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Optimization of hydro energy storage plants by using differential evolution algorithm

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ABSTRACT

The optimal dispatching of cascade Hydro Power Plants is known as a complex optimization problem. In order to solve this problem the authors have applied an adapted differential evolution algorithm by using a fixed and dynamic population size. According to the dynamic population size, the proposed algorithm uses novel random and minimum to maximum sort strategy in order to create new populations with decreased or increased sizes. This implementation enables global search with fast convergence. It also uses a multi-core processor, where all the necessary optimization data are sent to the individual core of a central processing unit. The main aim of the optimization process is to satisfy 24 h demand by minimizing the water quantity used per electrical energy produced. This optimization process also satisfies the desired reservoir levels at the end of the day. The models used in this paper were the real parameters' models of eight cascade Hydro Power Plants located in Slovenia (Europe). Also the standard model from the literature is used in order to compare the performance of the adapted optimization algorithm.

1. Introduction

Energy storage is a physical storage for energy [1] and the different types and technologies [2] are available nowadays. The pumped [3] and conventional [2] energy storages are used with HPP (hydro power plants) where the storage source is water, and the electricity produced is classified as renewable electricity [4]. Different research and developments related to sustainable and renewable electricity production according to different energy sources has been already made [5–8]. The authors' research focused focuses on cascade HPPs, where each individual HPP has its own reservoir and energy storage, respectively. Various combinations of reservoirs' charging and discharging produce different amounts of electricity.

The optimization process for HPPs electricity production could be used in at least in two different ways; to determine the optimal production for HPPs in regard to a day-ahead electricity market [9] and forecasted demands [10] or to produce energy in accordance with the system demand and all requirements of HPPs combined with thermal power plants in order to decrease thermal costs [11–16].

The optimization process used in this paper is focused on a 24-h interval with 1-h time steps. Therefore it refers to the term "short-term" hydro scheduling optimization [13,17–21] problem. In the past, a wide-range of optimization techniques [17] has been used to for successfully solving this complex non-linear constrained optimization problem. The complexities of the problem arise from a large number of co-dependent variables and various HPPs' constrains [22], such as reservoir levels, turbines' flows, denivelation speed, etc. Due to the generators' characteristics of HPPs, the outputs of which are generally non-linear functions of water discharge and net head, this optimization problem can also be marked as a non-linear problem [23]. The modern evolutionary algorithms [24] such as genetic algorithms [19], particle swarm optimization algorithm [20,21,25], evolutionary programming [26,27] and the differential evolution algorithm [13,28–33] are attracting more attention because of their efficiencies in solving hydro scheduling optimization problems.

The differential evolution (DE) algorithm is known as a powerful evolutionary algorithm for global optimization, as first mentioned by Storn and Price [32]. Because of its simple implementation, efficiency, and robustness it has been selected as an appropriate optimization algorithm.

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Nomenclature

Parameters

$a_{i,k}$	natural inflow to hydro plant i in hour k
$b_{i,k}$	biological minimum flow of hydro plant i in hour k
$\overline{v}_i$	maximal value of the storage of reservoir i
$\underline{v}_i$	minimal value of the storage of reservoir i
dv_i	allowed denivelation of reservoir i
$\overline{p}_i$	maximal output power of hydro plant i
$\underline{p}_i$	minimal output power of hydro plant i
$\overline{q}_i$	maximal water discharge of hydro plant i
$\underline{q}_i$	minimal water discharge of hydro plant i
K	number of hours of the scheduling period
I	total number of hydro power plants
D	number of parameters
CR	crossover control parameter
NP	population size
F	difference factor
w	weight for objectives
m	core number
dp	digit precision of float variable

Variables

$q_{i,k}$	discharge of hydro power plant i in hour k
$s_{i,k}$	water spillage by reservoir i in hour k
$v_{i,k}$	reservoir i storage in hour k
$p_{i,k}$	power generated by hydro plant i in hour k
G	denotes generation through algorithm steps
$\boldsymbol{x}_{i,G}$	value of i-th vector
$\boldsymbol{u}_{i,G}$	trial vector of i-th vector in generation G
f	objective function
dw_k	demand energy in hour k
$ow_{i,k}$	sum of optimal energy production in hour k

The authors in Ref. [28] used suitable penalty factors during the fitness evaluation of the DE algorithm using modified initialization and mutation steps which helped to satisfy the final reservoirs state. The classic DE algorithm was used in Ref. [33] where the parameter settings were found for each test system through trial and error, and consequently provide the optimal result.

Properly controlling the parameter set of a DE algorithm is a challenging task, therefore in Ref. [34] the authors highlighted the importance of an algorithm's control parameter set at such as differential factor *F*, crossover constant *CR*, and population size *NP*. In Ref. [28] the chaos theory [29] is proposed to determine the adequate parameters' settings of the DE algorithm. Specifically, they determine the sets of *F* and *CR* and the applied chaos sequences which consequently have an impact on population diversity and premature convergence towards a locally optimal solution. In Ref. [30] the authors combined an adaptive dynamic control mechanism for the *CR* parameter with a chaotic local search operation for the DE algorithm, which avoids premature convergence. The self-adaptive *F* and *CR* parameters for each individual in the population are proposed in Ref. [35]. The changing of the initial values for both control parameters did not have any significant impact on the final result. When the classic DE algorithm with fixed control parameters falls into locally optimal solution, usually it is hard to escape from it. Therefore, an adaptive Cauchy mutation is proposed in Ref. [13] which renews the diversity of the population and avoids premature convergence. The important control parameter of the DE algorithm is also the population size *NP*, which is chosen by the user and fixed throughout the generations in classic DE. In order to provide higher population diversity at the beginning of the evolutionary process and decreased total number of function evaluation, a gradual population size reduction is proposed throughout the generations in Refs. [36], where the population size is reduced by half in each block of predefined generation numbers.

In order to avoid the efforts needed to determine a proper set of control parameter, the proposed algorithm uses the self-adaptive control parameters *F* and *CR*. It also uses a novel method of varying the population size along the generation number. Population size is therefore referred to as dynamic population size. In this process the population can be decreased or even increased and this has a significant impact on the total number of function evaluations. When the algorithm increases the population size, new additional members are needed to fill up the new population size. In order to provide the additional members, the proposed algorithm uses a multi-core processor, where the population is separately and simultaneous processed by all cores. By the multiprocessing of the DE algorithm, the appropriate diversity of population is provided and the algorithm is more efficient in avoiding locally optimal solutions. According to the algorithm's increase population size, the missing members for the next generation are provided by the RSMM (random or the minimum to maximum sort strategy) described in Section 4.3. However, this paper presents a modified DE algorithm which was applied to hydro generation scheduling problem in order to satisfy the system demand and other objectives with fast convergence and decreased number of function evaluations, respectively.

The hydro scheduling problem formulation is described in Section 2, the classic DE algorithm in Section 3, the modification of DE algorithm in Section 4, the experimental results in Section 5, and the conclusion in Section 6.

2. Hydro scheduling problem formulation

In this paper, the hydro scheduling problem is formulated as a problem, where the main goal is to satisfy system demand by optimal scheduling across all HPPs. Cascade models of HPPs are used and therefore the production of downstream HPP is closely related with the upstream HPPs because of the upstream plant outflows' impact on downstream plant production. The system demand should be satisfied within the allowed deviation tolerance, usage of water quantity per electrical energy unit should be decreased and overflows should be also decreased and even eliminated, respectively. Since these goals should be achieved within acceptable CPU time, the hydro-scheduling problem can be solved by using the modified DE algorithm [32] with proposed dynamic population size and multi-processing. The final goal of the optimization problem is therefore conducted using three objectives, which are satisfied through single objective function by using the weighted sum method [37].

The optimal scheduling for connected HPPs can be obtained by searching the optimal schedule *p*, which is the function of flow through the turbine and the reservoir's volume,

$$p = f(v, q), \quad (1)$$

where *p* is power, *v* volume of reservoir and *q* water discharge. The discharge *q* can be used as the optimization parameter, but within the allowed interval (2).