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Short-term combined economic and emission hydrothermal optimization by surrogate differential evolution

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HIGHLIGHTS

- The fuel cost with valve-point effect is used.
- Optimal thermal schedules for all case studies are obtained and saved into a matrix.
- The surrogate values matrix is used during the hydrothermal optimization.
- Hydrothermal scheduling is solved by considering constraints and final reservoirs state.
- The satisfied 24-h system demand is obtained by using a new DE architecture.

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ABSTRACT

This paper present short-term combined economic and emission hydrothermal optimization, addressing total fuel costs and emissions minimization. This paper uses the fuel cost function with valve-point effect, which increases the degree of optimization problem difficulty. The optimal balance between the addressed objectives, that conflict with each other, can be obtained with appropriate hydro and thermal generation schedules. A surrogate differential evolution is applied in order to satisfy 24-h system demand and final states of hydro power plant reservoirs by minimized total fuel costs and emissions. This paper proposes a novel master–slave model optimization algorithm, where the optimal thermal schedules are obtained within the slave model. The data obtained from the slave model are saved into a matrix, which serves as a surrogate model for a master model, where the hydrothermal optimization with all objectives and constraints is conducted by using a parallel self-adaptive differential evolution algorithm. In order to show the effectiveness of the proposed method, different case studies are used: economic load scheduling, economic emission scheduling, and combined economic emission scheduling. The proposed method is verified on a model consisting of four hydro power plants and three thermal power plants.

1. Introduction

Hydrothermal optimization is a task where the main purpose is to satisfy system demand and simultaneously satisfying other system requirements by spreading its production between hydro power plants (HPP) and thermal power plants (TPP). The optimization process framework for hydrothermal scheduling can be divided into three main categories; short-term, middle-term, and long-term optimization [1]. The short-term hydrothermal optimization task [2] is used for scheduling time of up to 1 week, the medium term [3] for scheduling time of up to 2 years, and long term optimization [4] for scheduling time of longer than 2 years.

This paper focuses on solving the 24-h system demand using 1-h time steps [2]. The optimization process is carried out for three case studies; economic load scheduling (ELS), economic emission scheduling (EES), and combined economic emission scheduling (CEES). The ELS case, extended by taking the start-up and shutdown costs into account, is also found in scientific literatures as a unit commitment problem (UCP) [2,5–8]. In the scientific literature, the optimization ELS case is likewise conceived into economic load dispatch (ELD) [9–12].

The cost function for each thermal unit used during the optimization process is usually combined as a quadratic function without including valve-point effects [13–15], which brings some inaccuracies into the function results. The generator cost functions are modeled from the valve-points obtained during the "heat run" test. To obtain these valve-points, the input and output data are measured slowly varied through generator operating region [13].

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Nomenclature

Parameters

- $e_{i,t}$ natural inflow to hydro plant i in hour t
- $V_{i,\max}$ maximal storage of reservoir i
- $V_{i,\min}$ minimal storage of reservoir i
- T number of hours of the scheduling period
- $V_{i,T}$ desired storage of reservoir i in T-th hour
- $p_{SD,t}$ system demand in hour t
- $P_{hi,\max}$ maximal output power of hydro plant i
- $P_{hi,\min}$ minimal output power of hydro plant i
- $P_{si,\max}$ maximal output power of thermal plant i
- $P_{si,\min}$ minimal output power of thermal plant i
- $Q_{i,\max}$ maximal water discharge of hydro plant i
- $Q_{i,\min}$ minimal water discharge of hydro plant i
- I_h total number of hydro power plants
- I_s total number of thermal power plants
- N_{maxFeval} maximum number of evaluation function calls allowed during an evolutionary run
- D number of parameters to be optimized during an evolutionary run
- CR crossover control parameter
- NP population size
- $NP_{\min}$ minimal population size
- F difference amplification factor
- F_l lower limit of difference amplification factor
- F_u upper limit of difference amplification factor
- G_c epsilon constraint control generation threshold
- $z_{\max}$ number of population size reductions
- d number of inequality constraints
- m number of equality constraints
- ε equality constraint radius (level)
- C_z constraints relaxation reduction speed
- dif_t difference between system demand and hydro power plants production in hour t
- dig the resolution of digit-precision values in the pre-computed thermal power surrogate model
- pos_t position vector in hour t
- κ, ψ, ξ, w weights for objectives

Variables

- $q_{i,t}$ discharge of hydro plant i in hour t
- $s_{i,t}$ water spillage by reservoir i in hour t
- $v_{i,t}$ storage of reservoir i in hour t
- $p_{hi,t}$ power generated by hydro plant i in hour t
- $p_{si,t}$ power generated by thermal plant i in hour t
- G denotes generation counter value along algorithm iterations
- G_z generation in which to perform population reduction
- v_0 initial mean constraint violation per population
- $\mathbf{x}_{i,G}$ optimization parameters values of i-th vector in generation G
- $\mathbf{u}_{i,G}$ i-th trial vector in generation G
- $C_{i,t}$ fuel cost for thermal power plant i in hour t
- TC total fuel cost for thermal power plants production
- $E_{i,t}$ emission for thermal power plant i in hour t
- TE total emission for thermal power plants production
- n_m number of matrix elements in each row
- cfx correction factor
- g_i i-th inequality constraint function
- h_j j-th inequality constraint function
- G_i violation of i-th equality constraint
- H_i violation of i-th inequality constraint
- f single objective function

The wire drawing effects, occurring as each steam admission valve in the turbine starts to open, produce the rippling effects on the unit curve [13]. In order to take these valve-point effects into account, the sinusoid contribution must be added to the cost function. Such a cost function then increases the degree of the optimization problem's difficulty. The hydrothermal optimization process with fuel cost function using valve-point effect is therefore known as a large-scale, dynamic, nonlinear, and non-convex optimization problem [7,16].

The production from fossil fuel releases different contaminants into the atmosphere. The atmospheric pollution has inter alia causing global warming [17] at the end. Behind the fact that power generation in today's power market should meet cost-effective energy production, it should also deal with reducing contaminants into the atmosphere. In this context, the motivation behind this paper was to optimize production from hydrothermal units in such a way to satisfy system demand by minimizing not only total fuel costs, but also its emissions. The costs functions include TPPs fuel costs, since the power generation from HPPs typically has negligible direct costs [18].

Over recent years' different optimization methods and techniques have been proposed to solve this hydrothermal optimization problem [19]. Methods are generally classified into two groups; deterministic and heuristic methods [20]. Deterministic methods include methods which arrive at the same solution through the same sequence of solutions, such as Lagrangian relaxation [21] and Benders decomposition-based method [6], mixed-integer programming [22–24], dynamic programming [25], and linear programming [26]. The second group's methods, where the solution is built piece by piece, or where the solution from a previous step is used to find a better solution, belong to the heuristic methods. These methods include Particle Swarm Optimization (PSO) [27,28], Genetic Algorithms (GA) [10,29,30], Evolutionary Programming (EP) [17,31], and Differential Evolution algorithms (DE) [16,20,32,33].

Niknam et al. [6] proposed a new formulation based on benders decomposition approach for solving the UCP problem. The problem is decomposed into a master problem and a sub-problem. Li et al. [34] developed a model and technique for solving the combined hydrothermal UCP problem by a decomposition and coordination approach. Borghetti et al. [35] also successfully solved hydrothermal UCP problem by using lagrangian relaxation and assuming a linear hydro system model.

Rebennack et al. [36] present a modeling approach for greenhouse gas emissions quotas incorporated into a stochastic dual dynamic programming algorithm. The objective is the minimization of expected operational costs of the system over whole time interval and taking into account emission quotas. However, if emission quotas are exceeded, the additional fees must be paid.

In [17], the evolutionary programming technique is used for solving a short-term CEES problem. Mandal and Chakraborty [32] used a DE algorithm for solving a short-term CEES problem. They pointed out the importance of properly selecting the DE control parameters. In this paper, the DE algorithm uses self-adaptive control parameters. Sun and Lu [27] proposed an improved quantum-behaved PSO for short-term hydrothermal ELS, EES, and CEES case