},t}$	total real power losses at time t (MW)
$P_{i,t}^{\mathrm{TU}}$	power generation output of thermal unit i at time t (MW)
$\overline{P}_{i,t}^{\mathrm{TU}}$	upper limit of the ith thermal unit output power at time t (MW)
$\overline{P}_{i,t}^{\mathrm{TU}}$	upper limit of the ith thermal unit output power at time t (MW)
$P_{j,t}^{\mathrm{CHP}}$	power generation output of CHP unit j at time t (MW)
$\underline{P}_{j,t}^{\mathrm{CHP}}$	lower limit of the jth CHP unit output power at time t (MWth)
$\overline{P}_{j,t}^{\mathrm{CHP}}$	upper limit of the jth CHP unit output power at time t (MWth)
P_violate$_t$	power mismatch at time t (MW)
$\mathbf{Worst}^k$	worst position among all charged particles in iteration k

valve-point effects. The major deficiency of these methods is the “curse of dimensionality” when facing the DED problem especially in large-scale power systems. Consequently, these methods are not guaranteed to find the global optimum. Nowadays, the researchers' interest has been directed toward modern meta-heuristic algorithms. The objectives are to remove most of the inaccuracies in the family of classic optimization-based approaches.

A salient feature of this paper is that it studies the DED problem incorporating CHP units and simultaneously handles the SRRs constraints, ramp rate limits and other constraints so that both electric and heat load demands are met. Accordingly, a modified evolutionary technique based on Charged System Search Algorithm (CSSA) is applied to solve the RCCHPDED problem in realistic power system models for which the total production costs of TUs, CHP and heat-only units are minimized. Recently, CSSA has been effectively implemented to solve various problems [27]. The CSSA is a novel population-based meta-heuristic evolutionary algorithm on the basis of the Coulomb's law from electrostatics and the Newtonian's laws from mechanics [27]. This paper proposes two modifications in the original CSSA to enhance the performance and capability of it. Furthermore, in order to enhance the search ability of this algorithm, a new Self-Adaptive Learning Mechanism (SALM) is implemented in this paper. Using the proposed SALM, in each stage of the optimization process, the algorithm self-adaptively recognizes which mutation strategy is more beneficial to focus on. It is noteworthy that this modified algorithm is called Self-Adaptive Learning Charged System Search Algorithm (SALCSSA). The performance of the proposed approach is successfully validated by numerical models. The simulation results show that the new modified algorithm has the ability of finding better solutions while