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Ant lion optimization for short-term wind integrated hydrothermal power generation scheduling

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ABSTRACT

A novel nature inspired (NI) optimization algorithm, known as ant lion optimization (ALO) is used in this paper for solving practical hydrothermal power generation scheduling (HTPGS) problem with wind integration. The ALO algorithm mimics the unique, 6-step hunting activity of ant lions in nature which is modelled by (i) constructing ant lion traps using roulette wheel, (ii) creating random walk of ants, (iii) entrapment of ants in pits, (iv) adaptive shrinking of traps for sliding ant towards ant lion, (v) catching ants and rebuilding the pits, and (vi) applying elitism. The *random walk mechanism* and *roulette wheel operation* for building traps provide the ALO with a high exploration capability. The *shrinking of trap boundaries* and *elitism* operations increase exploitation efficiency of the ALO, making it a very powerful search technique for complex domains.

The wind integrated HTPGS is a non linear, non convex and highly complex optimization problem due to composite operational constraints associated with hydro, thermal and wind units. To demonstrate the applicability of the ALO algorithm for real-world problems, it is tested on four standard test systems. The obtained simulation results are compared with results of other algorithms reported in most recent literature. It is found that the proposed method is proficient in producing encouraging solutions for real-world problems.

Introduction

Modern power system is a large complex network consisting of electrical power generation, its transmission and distribution. With increase in demand of electrical power and phenomenal rise in the prices of fossil resources, economic dispatch becomes a crucial task in power system operation whose key objective is to minimize the fuel cost while all operating constraints are satisfied. Though the world is slowly shifting its focus towards renewable energy resources, majority of the power is still being generated from fossil fuels, which are also the major sources of atmospheric pollution. Optimal allocation and dispatch of the available hydro generation capacity is a very attractive alternative for meeting the growing demand for power, without increasing the fuel cost and emissions. Therefore the integrated optimal dispatch of hydro–thermal generating units assumes a great importance in power system operation.

The idea behind short-term hydro–thermal scheduling is to allot available water resources to hydro generators in each time interval and to dispatch the thermal generators in such a manner that the fuel cost of thermal units is minimized and operational constraints of both, thermal and hydro units are fully satisfied. The major constraints of the HTPGS problem are water discharge constraints between consecutive time intervals, practical limits on reservoir storage and turbine flow rate, the changing hourly reservoir inflows, the cascaded hydraulic network, prohibited operational zones of hydro units, ramping limits of thermal units, maintaining power balance with changing system load and the capacity limits of both thermal and hydro units.

In literature the HTPGS solutions are presented using analytical methods like dynamic programming (DP) [1], Lagrange relaxation (LR) [2] and Newton's method [3]. But these approaches may not perform satisfactorily due to the nonlinearity and composite constraints of the problem. Therefore, over the past few years, many populations based meta-heuristic techniques are introduced as alternatives to classical methods. These techniques begin with a set of randomly generated solutions which are iteratively improved using random operators. Due to the parallel search mechanism and randomness involved, the meta-heuristic techniques have a higher probability of escaping local minima and achieving the global best solution. These methods are unaffected by the nature of the problem because optimization is carried out

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independently using a black box concept, by utilizing only the inputs and associated outputs, without going for the problem derivative.

Amongst the meta-heuristics, evolutionary programming (EP) [4], [5] is proposed for the solution of the HTPGS problem based on adoption and evolution theory which follows natural selection process. Solution of HTPGS is also done using GA [6], which is based on selection, crossover and mutation operations.

Differential Evolution (DE) and its variants [7–12], particle swarm optimization (PSO) [13,14], teacher learner based optimization (TLBO) [15,16], chemical reaction optimization (CRO) [17,18], fish swarm optimization (FSO) [19], Artificial Bee Colony (ABC) algorithm [20] and clonal selection algorithm (CSO) [21] are successfully implemented for the HTPGS problem. Recently, covariance matrix adaptation evolution strategy (CMA-ES) improved with directed target to best perturbation (DTBP) approach has also been used very effectively [22].

Lately many new meta-heuristic algorithms have been proposed taking inspiration from natural organism and biological phenomena. The main challenge in these techniques is how to maintain balance between global (exploration) and local search (exploitation) so that population diversity is maintained and early convergence to a sub-optimal solution can be avoided [23].

The first generation of the nature inspired (NI) meta-heuristics, like genetic algorithm (GA), particle swarm optimization (PSO) and Differential Evolution (DE), experienced premature convergence issues which were subsequently handled by enhanced versions of these algorithms [7,8,10–12,14,20,24]. These improved variants proposed either parameter automation [11,12,20] or hybridization of different algorithms [25] to provide balance between exploration and exploitation capabilities. Moving one step ahead, the new NI methods provide separate operations for carrying out exploration and exploitation within the algorithm itself. For example, in Artificial Bee Colony (ABC) algorithm two separate phases, employed bee phase and onlooker bee phase are used for carrying out exploration and exploitation respectively. The ant lion optimization (ALO) developed by Mirjalili [26] is also one such algorithm where features for both, exploration through global search and exploitation through local search, are embedded in the algorithm. ALO is a nature inspired optimization tool which formulates the intelligent behaviour of ant lion while hunting ants in their constructed trap during optimization process. In the ALO, there is a powerful inherent mechanism for improving the search efficiency through extensive global search and intensive local search.

Some other newly developed NI techniques are water wave optimization (WWO) [27], moth-flame optimization (MFO) [28], stochastic fractal search (SFS) [29], social spider algorithm (SSA) [30] and lightning search algorithm (LSA) [31]. The WWO [27] which is inspired by shallow water wave model employs propagation, refraction, and breaking operations for improving exploration and exploitation. The MFO [28] is based on how moths take a spiral path around source of light which finally brings them to the source. The SFS [29] makes use of the concept of creating fractals for conducting a search through the problem domain. The random fractals are generated by using any mathematical method like Levy flight, Gaussian walks, percolation clusters or Brownian motion. The SSA [30] is inspired by the foraging behaviour of social spiders, which locate the prey on their web by sensing vibrations. The LSA [31] is inspired by the lightening phenomenon in sky and the mathematical model for search and exploration is based on the manner in which the projectiles propagate towards ground.

Wind power is a clean and renewable energy which is gaining acceptance for solving energy demand at low cost without producing any harmful emissions. Due to these advantages now-a-days various researchers are focussing on issues arising due to integration of renewable energy such as wind and solar power with conventional thermal units [32–42]. Due to the highly unpredictable and random nature of wind power, the wind uncertainty costs also need to be included in the optimization problem. Suitable probability density functions (*pdf*) are used for wind power characterization and for the computation of over and under estimation penalties [32]. Wind-thermal scheduling models for Gencos [33], for multi-area operation [34] and for mid-term generation scheduling [35] have been recently presented. The unpredictability of renewable generation makes it difficult to accommodate economic considerations in real time economic dispatch, therefore the 'best-fit' participation factors are evaluated by considering the minute-to-minute volatility of solar and wind power and load demand [36]. The best fit day-ahead optimal scheduling for hybrid power systems consisting of thermal, wind and solar PV has been conducted in [37] taking into consideration the uncertainties in load and generation to minimize real-time costs, including the revenue from renewable energy certificates.

Some researchers have also shown the impact of wind integration on cost and emission [38,39] and reserve dispatch [40] through multi-objective models. In [40] the energy/spinning reserve costs and emission reduction objectives are included in the multi-objective model. A multi-objective market clearing model to simultaneously minimize cost as well as system risk level is proposed in [41]. Wind uncertainty is modelled using Weibull distribution [38–41] where as load forecasting uncertainty is represented by a normal distribution [40,41]. In [42] a day ahead and real time market clearing scheme is proposed to minimize the adjustment costs and to maximizes social welfare, using a two stage optimization approach based on GA and two-point estimate OPF and GA and Monte Carlo simulation.

In this paper ALO algorithm is applied to solve HTPGS problem with wind integration with complex practical operating constraints. To demonstrate the efficiency and applicability of ALO for HTPGS problems its performance is compared and validated with many different algorithms available in recent literature. To the best of authors' knowledge, the ALO algorithm has not yet been tested on a complex, constrained optimization problem such as the hydro–thermal generation scheduling problem. Wind power uncertainty modelling further complicates the already complex HTPGS problem.

The results demonstrate the ability of ALO to get good solutions while satisfying a large number of practical operating constraints of hydro, thermal and wind generation. The simplicity, simultaneous focus on exploration and exploitation, guaranteed convergence, ability to avoid local optima, ability to maintain population diversity, absence of tuning parameters and high solution quality present ALO as an attractive alternative methodology for solving complex, real-world optimization problems.

Problem formulation of hydrothermal power generation scheduling with wind integration

The HTPGS problem with wind integration has complex equality and inequality constraints associated with thermal, hydro and wind generating units. Due to zero fuel cost of hydro power generating units, the prime objective becomes minimization of fossil fuel cost of thermal units along with cost of wind power generating units. The objective function to be minimized is

$$F_T = \sum_{t=1}^{T}\left\{\sum_{i=1}^{Ns}[f_{it}(P_{sit})] + \sum_{k=1}^{N_w}[f_{wkt}(P_{wkt})]\right\} \tag{1}$$

Here F_T is the total operating cost of thermal and wind generators, the total number of thermal and wind units is N_s and N_w respectively. The interval length is T which consists of several sub intervals. At t^{th} interval, the scheduled power of i^{th} thermal and