An Efficient Cuckoo-Inspired Meta-Heuristic Algorithm for Multiobjective Short-Term Hydrothermal Scheduling

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Abstract. *This paper proposes an efficient Cuckoo-Inspired Meta-Heuristic Algorithm (CIMHA) for solving multi-objective short-term hydrothermal scheduling (ST-HTS) problem. The objective is to simultaneously minimize the total cost and emission of thermal units while all constraints such as power balance, water discharge, and generation limitations must be satisfied. The proposed CIMHA is a newly developed meta-heuristic algorithm inspired by the intelligent reproduction strategy of the cuckoo bird. It is efficient for solving optimization problems with complicated objective and constraints because the method has few control parameters. The proposed method has been tested on different systems with various numbers of objective functions, and the obtained results have been compared to those from other methods available in the literature. The result comparisons have indicated that the proposed method is more efficient than many other methods for the test systems in terms of total cost, total emission, and computational time. Therefore, the proposed CIMHA can be a favorable method for solving the multi-objective ST-HTS problems.*

Keywords

Cuckoo-inspired meta-heuristic algorithm, economic dispatch, emission dispatch, levy flights, multiobjective hydrothermal scheduling.

1. Introduction

The main task of the short-term hydro-thermal scheduling (ST-HTS) problem is to determine the optimal power generation of the available thermal and hydro power plants so as the total fuel cost of thermal units over a schedule time is minimized satisfying both equality and inequality constraints such as the quantity of available water, power balance, and upper and lower limits on generations. In addition, a large amount of the electric power in the world is mainly generated by thermal plants using oil, coal or natural gasses. Therefore, several contaminants such as nitrogen oxides (NO_x), sulfur dioxide (SO_2), and carbon dioxide (CO_2) have been released into the atmosphere due to the process of electricity generation from the thermal units [1]. In addition to the fuel cost objective, the gaseous emission is also another important objective which needs to be considered in the ST-HTS problem. As a result, a multi-objective ST-HTS problem is formed. Therefore, the multi-objective ST-HTS problem is more complex than the conventional one since it needs to find a set of non-dominated solutions for determining the best compromise solution, which is considered as the most reasonable one for the acceptable trade-off between fuel cost and emission objectives.

Many conventional methods have been applied for solving the ST-HTS problem such as the method based on Lagrange multiplier theory [2], lambda-gamma iteration method (LGM) [3], dynamic programming (DP)

$$F_1 = \sum_{m=1}^{M} \sum_{i=1}^{N_1} t_m \left\{ a_{si} + b_{si} P_{si,m} + c_{si} P_{si,m}^2 + \left| e_{si} \times \sin(f_{si} \times (P_{si}^{min} - P_{si,m})) \right| \right\}. \quad (1)$$

[4], Lagrange relaxation (LR) method [5], and decomposition and coordination method [6], and artificial intelligence based methods such as particle swarm optimization (PSO) [7], or predator-prey optimization technique (PPO) [8]. Generally, these conventional methods have a common characteristic that they can be applicable only to optimization problems with differentiable objective and constraints. In recent years, several artificial intelligence based methods have been implemented for solving the multi-objective ST-HTS problem. Simulated annealing-based goal-attainment (SA-BGA) method [1] has been successfully applied for the problem, but the method has coped with long execution time. In [9], gamma based method (γ-PSO) have been demonstrated to be superior to conventional PSO but the improved version cannot deal with systems with nonconvex fuel cost function. Genetic algorithm is one of the earliest artificial intelligence methods but its applicability on complex systems is still competitive [10] and it is slower than PSO[11]. Therefore, several improved versions of it have been introduced such as non-dominated sorting genetic algorithm-II (NSGA-II) [12], improved genetic algorithm (IGA) [13], multiplier updating and the ϵ-constraint technique (IGA-MU) [13]. Predator-prey optimization and Powell search (PPO-PS) method [14] is complicated to implement for the problem; however, its achievement can satisfy researchers since it is more efficient than all improved versions of GA in [12], [13]. Augmented Lagrage Hopfield network (ALHN) method [15] is very fast for convergence with high accuracy; however, its application also ends at systems with nonconvex fuel cost function similar to γ-PSO. In general, the artificial intelligence based methods can find near optimum solution for non-convex optimization problems with non-differentiable objective and constraints. However, since the artificial intelligence based methods are generally based on the random search of a population in the problem space, they need to be run several times to obtain the best solution.

In this paper, the CIMHA, first developed by Yang and Deb in 2009 [16], is proposed for solving the multiobjective ST-HTS problem considering power losses in transmission systems and valve point loading effects in fuel cost function of thermal units. The proposed method has been tested on different systems with different numbers of objective function, and the obtained results have been compared to those from other methods available in the literature.

2. Problem Formulation

Consider an electric power system having N_1 thermal plants and N_2 hydro plants scheduled in M subintervals. The goal of the multiobjective ST-HTS problem is to simultaneously minimize the fuel cost and gaseous pollutant emission level of thermal plants while satisfying various operational constraints of a system and thermal and hydro units.

2.1. Fuel Cost Objective

The fuel cost function of thermal units is represented as Eq. (1) [10], where a_{si}, b_{si}, c_{si}, e_{si}, f_{si} are fuel cost coefficients of thermal plant i; $P_{si,m}$ is power output of thermal unit i at subinterval m; t_m is the duration of subinterval m; and N_1 is total number of thermal plants.

2.2. Emission Objective

The emission of thermal units including sulfur dioxides (SO_2), carbon dioxides (CO_2), and nitrogen oxides (NO_x) released into the air by fossil-fueled thermal plants is represented as follows [9]:

$$NO_{si,m} = \alpha_{1si} + \beta_{1si} P_{si,m} + \gamma_{1si} P_{si,m}^2, \quad (2)$$

$$SO_{si,m} = \alpha_{2si} + \beta_{2si} P_{si,m} + \gamma_{2si} P_{si,m}^2, \quad (3)$$

$$CO_{si,m} = \alpha_{3si} + \beta_{3si} P_{si,m} + \gamma_{3si} P_{si,m}^2, \quad (4)$$

and the total emission can be combined as follows[9]:

$$F_2 = w_1 NO_{si,m} + w_2 SO_{si,m} + w_3 CO_{si,m}, \quad (5)$$

where w_1, w_2, and w_3 are positive weighting factors of different gaseous emissions contributing to the emission objective; α_{1si}, β_{1si}, and γ_{1si} are emission coefficients for NO_x; α_{2si}, β_{2si}, and γ_{2si} are emission coefficients for SO_2; and α_{3si}, β_{3si}, and γ_{3si} are emission coefficients for CO_2.

In addition, the amount of emissions from each thermal unit can also be expressed in a form of a quadratic and exponential function as Eq. (6) [12], where α_{si}, β_{si}, and γ_{si}, η_{si}, and δ_{si} are emission coefficients of thermal unit i.

$$F_2 = \sum_{m=1}^{M} \sum_{i=1}^{N_1} t_m \left[\alpha_{si} + \beta_{si} P_{si,m} + \gamma_{si} P_{si,m}^2 + \eta_{si} \exp(\delta_{si} P_{si,m}) \right]. \tag{6}$$

2.3. System and Unit Constraints

1) Load Demand Constraint

The total power generation from thermal and hydro units must satisfy the load demand and power losses in transmission lines:

$$\begin{gathered} \sum_{i=1}^{N_1} P_{si,m} + \sum_{j=1}^{N_2} P_{hj,m} - P_{L,m} - P_{D,m} = 0, \\ m = 1, \dots, M, \end{gathered} \tag{7}$$

where the power losses in transmission lines are calculated using Kron's formula as follows:

$$\begin{gathered} P_{L,m} = \sum_{i=1}^{N_1+N_2} \sum_{j=1}^{N_1+N_2} P_{i,m} B_{ij} P_{j,m} + \\ + \sum_{i=1}^{N_1+N_2} B_{0,i} P_{i,m} B_{0,0}, \end{gathered} \tag{8}$$

where N_2 is total number of hydro plants; $P_{hj,m}$ is power output of hydro unit j at subinterval m; $P_{D,m}$ and $P_{L,m}$ are total system load demand and total transmission loss at subinterval m, respectively; $P_{i,m}$ is power output of hydro or thermal unit i; and B_{ij}, B_{0i}, B_{00} are matrix coefficients for transmission power losses.

2) Water Availability Constraints

The total water discharge for each hydro unit during the scheduled period is limited by an available amount of water for that unit:

$$\sum_{m=1}^{M} t_m q_{j,m} = W_j, j = 1, \dots, N_2, \tag{9}$$

where the water discharge $q_{j,m}$ for hydro unit j at subinterval m is determined by:

$$q_{j,m} = a_{hj} + b_{hj} P_{hj,m} + c_j P_{hj,m}^2, \tag{10}$$

where a_{hj}, b_{hj}, c_{hj} are water discharge coefficients of hydro unit j; and W_j is the volume of water available for generation by hydro plant j during the scheduled period.

3) Generator Operating Limits

The power out of thermal and hydro units is limited between their upper and lower limits:

$$\begin{gathered} P_{si,min} \leq P_{si,m} \leq P_{si,max}, \\ i = 1, 2, \dots, N_1, m = 1, 2, \dots, M, \end{gathered} \tag{11}$$

$$\begin{gathered} P_{hj,min} \leq P_{hj,m} \leq P_{hj,max}, \\ j = 1, 2, \dots, N_2, m = 1, 2, \dots, M, \end{gathered} \tag{12}$$

where $P_{si,max}$, $P_{si,min}$ are maximum and minimum power output of a thermal unit i, respectively; and $P_{hj,max}$, $P_{hj,min}$ are maximum and minimum power output of hydro plant j, respectively.

3. Cuckoo-Inspired Meta - Heuristic Algorithm for Multiobjective ST-HTS Problem

3.1. Cuckoo-Inspired Meta-Heuristic Algorithm

The overall CIMHA method is summarized in the three main principal rules [16] including 1) a cuckoo bird put its egg in other bird's nest; 2) the Cuckoo egg is hatched and continues to lay their egg, 3) The Cuckoo egg is discovered by host bird and it is abandoned.

Among the rules, the first one is applied to build an initial population of nests whereas the second rule and the third rule enable the CIMHA to produce new solutions, which is regarded as a special point and advantage of the CIMHA compared to other meta-heuristic algorithms.

3.2. Calculation of Power Output for Hydro Units and Slack Thermal Unit

In the considered hydrothermal scheduling in the paper, there are two sets of equality constraints consisting of power balance constraint Eq. (7) and water availability constraint Eq. (9). In order to satisfy the equality constraints, two sets of corresponding slack variables will be used including the first thermal unit generation in each of M subintervals $P_{s1,m}$ $(m = 1, 2, \ldots, M)$ and water discharge for each hydro unit at M^{th} subinterval $q_{j,M}$ $(j = 1, 2, \ldots, N_2)$. Consequently, the power output of each hydro unit is first calculated from its corresponding water discharge in each subinterval and the slack thermal unit is then obtained by using equation Eq. (7). The detailed calculation of slack variables can be found in [17].

3.3. Implementation of Cuckoo-Inspired Meta-Heuristic Algorithm

The steps for implementation of the CIMHA method for solving the multiobjective ST-HTS problem are described as follows:

1) Initialization

In the CIMHA, each egg represents a solution which is randomly generated in the initialization. A population of N_p host nests is represented by $X = [X_1, X_2, \ldots, X_{Np}]^T$, in which each $X_d(d = 1, ..., N_p)$ represents a solution vector of variables given by $X_d = [P_{si,m,d}, q_{j,m,d}]$, where $P_{si,m,d}$ is the power out of thermal unit i at subinterval m corresponding to nest d and $q_{j,m,d}$ is the water discharge for hydro unit j at subinterval m corresponding to nest d. Therefore, vector X_d of nest d is represented in detail by $X_d = [P_{s2,m,d}, P_{s3,m,d}, ..., P_{sN_1,m,d}, q_{1,m,d}, q_{2,m,d}, ..., q_{N_2,m,d}]$, which includes the thermal units from 2 to N_1 for M subintervals and water discharges for hydro units from 1 to N_2 for the first $(M - 1)$ subintervals. Consequently, nest d only contains thermal units from 2 to N_1 at subinterval M. Certainly, the upper and lower limits of each nest are respectively $X_{dmin} = [P_{simin}, q_{jmin}]$ and $X_{dmax} = [P_{simax}, q_{jmax}]$. The power output of the thermal units and water discharges in the N_p nests are randomly initialized satisfying $P_{si,min} \leq P_{si,m,d} \leq P_{si,max}$ and $q_{j,min} \leq q_{j,m,d} \leq qj, max$. Each element in nest d of the population is randomly initialized as follows:

$$P_{si,m,d} = P_{si,min} + rand_1 \cdot (P_{si,max} - P_{si,min}),$$
$$i = 2, ..., N_1,\ m = 1, ..., M, \tag{13}$$

$$q_{j,m,d} = q_{j,min} + rand_2 \cdot (q_{j,max} - q_{j,min}),$$
$$j = 2, ..., N_2,\ m = 1, ..., M - 1, \tag{14}$$

where $rand_1$ and $rand_2$ are uniformly distributed random numbers in [0,1].

Based on the initial value of nests, the fitness function including objectives functions together with penalty terms for the slack thermal unit for all M subintervals and slack water discharge for all hydro units at subinterval M corresponding to each nest for the problem is calculated by:

$$\begin{aligned} FT_d = \textstyle\sum_{m=1}^{M} \sum_{m=1}^{N_1} (w \cdot F_1(P_{si,m,d}) + \\ +(w-1) \cdot F_2(P_{si,m,d})) + \\ +K_s \textstyle\sum_{m=1}^{M} (P_{s1,m,d} - P_{s1}^{lim})^2 + \\ +K_q \textstyle\sum_{j=1}^{N_2} (q_{j,m,d} - q_j^{lim})^2, \end{aligned} \tag{15}$$

where $0 \leq w \leq 1$ is weighting factor for a combination of objectives [18]; K_s and K_q are penalty factors for the slack thermal unit and available water, respectively; $P_{s1,m,d}$ is power output of the slack thermal unit 1 at subinterval m corresponding to nest d in the population; $q_{j,M,d}$ is the water discharge of all hydro plants at subinterval M corresponding to the nest d in the population.

The limits for the slack thermal unit and water discharge at subinterval M in Eq. (15) are determined as follows:

$$P_{s1}^{lim} = \begin{cases} P_{si,max} \text{ if } P_{s1,m,d} > P_{s1,max} \\ P_{si,min} \text{ if } P_{s1,m,d} < P_{s1,min}, \\ (m = 1, ...M) \\ P_{si,m,d} \text{ otherwise} \end{cases} \tag{16}$$

$$q_j^{lim} = \begin{cases} q_{j,max} \text{ if } q_{j,m,d} > q_{j,max} \\ q_{j,min} \text{ if } q_{j,m,d} < q_{j,min}, \\ (j = 1, ...N_2) \\ q_{j,m,d} \text{ otherwise} \end{cases} \tag{17}$$

where $P_{s1,max}$ and $P_{s1,min}$ are the maximum and minimum power outputs of the slack thermal unit 1, respectively; $q_{j,max}$ and $q_{j,min}$ are the maximum and minimum water discharge of the hydro plant j.

The initial value of nests in the population is set to the best value of each nest $Xbest_d(d = 1, \ldots, N_d)$ and the nest corresponding to the best fitness function in Eq. (15) is set to the best nest G_{best} among all nests in the population.

2) Generation of New Solution via Levy Flights

The new solution is calculated via Levy flights based on exchanging information between the previous best nests and each previous nest. In the proposed method, the optimal path for the Levy flights is calculated by

Mantegna's algorithm [19]. The new solution by each nest is obtained by:

$$X_d^{new} = Xbest_d + \alpha \times rand_3 \times \Delta X_d^{new}, \tag{18}$$

where $\alpha > 0$ is the updated step size; $rand_3$ is a normally distributed stochastic number; and ΔX_d^{new} is an increased value [9].

In case the new obtain solution violate the limits, they will be redefined as below:

$$X_d^{new} = \begin{cases} X_{d,max} \text{ if } X_d^{new} > X_{d,max} \\ X_{d,min} \text{ if } X_d^{new} < X_{d,min}. \end{cases} \tag{19}$$

Using Section 3.2. , the power output of N_2 hydro units and the slack thermal unit are obtained. The fitness value is then calculated using Eq. (15) and each nest is set to $Xbest$. The nest with the best fitness function $Gbest$ is not required to determine because its information is not used to obtain the new solution in the next section.

3) Alien Egg Discovery and Randomization

The second phase of new solution generation in this section is to improve the quality of the previously obtained solution. Like the Levy flights, the action of alien eggs discovery in the nests with a probability of pa can also generate a new solution for an optimization problem. The new solution is created by:

$$X_d^{dis} = \begin{cases} X_d + rand(X_{r1} - X_{r2}) \text{ if } rand < p_a \\ X_d \text{ otherwise.} \end{cases} \tag{20}$$

The newly obtained solutions also need to be redefined using Eq. (20) in case they violate upper and lower limits. The fitness value is calculated using equation Eq. (15) and the nest corresponding to the best fitness function is set to the best nest $Gbest$.

4) Stopping Criteria

In this research, the proposed algorithm is stopped when the maximum number of iterations is reached.

3.4. Best Compromise Solution by Fuzzy-Based Mechanism

In a multiobjective problem, there often exists a conflict among the objectives. To deal with this issue, a set of optimal non-dominated solutions is found instead of only one optimal solution. In this paper, the best compromise solution from the set of non-dominated solutions is found using the fuzzy satisfying method [18].

4. Numerical Results

The proposed CIMHA has been tested on three systems including two systems with quadratic fuel cost function and one system with nonconvex fuel cost function of thermal units. The proposed CIMHA is coded in Matlab platform and run on a 1.8 GHz PC with 4 GB of RAM.

4.1. Selection of Parameters

By experiments, the number of nests in this paper is set from 20 to 50 depending on the system size and the maximum number of iterations N_{max} is chosen from 300 for small systems to 2 500 for large-scale systems. Unlike N_p and N_{max}, the value of the probability p_a has no influence on execution time but the final optimal solution. Different optimal solutions can be obtained corresponding to different predetermined values of p_a. Therefore, the value of p_a has to be selected in turn in the range from 0.1 to 0.9 with a step of 0.1 in this paper.

4.2. Systems with Quadratic Fuel Cost Function of Thermal Units

1) The First System with Two Objective Functions

The test system with two hydro and two thermal units, in this case, includes a total cost function and one emission function [12]. The system is scheduled in a 24 hour period in three subintervals with eight hours for each. The proposed CIMHA is applied for obtaining the optimal solutions for the economic, emission and economic-emission dispatches.

The number of nests and the maximum number of iterations for this system are respectively set to 20 and 300 in advance for each value of w. The value of probability pa is chosen as follows. For the case of economic dispatch ($w = 1$) and emission dispatch ($w = 0$), the value of the probability p_a changes in the range from 0.1 to 0.9 with the step of 0.1. As a result, the best solution for economic dispatch and emission dispatch can be obtained at the same value of $p_a = 0.9$. The value of $p_a = 0.9$ is then used again to perform the proposed CIMHA method 20 independent runs for rest of values of w which is different from 1 and 0 corresponding to economic dispatch and emission dispatch. There have been 20 non-dominated solutions obtained. By using the fuzzy mechanism for determination of the best compromise for this case, the weight factor is determined at $w = 0.07$.

Tab. 1: Result comparison for the first system with quadratic fuel cost function of thermal units.

Method	Economic dispatch		Emission dispatch		Compromise dispatch		
	Cost ($)	CPU (s)	Emission (lb)	CPU (s)	Cost ($)	Emission (lb)	CPU (s)
RCGA [12]	66031	21.63	586.14	20.27	-	-	-
NSGA-II [12]	-	-	-	-	66331	618.08	27.85
MODE [12]	-	-	-	-	66354	619.42	30.71
SPEA-2 [12]	-	-	-	-	66332	618.45	34.87
PSO-PM [14]	65741	18.25	585.67	18.00	65,821	620.78	18.98
PSO [14]	65241	18.32	579.56	18.31	65731	618.78	19.31
PPO-PM [14]	64873	16.14	572.71	15.93	65426	612.34	16.53
PPO [14]	64718	15.99	569.73	15.18	65104	601.16	16.34
PPO-PS-PM [14]	64689	15.98	568.78	15.92	65089	600.24	16.15
PPO-PS [14]	64614	15.89	564.92	15.45	65058	594.18	16.74
CIMHA	64606	0.7	564.81	0.65	65,055	593.97	0.76

Tab. 2: Result comparisons for the second system with quadratic fuel cost function of thermal units.

Method			LGM [9]	EPSO [9]	γ-PSO [9]	CIMHA
Economic dispatch	Fuel cost ($)		53053.791	53053.793	53053.790	53051.476
	CPU (s)		-	-	-	50.1
Emission dispatch	Emission (kg)	NOx	21739.271	21739.270	21739.185	21370.479
		SO2	74131.817	74131.817	74131.681	73924.733
		CO2	373122.569	373122.568	373121.273	368209.983
	CPU (s)		-	-	-	50.5
Combined economic and emission dispatch	Fuel cost ($)		54337.014	54337.027	54336.888	54333.564
	Emission (kg)	NOx	21745.127	21745.138	21745.021	21540.195
		SO2	74114.989	74115.007	74114.821	73868.9859
		CO2	373165.020	373165.186	373163.420	370203.756
	CPU (s)		-	-	-	49.9
Total CPU time for three dispatch cases			12.26	100.65	49.01	150.5

Tab. 3: Result comparison for the system with valve point loading effects of thermal units.

Method	Economic dispatch		Emission dispatch		Economic emission dispatch		
	Cost ($)	CPU (s)	Emission (lb)	CPU (s)	Cost $)	Emission (lb)	CPU (s)
SA-BGA [1]	70718	-	23200	-	73612	26080	1492
RCGA [12]	66516	40.36	23222	41.98	-	-	-
NSGA-II [12]	-	-	-	-	68333	25278	45.42
MODE [12]	-	-	-	-	68388	25792	46.76
SPEA-2 [12]	-	-	-		68392	26005	57.02
GA-MU [13]	67751	90.15	23223	78.27	68521	26080	96.10
IGA-MU [13]	66539	51.63	23223	42.87	68492	26080	53.54
PSO-PM [14]	66349	33.14	23167	33.63	67994	25902	34.11
PSO [14]	66223	32.15	23112	32.34	67892	25773	34.52
PPO-PM [14]	65912	21.03	23078	21.18	67211	25606	22.04
PPO [14]	65885	21.45	22966	21.56	67170	25601	22.11
PPO-PS-PM [14]	65723	21.12	22912	24.74	67092	25600	24.90
PPO-PS [14]	65567	22.00	22828	21.98	66951	25596	22.76
CIMHA	64989	16.4	22817	16.8	66530	25247	16.30

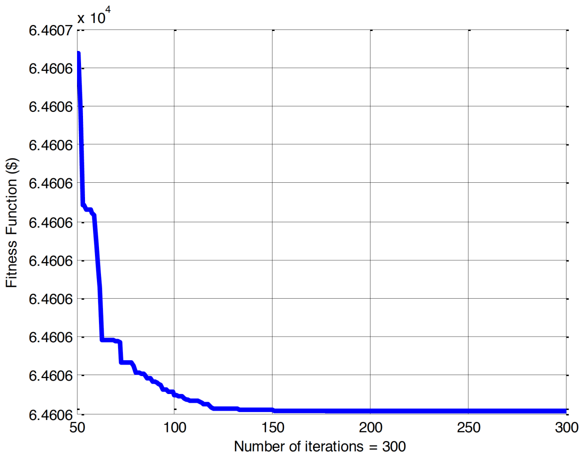

Fig. 1: Fitness function convergence characteristic for economic dispatch of system 1.

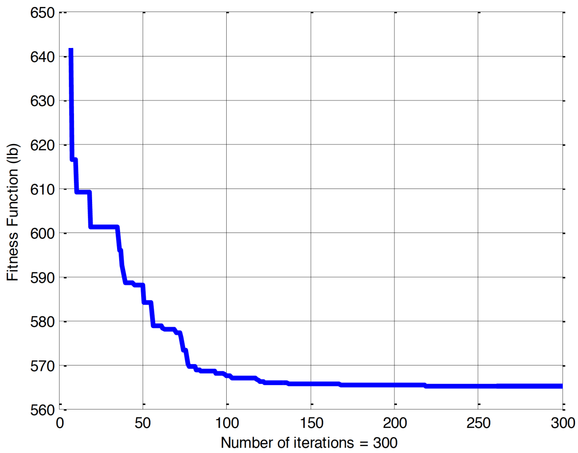

Fig. 2: Fitness function convergence characteristic for emission dispatch of system 1.

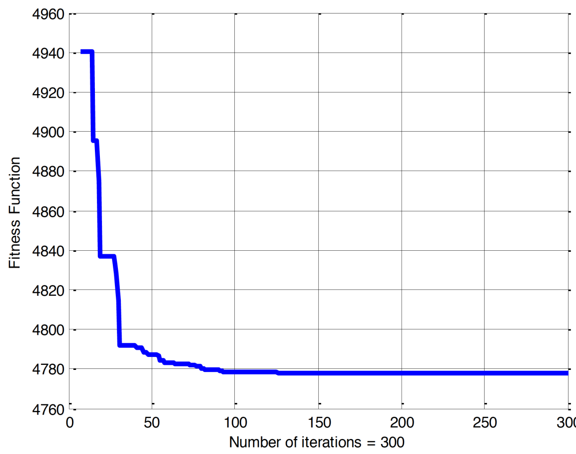

Fig. 3: Fitness function convergence characteristic for compromise dispatch of system 1.

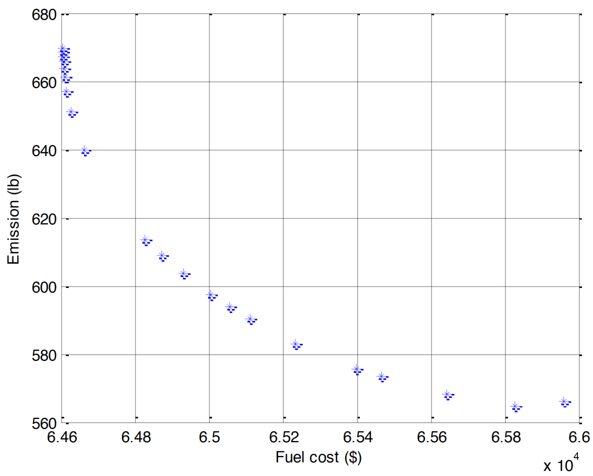

Fig. 4: Pareto-optimal front for fuel cost and emission of system 1.

The cost for economic dispatch, the emission for emission dispatch, and the cost and emission for economic emission dispatch from the proposed CIMHA method have been compared to those from other methods as in Tab. 1. Obviously, the proposed method can obtain better solutions than all compared methods for the three dispatch cases. Moreover, the computational time for performing the CIMHA method is significantly shorter than that from other methods. Note the methods in [12] have been implemented on a Pentium-IV 3.0 GHz PC. There is no computer reported for the methods in [14].

Figures 1, Fig. 2, and Fig. 3 respectively show the fitness function convergence characteristic for economic dispatch, emission dispatch, and combined economic and emission dispatch in addition to the Pareto-optimal front depicted in Fig. 4.

2) The Second System with Four Objective Functions

The combined objective of this system with two hydro and two thermal units includes a total cost function and three emission functions of NO_x, CO_2 and SO_2. The system is scheduled in a 24 hour period with one hour for each subinterval. The emission data of the system is from [20] and the rest of data is from [2]. The proposed CIMHA is implemented to obtain the optimal solution for the cases of economic dispatch ($w = 1, w_1 = w_2 = w_3 = 0$), emission dispatch ($w = 0, w_1 = w_2 = w_3 = 1/3$), and the compromise case ($w = 0.5, w_1 = w_2 = w_3 = 0.5/3$). The number of nests, maximum number of iteration, and value of the probability pa are respectively set to 40, 1800 and 0.9 for the three cases. For each case of dispatch, the CIMHA method is run 20 independent trials. The result comparison for the three cases from the proposed CIMHA with other methods including LGM, EPSO, and γ-PSO in [9] are given in Tab. 2. As observed, the proposed CIMHA method can obtain better solution than LGM, EPSO, and γ-PSO in [9] for the three dispatch cases. The comparison of total computational time has indicated that the proposed CIMHA method is slower than all methods in [9]. However, the three methods cannot deal with problems with nonconvex fuel cost of thermal units, leading to difficulty for dealing with complex systems. This advantage of the CIMHA method over the three methods will be demonstrated in Section 4.3. There is no computer reported for the methods in [9].

4.3. System with Nonconvex Fuel Cost Function of Thermal Units and two Objective Functions

The system consists of two hydro plants and four thermal plants with nonconvex fuel cost and emission functions from [13] scheduled in four subintervals with 12 hours for each. The number of nests and the maximum number of iteration are set to 50 and 2500 and meanwhile P_a is in range from 0.1 to 0.9 for all economic, emission and economic-emission dispatches. As a result, the best value of P_a for the three dispatch cases is obtained at 0.9. The result comparison with other methods for the economic, emission, and compromise dispatches is given in Tab. 3. As observed from the table, the CIMHA can obtain better total cost and emission than other methods for the case of economic dispatch, emission dispatch and economic emission dispatch. Moreover, the computational time from the proposed method is also faster than that from the other methods. The total computational time for finding solutions for economic dispatch, emission dispatch and economic emission dispatch by SA-BGA [1] is 24 minutes and 52 seconds based on the Matlab 6.0 platform and a Pentium 3 PC. The computational times of GA-MU and IGA-MU in [13] were from a PIII PC. There is no computer reported for the methods in [14].

5. Discussion

5.1. Stopping Criteria

Generally, the stopping criteria for methods solving optimization problems are usually based on the iterative error of two consecutive iterations, constraint mismatch, and maximum number of iterations. In fact, depending on the applied solution methods, the stopping criteria may be used in different ways as long as the final solution is a feasible one. In this paper, the stopping criteria of the proposed CIMHA method are only based on the maximum number of iterations like other meta-heuristic search methods since the equality constraints of the problem are always satisfied by the slack variables. Moreover, the iterative error of two consecutive iterations is also not considered since the proposed method is a population-based method using random search and it may happen that the obtained solution after several iterations is not improved. That means, the solution obtained after several iterations is still the same and it cannot be used as stopping criteria since it may lead to the termination of the algorithm with non-optimal solution. In fact, the stopping criteria of population based methods are always based on the maximum number of iterations. However, a small number of iterations may lead to a non-optimal solution. On the contrary, a large number of iterations will lead to the excessive time consumption. In addition, the value of the maximum iteration is dependent on the scale and the complexity of considered systems. Therefore, a proper selection of maximum number of iterations for each system is based on experiments.

5.2. Convergence Analysis

Although there is no mathematical relationship between CIMHA method and the multi-objective ST-HTS problem, the CIMHA can properly deal the multi-objective ST-HTS problem based on the problem formulation as an optimization problem. For implementation of CIMHA method to the multi-objective ST-HTS problems, each nest in the population represents the power outputs of thermal units and the water discharge of hydro units. During the search process, the quality of each nest will be evaluated via a fitness function which is defined as a combination of objective function and penalties for violated constraints. The nest with lower fitness function value has better quality than that with higher fitness function value. The final solution will be the nest with the lowest fitness function value at the end of the iterative process. For each system, the proposed method is run twenty independent trials and the rate of success is 100 %. The convergence characteristics for test system 1 have been given in form of the numerical results in the paper. The obtained results have shown the appropriateness and effectiveness of the CIMHA method for the multi-objective ST-HTS problem.

5.3. Diversity of the Search Space

Before obtaining the optimal solution, the CIMHA method performs an iterative search process where two times new solutions are generated at each iteration consisting of the first new solution generation via Levy flights as in Section 3.3.2) and the second generation via the action of alien eggs to be abandoned as in Section 3.3.3). In each step, if the new obtained solution is out of the limits of variables, the solution will be fixed in the limits. In fact, the second generation refines the result obtained from the first generation via Levy flights. For each test system in each case, the obtained results including maximum cost, minimum cost, average cost and standard deviation will reveal the solution quality of the proposed method for the problem. In fact, the difference between the maximum cost and minimum cost for economic dispatch is very low and the standard deviation is close to zero for several cases of the systems. Consequently, it can be stated that the quality of solution is very high.

5.4. Efficiency

In this paper, the performance of the CIMHA is validated by testing on three test systems where the challenges are not only the large-scale of system but also the complexity of the objective functions including nonconvex fuel cost objective function and exponential emission objective function together with many objective functions including three emission objective functions and one fuel cost objective function of test system 2. The comparison of fuel cost, emission and execution time between the proposed CIMHA method and other methods in the literature have indicated that the CIMHA method can obtain better solution quality than the other methods with faster computational time, especially for systems with complicated objective functions. The result comparison as reported in the numerical results section has shown the efficiency of the proposed CIMHA method for each test case. Consequently, the CIMHA method is very efficient for solving the multi-objective ST-HTS problem.

5.5. Measurement of Robustness

The optimal solution by the proposed CIMHA method depends on many parameters, such as number of nests, maximum number of iterations, and probability of alien egg discovery. The quality of the obtained solutions by the proposed CIMHA is evaluated via the standard deviation where the smaller standard deviation of the obtained results reflects the better solution quality for the solution method. By experiments, these parameters have been selected for each test system. For obtaining optimal solution for the test systems, the proposed CIMHA method is a subject of twenty independent trials. The standard deviation for the system in each case is very low (close to zero or just slightly higher than zero) and the solution quality is, therefore, considered very high.

6. Conclusion

In this paper, the proposed CIMHA method has been successfully applied for solving the multiobjective ST-HTS problem. The effectiveness of the CIMHA method is based on two main features including the Lévy flights and probability of discovery of a strange egg in a host bird's nest. The advantage of the CIMHA method is that it is effective for finding the optimal solution with few control parameters. The proposed method has been tested on three hydrothermal systems with different numbers of objective functions. The result comparison has indicated that the proposed method can obtain better solution quality with shorter computational time than many other methods for the test systems. Therefore, the proposed CIMHA can be an alternative method for dealing with multiobjective short-term hydrothermal scheduling problems. In the future research, the CIMHA will be implemented for solving the multi-objective variable-water head short-term hydrothermal scheduling problem where the hydro generation is a function of water discharge and reservoir volume because the water head is not a constant. Moreover, a more complex hydrothermal scheduling problem with a set of cascaded reservoirs of hydropower plants can also be considered to verify the efficiency of CIMHA method for different hydrothermal scheduling problems.

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