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Improved genetic algorithm for economic load dispatch in hydropower plants and comprehensive performance comparison with dynamic programming method

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ABSTRACT

This paper presents a practical genetic algorithm (GA)-based solution for solving the economic load dispatch problem (ELDP) and further compares the performance of the improved GA (IGA) with that of dynamic programming (DP). Specifically, their performance is comprehensively evaluated in terms of addressing the ELDP through a case study of 26 turbines in the Three Gorges Hydropower Plant with a focus on calculation accuracy, calculation time, and algorithm stability. Evaluation results show that the improved GA method can significantly reduce the ineffectiveness of the GA in current use and could avoid the running of the turbines in the cavitation/vibration zone, thereby ensuring the safety of the turbines during generating operations. Further, the analysis comparing the performance of the IGA and DP show that the IGA is superior to DP when a small number of turbines are involved. However, as the number of turbines increases, the IGA requires more calculation time than DP; moreover, its calculation accuracy and convergence rate are significantly reduced. It is difficult to guarantee the stability of IGA in high-dimension space even though the population grows, on account of the exponential expansion of the calculation dimension, the algorithm's premature convergence, and the lack of a local search capability. The improvement of the GA as well as the evaluation method proposed in this paper provide a new approach for choosing and improving optimization algorithms to solve the ELDP of large-scale hydropower plants.

1. Introduction

A hydropower plant usually has multiple turbines that are run side by side. Because of differences in the turbines' operating characteristics, the generation discharge varies sharply in different combinations of committed turbines. The purpose of an economic load dispatch problem (ELDP) study is to develop load-specific turbine operation strategies that clarify the number and timing of start and stop orders and the power load allocation of committed turbines (Ding et al., 2015). The ELDP study is of great importance for reducing the generation discharge of hydropower plants and improving their economy of operation (Kamboj, 2016). The economical operation of a hydropower plant has traditionally been based on algorithms for optimizing load dispatching. Improvements in the scheduling algorithm of the committed turbines are therefore able to generate significant economic benefits (Kumar et al., 2015). However, in practice, the operating ranges of the turbines are not always available for optimal load allocation on account of their physical operation limitations (Zhang et al., 2013). Turbines can have prohibited operating zones because of faults in the machines themselves or in the associated auxiliaries (He et al., 2008). Such faults usually lead to instabilities in certain ranges of the turbine load, rendering them unable to carry a load for any appreciable time in these operating zones (Niknam et al., 2012). Therefore, the input-output characteristics of large turbines are inherently highly nonlinear and probably non-convex (Séguin and Côté, 2016), which makes the economic load dispatch problem (ELDP) a large-scale highly nonlinear constrained optimization problem that is difficult to solve (Hidalgo et al., 2014).

The primary objective of the ELDP is to schedule the committed turbine outputs to meet the required load demand at the minimum discharge volume while satisfying the equality and inequality constraints for all turbines and for the system (Santra et al., 2016; Cheng et al., 2000). For this purpose, a continuous balance must be maintained between power generation and varying load demand (Lu et al., 2015). Meanwhile, the system frequency,

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Nomenclature

dN, dN'	the discrete step lengths of DP and the GA (IGA), respectively
Gen	the termination generation of the evolution process
H	the average water head for the given period (m)
i, j, k, l	the sequence number of the turbine, the sequence number of the cavitation/vibration zone of the turbine, the serial number of an individual in the GA (IGA) population, and the serial number of a state variable in DP, respectively
ind_1, ind_2	two individuals involved in the crossover operation
$\mathrm{int}[\cdot]$	Gaussian rounding function
INF	the maximum value of the penalty term
n	the number of turbines
n_T, n_S	the number of tests and the number of convergences, respectively
N	the total number of turbines
N_{DP}	a solution in the set of optimal DP solutions, Ω_{DP}
N_i	the power output of turbine i (MW)
$N_{i,IGA}$	the optimal solution of IGA test i
$N'_{\max_{k,i}}$, $N'_{\min_{k,i}}$	the upper and lower limits, respectively, of the corresponding cumulative output
$N''_{\max_{k,i}}$, $N''_{\min_{k,i}}$	the upper and lower limits, respectively, of the cumulative output variation
Nd	the power grid load (MW)
$Ns_{i,l}$	the variable value of state l for phase i
NH_i	the expected output of turbine i (MW)
NY_t	the installed capacity of turbine t (MW)
$\overline{N_{i,j}}$	the upper output limit of turbine i in zone j with given water head H (MW)
$\underline{N_{i,j}}$	the lower output limit of turbine i in zone j with given water head H (MW)
$\overline{Ntmp}$, $\overline{Ntmp}$	$\max\{\sum_{t=1}^{i} N_t - NY_i, 0\}$ and $\min\{\sum_{t=1}^{i} N_t, \sum_{t=1}^{i-1} NY_t\}$, respectively
OPT_{DP}, OPT_{IGA}	the optimal values obtained using the DP and the IGA approaches, respectively
$p_{k,i}$	the cumulative output code of turbine i of individual k
$p''_{k,i}$	the individual $p_{k,i}$ after variation
p_m	the variation probability of the GA (IGA)
p_{opdt}	the output discrete step length of IGA
P, P', P''	the parent population, the crossover population, and the mutant population in the GA (IGA), respectively
Pop	the population size
PS_{eps}	the threshold for completion of the IGA calculations (%)
$q_i(\cdot)$	the generation discharge of turbine i (m^3/s)
Q	the generation discharge (m^3/s)
$Q_i^*(\sum_{t=1}^{i} N_t)$	the optimal accumulated generation discharge in the remaining period
$Rnd, Rnd', Rnd'', Rndmut, \alpha$	random numbers evenly distributed in the interval (Ding et al., 2015)
$Snum$	the number of evolutionary generations
t	time period
$Teps$	the accuracy coefficient
TC_{DP}, TC_{IGA}	the calculation times using DP and the IGA, respectively (s)
α_1, α_2	the penalty coefficients for the operating constraint and the output domain constraint, respectively
Δq_i	the penalty term to constraints on the operating condition
Δqp_i	the penalty term to constraints on the output domain
ΔPC, ΔTC, PS	the accuracy indicator, the calculation time indicator, and the algorithm stability indicator, respectively
ε	the convergence threshold
$\Omega_i(H)$	the cavitation/vibration zone of turbine i
Ω_{DP}	the optimal state set

voltage levels, and security must also be kept constant (Miao and Fan, 2016). In addition, the load dispatch has strict requirements on the calculation time because real-time ELDP is generally performed every 5 min and determines the active power output of all committed dispatchable turbines for the next 5-min interval (Bakirtzis et al., 2014). Therefore, the ELDP algorithm optimizes with the objective of minimizing the total amount of water discharged from the reservoir and completing the required operation in the shortest amount of time (Li et al., 2014).

To obtain accurate dispatch results in a timely manner, a demand exists for techniques that have no restrictions on characteristics of the turbines (Bortoni et al., 2015). A variety of optimization techniques have been tried, including mixed-integer, linear, and nonlinear programming approaches (Lu et al., 2010). The mixed-integer linear programming (MILP) technique circumvents the nonlinearity by assuming a constant net water head and a fixed power load (Chen et al., 2016). This assumption simplifies the modeling process; however, it can lead to remarkable inaccuracy because of the inevitable errors and uncertainties that are induced by the use of piecewise linear approximation and the introduction of discreteness to the problem via the addition of integer variables or constraints (Cheng et al., 2016). Furthermore, this approach may not be precise enough for a large hydropower plant when long-term scheduling is considered. On the other hand, both lambda-iteration and gradient-technique methods in conventional approaches to solving these problems are calculus-based techniques (Subramanian et al., 2016) that require a smooth and convex function and strict continuity of the search space (Suman et al., 2016). The dynamic programming (DP) approach (Li et al., 2014) imposes no restrictions on the nature of the turbine operating curves; therefore, it can solve ELDPs that have inherently nonlinear and discontinuous physical operation limitations (Nanda et al., 1994).

Evolutionary computation is one such tool that has demonstrated its ability to solve these complex problems (Nahas and Abouheaf, 2016; Yang et al., 2012). Evolutionary computation methods mimic biological population genetics in a search for the optimal solution (Abido, 2006). They can be implemented in