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Application of Dynamic Non-Linear Programming Technique to Non-Convex Short-Term Hydrothermal Scheduling Problem

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Academic Editor: Ånund Killingtveit

Received: 22 August 2017; Accepted: 16 September 2017; Published: 19 September 2017

Abstract: Short-term hydro-thermal scheduling aims to obtain optimal generation scheduling of hydro and thermal units for a one-day or a one-week scheduling time horizon. The main goal of the problem is to minimize total operational cost considering a series of equality and inequality constraints. The problem is considered as a non-linear and complex problem involving the valve-point loading effect of conventional thermal units, the water transport delay between connected reservoirs, and transmission loss with a set of equality and inequality constraints such as power balance, water dynamic balance, water discharge, initial and end reservoir storage volume, reservoir volume limits and the operation limits of hydro and thermal plants. A solution methodology to the short-term hydro-thermal scheduling problem with continuous and non-smooth/non-convex cost function is introduced in this research applying dynamic non-linear programming. In this study, the proposed approach is applied to two test systems with different characteristics. The simulation results obtained in this paper are compared with those reported in recent research studies, which show the effectiveness of the presented technique in terms of total operational cost. In addition, the obtained results ensure the capability of the proposed optimization procedure for solving short-term hydro-thermal scheduling problem with transmission losses and valve-point effects.

Keywords: dynamic non-linear programming; non-smooth/non-convex optimization problem; short term hydro-thermal scheduling; transmission losses; valve point loading effect

1. Introduction

Power systems are faced with a series of challenging issues taking into account the advances and improvements within them. Remarkable research is being carried out in various areas such as the application and analysis of micro-grids (MGs) and distributed generations (DGs) in the optimal operation of power systems [1], transient stability analysis in power systems [2], dynamic operation and control of the systems [3], connection decisions of distribution transformers [4], and fault current analysis of power systems [5,6]. The authors implemented a direct search method (DSM) in [1] for solving economic dispatch (ED) of a medium-voltage MG considering several kinds of DGs. A modified artificial bee colony (MABC) optimization technique is applied in [7] for obtaining the optimal solution of the ED problem, where a novel mutation strategy based on the differential evolution (DE) method is used for improving the capability of the method in providing the optimal solution.

The valve-point loading effect of conventional thermal plants is considered in this study. The authors proposed a three-stage technique in [8] to solve the ED problem of distribution-substation-level MGs, where the main power grid and MGs are studied as two key parts of the system. In this reference, the ED of the main grid and local MGs are solved using sensitive factors and an improved direct search method in stages I and II, respectively, and the optimal reschedules from the original dispatch solutions are provided in stage III. The authors have addressed the ED problem considering voltage magnitudes and reactive power flows in [9], where linear programming method is utilized for solving the problem. In this study, thermal capacities of transmission lines and line power transmission, and exponential loads are studied using piecewise linear models. Power system expansion planning is studied in [10], where costs associated with the fuel and buying emission allowances, and benefits from selling emission allowances are considered. A piecewise linear objective function is proposed for calculating the sensitivity of operation cost with respect to limitations of emission.

Short-term hydro-thermal scheduling (STHTS) is defined as one of the most important and challenging issues in power systems operation. Thermal power plants operational costs are high; however, the initial costs of such generation units are lower. On the other hand, the operational costs of hydro power plants are insignificant; however, the construction costs of such plants are high [11,12]. Accordingly, the combination of these two types of power plants can be considered as an appropriate choice considering economic viewpoints. The main goal of short-term scheduling of hydro-thermal system is determining the optimal power generation of the hydro and thermal plants. The optimal solution provides the minimum total operational cost of the thermal units, while satisfying load demand and a series of equality and inequality constraints of the hydraulic and thermal power system network. The STHTS problem is proposed as a complex non-linear, non-convex and non-smooth optimization problem considering the water transport delay between connected reservoirs, the valve-point loading effect related to the thermal units, transmission loss and many equality and inequality constraints [13,14].

Different optimization methods are employed to obtain optimal solution of generation planning of hydrothermal systems, including heuristic and classical methods. A modified dynamic neighborhood learning based particle swarm optimization (MDNLPSO) method is introduced in [15] to solve the STHTS problem. In this reference, the proposed approach is applied on two test systems with different characteristics. STHTS problem is solved in [16] by employing quadratic approximation based on differential evolution with valuable trade-off (QADEVT) that minimizes fuel cost and pollutant emission simultaneously. The predator prey optimization (PPO) procedure is used in [17] to obtain the optimal power production planning of hydro and thermal units. In [18], a hybrid method differential evolution with adaptive Cauchy mutation is utilized to obtain the optimal generation scheduling of hydro and thermal units, in which water transport delay between connected reservoirs and the effect of valve-point loading of thermal power plants is taken into account. Particle swarm optimization (PSO) is introduced in [19] to deal with STHTS problem with non-convex and non-smooth cost function. The real coded genetic algorithm (RCGA) is used for the solution of STHTS problem with a series of equality and inequality restrictions and non-smooth/non-convex cost function. The suggested algorithm in this reference is armed with a restriction-management approach which eliminates the requirement of penalty parameters. In [20], by using the Lagrangian Relaxation (LR) method, not only are the electrical and hydraulic constrains handled, but also the existing network constraints are considered by employing DC power flow. The lexicographic optimization and hybrid augmented-weighted ε-constraint method are applied in [21] to produce Pareto optimal solutions for STHTS problem. In this reference, mixed integer programming (MIP) is introduced to obtain the optimal power generation planning of hydrothermal system in a day-ahead joint energy and reserve market. In [22], an improved merit order (IMO) and augmented Lagrangian Hopfield network (ALHN) is proposed to solve short-term hydrothermal scheduling with pumped-storage hydro units. The proposed method in this reference considers thermal, hydro and pumped-storage unit commitment (UC). The STHTH problem is solved in [23] with the consideration of AC network constraints, which is implemented a combination of the Benders decomposition method and Bacterial Foraging oriented by Particle Swarm Optimization (BFPSO) method. The application of chaotic maps in a particular game problem called the Parrondo Paradox is studied in [24]. The proposed approach was used in a three-game problem and a more general N-game problem in which non-linear optimization problem is considered to define the parameters for the studied game.

In this study, the STHTS problem is solved using dynamic non-linear programming (DNLP) using general algebraic modeling system (GAMS) software. The valve-point effect of conventional thermal plants, which increases the complexity of solving STHTS problem, is considered in the solution of the problem. In addition, the power transmission loss of the hydro-thermal system is studied in the proposed study. Different case studies are solved to evaluate the performance and ensure the effectiveness of the introduced method. The optimal solutions are compared with those reported in previous studies in terms of total operational cost, which demonstrates the capability of the proposed method to identify solutions having less operational cost. In addition, optimal solutions obtained in this paper ensures the capability of the proposed method to deal with valve-point loading effect of thermal units and system power transmission loss.

The rest of the paper is organized as follows: The mathematical formulation of the STHTS problem is provided in Section 2. Section 3 introduces the proposed solution method for STHTS problem. In Section 4, the proposed approach is implemented on two test systems and the obtained optimal solutions are compared with those reported in previous studies. Finally, the paper is concluded in Section 5.

2. Problem Formulation

The optimal scheduling of hydro-thermal plant includes a non-linear optimization problem involving objective function and a set of linear, non-linear and dynamic constraints. The objective function and equality and inequality constraints of the STHTS problem are explained in the following [25].

2.1. Objective Function

The main goal of short-term planning of hydro-thermal system is determining the optimal power generation of the hydro and thermal plants so as to minimize the total operation cost of the thermal units since the cost of hydro production is insignificant. It should be mentioned that various constraints on the hydraulic and thermal power system network should be considered in the solution of the problem. The objective function to be minimized can be represented as follows [26]:

$$C(P) = \sum_{t=1}^{24} \sum_{i=1}^{N_s} a_i + b_i\, P_i^t + c_i\, (P_i^t)^2 + \left| e_i\, sin(f_i(P_i^{min} - P_i^t)) \right| \tag{1}$$

where $C(P)$ is the total fuel cost. $\mathrm{N_S}$ is indicator used for the number of thermal plants. Moreover, P_i^t is power generated by the ith thermal plant at time t. a_i, b_i, and c_i are the cost coefficients of ith thermal plant. Considering multiple steams valves in conventional thermal power plants, it is essential to model the effect of valve-points on fuel cost. Valve-points effect can be modeled by a sinusoidal term, which will be added to the quadratic cost function [27]. P_i^{min} is minimum power generation of thermal unit i. Moreover, e_i and f_i are valve-point coefficients of cost function of thermal unit i.

2.2. Power Balance Constraint

The total power generated by hydro and thermal plants should be equal to the sum of total load demand and transmission line losses.

$$\sum_{i=1}^{N_S} P_i^t + \sum_{j=1}^{N_h} P_j^t = P_D^t + P_L^t \tag{2}$$

where N_h is the number of hydro units. P_j^t is the generation of hydro units in megawatts (MW). Moreover, P_D^t and P_L^t are load demand and total transmission loss in MW, respectively. P_L^t can be calculated using the Kron's loss formula known as B-matrix coefficients [28]. Equation (3) calculates power transmission loss utilizing Kron's loss formula, which is defined as B-matrix coefficients method in this paper as follows:

$$P_L^t = \sum_{i=1}^{N_h+N_s} \sum_{j=1}^{N_h+N_s} P_i^t B_{ij} P_j^t + \sum_{i=1}^{N_h+N_s} B_{io} P_i^t + B_{00} t = 1, 2, \ldots, T \tag{3}$$

The coefficients are Kron's loss formulation used to calculate power transmission of the hydrothermal system. The power loss of the system taking into account N_s hydro plants and N_h thermal units can be calculated by using such formulation. B-matrix coefficients for calculating the power loss are shown by B_{ij}, B_{io}, and B_{00}. In such formulation, B_{mn} is element of matrix B with dimension of $(N_S + N_h) \times (N_S + N_h)$. In addition, B_{0n} is vector of the same length as P, and B_{00} is considered as a constant.

The hydro power generation, P_j^t, is a function of water discharge and storage volume, which can be calculated as follows:

$$P_j^t = C_{1,j}\left(V_j^t\right)^2 + C_{2,j}\left(Q_j^t\right)^2 + C_{3,j} V_j^t Q_j^t + C_{4,j} V_j^t + C_{5,j} Q_j^t + C_{6,j} \tag{4}$$

where V_j^t is the storage volume of reservoir in m^3, and $C_{1,j}$, $C_{2,j}$, $C_{3,j}$, $C_{4,j}$, $C_{5,j}$, and $C_{6,j}$ represent hydro power generation coefficients. Moreover, Q_j^t is the water discharge amount in m^3.

2.3. Limitations of Power Production

The generator capacity constraints are expressed as:

$$\begin{gathered} P_i^{\min} \le P_i^t \le P_i^{\max} \\ P_j^{\min} \le P_j^t \le P_j^{\max} \end{gathered} \tag{5}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the respective lower and upper bounds of power generation of thermal units. In addition, the minimum and maximum amounts of power production of hydro units are indicated by $P_j^{\min}$ and $P_j^{\max}$, respectively.

2.4. Hydraulic Network Constraints

2.4.1. Water Dynamic Balance

The reservoir storage of hydro unit is related to previous inflow and spillage, and storage of reservoir discharge from upstream reservoirs, which can be formulated as:

$$V_j^t = V_j^{t-1} + I_j^t - Q_j^t - S_j^t + \sum_{m=1}^{\phi_j} \left[Q_{m(t-\tau_{mj})}^t + S_{m(t-\tau_{mj})}^t\right], \, m \in \phi_j \tag{6}$$

where I_j^t is the inflow rate of the reservoir, ϕ_j is set of instant upstream hydro plants of the j^{th} reservoir. Additionally, τ is time delay of immediate downstream plants.

2.4.2. Reservoir Storage Volume Limits

The operating volume of reservoir should be limited in interval between minimum and maximum values, which can be stated as:

$$V_j^{\min} \le V_j^t \le V_j^{\max} \tag{7}$$

where $V_j^{\min}$ and $V_j^{\max}$ are the respective lower and upper bounds of operating volume of the reservoir of *i*th hydro unit.

2.4.3. Water Release Limits

The water release of hydro units should be limited to minimum and maximum values, which can be considered as:

$$Q_j^{\min} \leq Q_j^t \leq Q_j^{\max} \tag{8}$$

where $Q_j^{\min}$ and $Q_j^{\max}$ are the minimum and maximum release of the water reservoir of the *i*th hydro plant.

2.4.4. Initial and Final Reservoir Storage Volume

Initial and final volumes of reservoir storage should be taken into account in the formulation of STHTS problem as:

$$\begin{aligned} V_j^t\Big|_{t=0} &= V_j^{begin} \\ V_j^t\Big|_{t=\tau} &= V_j^{end} \end{aligned} \tag{9}$$

where V_j^{begin} is the elementary volume of the reservoir and V_j^{end} is the final volume of the reservoir.

3. Solution Methodology

GAMS is defined as a practical tool to handle general optimization problems, which consists of a proprietary language compiler and a variety of integrated high-performance solvers. GAMS is specifically designed for large and complex problems, which allows creating and maintaining models for a variety of applications. GAMS is able to formulate models in many different types of problem classes, such as linear programming (LP), nonlinear programming (NLP), mixed-integer linear programming (MILP), mixed-integer nonlinear programming (MINLP) and dynamic nonlinear programming (DNLP). Nonlinear models created in GAMS area should be solved by using an NLP algorithm. This paper offers a novel approach based on the NLP method to obtain optimal planning of hydrothermal systems. Accordingly, the STHTS is modeled as a NLP in this study, and is solved by implementing OptQuest/NLP (OQNLP) solver. The STHTS problem is formulated as a nonlinear problem, which can be solved by GAMS software [29] using OQNLP solver [30]. OQNLP is a multi-start heuristic technique, which calls an NLP solver from different starting points. All feasible solutions obtained by such solvers are kept, and the best solution is reported as the final optimal solution. Such a method is capable of finding global optimal solutions of smooth constrained NLPs. A scatter search implementation called OptQuest is employed by OQNLP to compute starting points [31]. OQNLP is able to obtain global optimal solutions of smooth NLPs and MINLPs. A simplified pseudo-code is provided in Figure 1 for introducing the application of OQNLP to find the optimal solution of the optimization problems, which is divided into two levels. The first level generates candidate starting points and selects the best starting point among all of the points. Then, in the second level, new points are generated and evaluated in order to obtain the best solution in terms of generation cost.

Level 1
for *i = 1 to* n_1, **do**
production of candidate starting points by employing starting point generator
calculation of penalty value for each starting point
end for
select candidate point with best penalty function value among candidate starting points
initialize merit filter threshold (the starting point for the next call is based on the point with the smallest of penalty value)
Level 2
for *i = 1 to* n_2, **do**
iteration for n_2 *candidate points*
production of the next candidate n_1+1
calculation of penalty value for the produced point
perform merit and distance filter tests for starting L at a small fraction of the candidate starting points
storage of the solver output
end for

Figure 1. Pseudo-code of the applied OptQuest/NLP (OQNLP) method.

4. Case Studies and Simulation Results

In this paper, the performance of the proposed solution is evaluated in several test systems. A Pentium IV PC with 2.8 GHz CPU and 4 GB RAM PC is used to solve the problem in GAMS. The scheduling horizon is chosen as 24 h of a day.

4.1. Test System 1

First test system consists of four hydro plants and an equivalent thermal plant. The hydraulic communication among hydro units of this system is demonstrated in Figure 2. Transmission losses are not considered in this test system. Cost coefficients of thermal plants are a_i = 0.002, b_i = 19.2, and c_i = 5000. The lower and upper operation limits of this thermal plant are 500 and 2500 MW, respectively. Data of thermal unit and hydro plants are adopted from [25]. Two different cases including convex and non-convex cost function are studied for this test system.

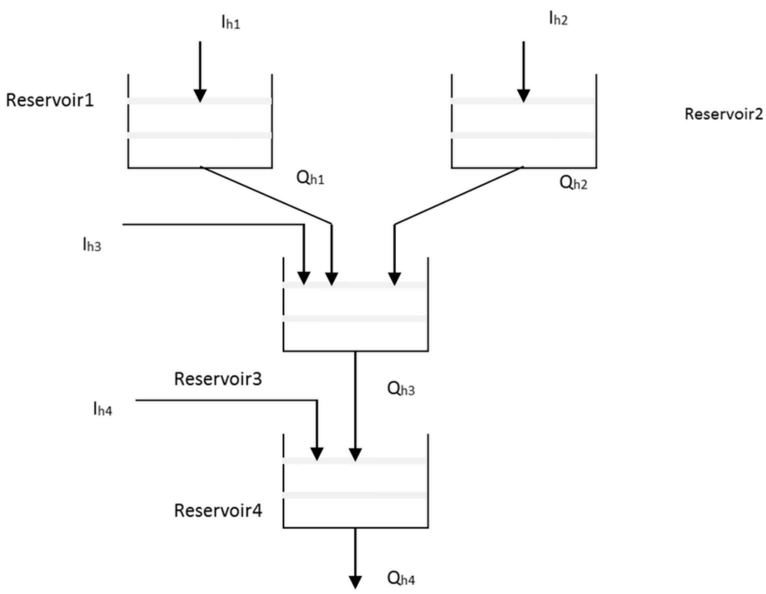

Figure 2. Hydro subsystem used in the all test systems.

4.1.1. Test System 1 Case 1: Quadratic Cost without Valve-Point Loading Effect

In this case, optimal generation scheduling of test system 1 is solved without consideration of valve-point loading impact. The hourly water discharge of the hydro plants and hydro power production, which is calculated by employing Equation (7), are shown in Table 1. In addition, thermal power production for case 1 is provided in Table 1. According to Table 1, the sum of power generation by four hydro units and one thermal plant meets total demand of the system. Hourly hydro discharges of the optimal solution are demonstrated in Figure 3. Considering Figure 3, hydro plant 4 has the maximum discharge among four hydro units, which shows that the power generation of hydro plant 4 is more than the others. In addition, hourly hydro and thermal plant generations are illustrated in Figure 4. The thermal units participates in power demand supply more than the hydro plants according to Figure 4. Moreover, total load demand is satisfied by the power generation of four hydro units and the thermal plants, which is obvious in Figure 4.

Table 1. Hourly plant discharges, power outputs and total thermal generation (test system 1, case 1).

Hour	Hydro Plant Discharges (10^4 m^3)				Hydro Power Output (megawatts (MW))				Thermal Generation (MW)	Total Generation (MW)
	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant3	Plant 4		
1	6.254	6.000	11.632	15.344	61.528	45.316	56.480	224.231	982.445	1370
2	6.488	6.000	11.914	16.919	64.339	46.576	55.928	219.694	1003.464	1390
3	6.594	6.000	12.303	18.537	65.777	47.804	56.376	209.020	981.024	1360
4	6.592	6.000	12.741	20.000	66.102	49.586	57.320	189.900	927.092	1290
5	6.431	6.000	13.129	20.000	64.972	51.296	57.694	306.000	810.039	1290
6	6.617	6.000	13.531	20.000	66.284	52.396	58.133	306.000	927.187	1410
7	7.005	6.000	13.923	20.000	69.238	52.934	58.611	306.000	1163.217	1650
8	7.545	6.000	14.254	20.000	73.259	52.934	58.728	306.000	1509.079	2000
9	7.927	6.000	14.568	20.000	76.166	53.464	58.565	306.000	1745.805	2240
10	8.109	6.000	14.894	20.000	77.851	54.500	58.136	306.000	1823.512	2320
11	8.087	6.000	15.277	20.000	78.367	55.994	57.612	306.000	1732.027	2230
12	8.272	6.000	15.621	20.000	80.353	57.416	57.056	306.000	1809.175	2310
13	8.165	6.254	16.047	20.000	79.963	60.180	56.475	306.000	1727.382	2230
14	8.124	6.613	16.494	20.000	80.131	63.512	56.112	306.000	1694.245	2200
15	8.043	6.927	16.939	20.000	80.074	66.727	55.351	306.000	1621.848	2130
16	7.930	7.272	17.137	20.000	79.565	69.947	54.948	306.000	1559.540	2070
17	7.950	7.670	15.694	20.000	79.858	72.868	57.561	306.000	1613.712	2130
18	7.768	7.950	14.281	20.000	78.597	74.372	59.277	306.000	1621.754	2140
19	7.662	8.374	12.888	20.000	77.830	76.131	60.031	306.000	1720.008	2240
20	7.452	8.751	18.733	20.000	76.216	77.728	51.940	306.000	1768.116	2280
21	7.063	15.000	19.145	20.000	73.145	101.607	49.988	303.055	1712.205	2240
22	11.991	15.000	19.676	20.000	101.750	98.082	47.637	298.534	1573.998	2120
23	11.931	15.000	20.368	20.000	100.691	94.269	44.320	292.356	1318.364	1850
24	15.000	15.000	13.133	20.000	107.020	80.950	59.005	284.400	1058.625	1590

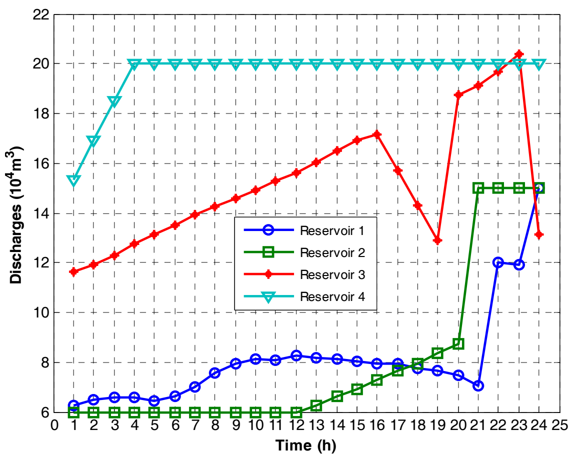

Figure 3. Hourly hydro discharges volumes of the optimal solution for test system 1, case 1.

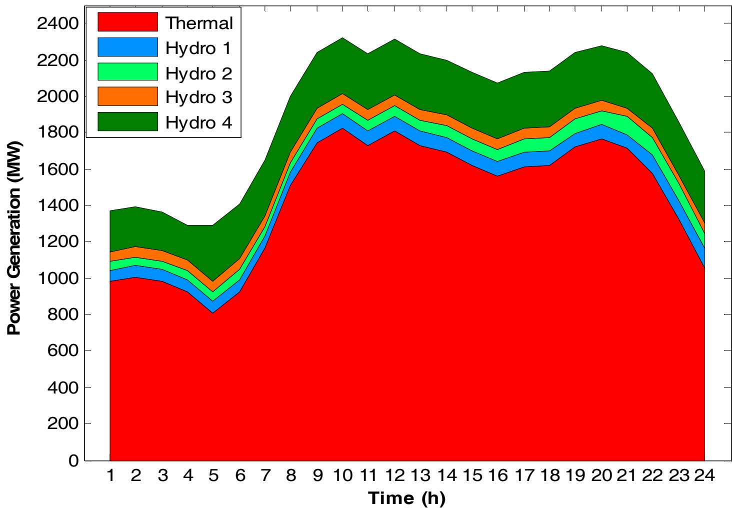

Figure 4. Hourly hydro and thermal plant generations for test system 1, case 1.

The obtained results are compared with those obtained by employing quantum-inspired evolutionary algorithm (QEA) [25], quantum-inspired evolutionary algorithm (WDA) [32], small population-based particle swarm optimization (SPSO) [33], real coded genetic algorithm (RCGA) [34], real-coded quantum-inspired evolutionary algorithm (RQEA) [25], DE [25], modified differential evolution (MDE) [33], differential real-coded quantum-inspired evolutionary algorithm (DRQEA) [25], hybrid chemical reaction optimization (HCRO)-DE [35], modified adaptive particle swarm optimization (MAPSO) [36], real-coded genetic algorithm and artificial fish swarm algorithm (RCGA-AFSA) [34], teaching learning-based optimization (TLBO) [37], smallpopulation-based particle swarm optimization (SPPSO) [33], self-organizing hierarchical particle swarm optimization technique with time-varying acceleration coefficients (SOHPSO_TVAC) [38], PSO [39], improved differential evolution (IDE) [40], fuzzy adaptive particle swarm optimization (FAPSO) [39], dynamic neighborhood learning based particle swarm optimization (DNLPSO) [15], and modified dynamic neighborhood learning based particle swarm optimization (MDNLPSO) [15], and is shown in Table 2. As it can be observed from this table, the best reported cost for this case is equal to $914,660, which is related to FAPSO [39], while total operational cost of the solution obtained by the proposed method is $884,733.965. Accordingly, the proposed method is capable to find better solution in comparison with previous methods in terms of total operational cost.

4.1.2. Test System 1 Case 2: Quadratic Cost Function with Valve-Point Loading

In this case, optimal power scheduling of test system 1 is obtained with consideration of valve-point loading effect. The parameters of valve-point loading impact of thermal unit are $e_i = 700$ and $f_i = 0.085$. The simulations are provided for case 2 with non-convex fuel cost. The optimal planning of discharge of four hydro units are reported in Table 3. In addition, power generation of hydro units, which is obtained by applying Equation (7), are provided in this table. In addition, power production of thermal power plants are presented in Table 3. It can be observed from Table 3 that the power demand during 24-h scheduling time is satisfied by total power generation of four hydro units and one thermal unit.

The optimal solution obtained in this research study is compared with those reported in recent paper, which include QEA [25], DE [25], RCGA-AFSA [34], RQEA [25], DRQEA [25], CRQEA [25], RCCRO [41], ACDE [42], MAPSO [36], TLBO [37], RCGA [34], RQEA [25], DE [25], MDE [33], DRQEA [25], HCRO-DE [35], MAPSO [36], MDNLPSO [15], IDE [41], TLBO [37], RCGA-AFSA [34], SPPSO [33], SOHPSO_TVAC [38], PSO [39], Improved DE [40], IDE [40], and FAPSO [39], and is shown in Table 4. As it can be seen in this table, the minimum total operational cost reported for this case is $914,660.00, which is obtained by applying FAPSO [39]; however, the proposed method in this paper obtained the minimum cost equal to \$901,191.9735, which shows the capability of the proposed method in obtaining optimal solution of the STHS problem for test system 1, case 2 with respect to other optimization methods.

Table 2. Comparisons of simulation results for test system 1, case 1. Employing quantum-inspired evolutionary algorithm (QEA); quantum-inspired evolutionary algorithm (WDA); small population-based particle swarm optimization (SPSO); real-coded genetic algorithm (RCGA); real-coded quantum-inspired evolutionary algorithm (RQEA); modified differential evolution (MDE); differential real-coded quantum-inspired evolutionary algorithm (DRQEA); hybrid chemical reaction optimization-differential evolution (HCRO-DE); modified adaptive particle swarm optimization (MAPSO); real coded genetic algorithm and artificial fish swarm algorithm (RCGA-AFSA); teaching learning-based optimization (TLBO); SPPSO; self-organizing hierarchical particle swarm optimization technique with time-varying acceleration coefficients (SOHPSO_TVAC); particle swarm optimization (PSO); improved differential evolution (IDE); fuzzy adaptive particle swarm optimization (FAPSO); dynamic neighborhood learning based particle swarm optimization (DNLPSO) and; modified dynamic neighborhood learning based particle swarm optimization (MDNLPSO).

Optimization Method	Min. Cost (\$)	Max. Cost (\$)	Ave. Cost (\$)
QEA [25]	926,538.29	930,484.13	928,426.95
WDA [32]	925,618.5	-	928,219.8
SPSO [33]	925,308.86	923,083.48	926,185.32
RCGA [34]	923,966.285	924,108.731	924,232.072
RQEA [25]	923,634.53	926,957.39	924,992.46
DE [25]	923,234.56	928,395.84	925,157.28
MDE [33]	922,556.38	923,201.13	923,813.99
DRQEA [25]	922,526.73	925,871.51	923,419.37
DNLPSO [15]	922,498	923,580	922,837
HCRO [35]	922,444.79	922,513.62	922,936.17
MAPSO [36]	922,421.66	923,508	922,544
RCGA-AFSA [34]	922,339.625	922,346.323	922,362.532
TLBO [37]	922,373.39	922,873.81	922,462.24
SPPSO [33]	922,336.31	922,362.532	923,083.48
SOHPSO_TVAC [38]	922,018.24	-	-
PSO [39]	921,920	-	-
IDE [40]	917,237.7	917,277.8	917,250.1
FAPSO [39]	914,660	-	-
Proposed method	884,733.965	-	-

Table 3. Hourly plant discharges, power outputs and total thermal generation (test system 1, case 2).

Hour	Hydro Plant Discharges (10^4 m^3)				Hydro Power Output (MW)				Thermal Generation (MW)	Total Generation (MW)
	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant 3	Plant 4		
1	5.212	6.000	10.730	13.080	53.156	45.316	55.550	198.539	1017.439	1370
2	5.555	6.487	10.976	16.211	57.199	49.935	55.337	210.090	1017.439	1390
3	5.148	6.000	10.252	15.327	54.329	47.508	54.789	185.936	943.519	1360
4	5.023	6.000	10.000	19.571	53.613	49.302	55.220	188.347	832.639	1290
5	5.052	6.000	17.571	20.000	54.126	51.024	52.771	299.440	943.519	1290
6	5.150	6.000	10.000	19.615	55.150	52.133	55.526	303.672	1168.561	1410
7	5.605	6.574	12.835	20.000	59.407	56.704	59.328	306.000	1586.197	1650
8	5.257	6.196	12.065	12.500	56.689	53.757	59.195	244.162	1756.637	2000
9	5.613	6.661	12.694	20.000	60.242	57.427	59.693	306.000	1762.699	2240
10	13.476	13.306	13.137	19.485	104.423	90.251	59.762	302.866	1719.677	2320
11	11.589	6.021	10.104	19.739	98.015	51.320	56.792	304.196	1793.597	2230
12	11.752	6.122	11.916	19.739	98.732	53.678	59.620	304.373	1740.260	2310
13	9.254	6.170	21.626	20.000	86.633	55.018	42.089	306.000	1756.637	2230
14	8.274	6.137	27.943	19.921	80.932	55.725	1.827	304.880	1675.480	2200
15	5.000	6.000	21.954	19.476	55.068	56.152	40.489	302.810	1608.797	2130
16	5.320	6.544	21.608	20.000	58.135	61.472	41.271	300.325	1645.757	2070
17	5.234	8.595	14.157	19.978	57.184	75.322	60.241	291.496	1645.757	2130
18	7.821	6.640	14.810	20.000	79.151	62.077	59.593	293.422	1719.677	2140
19	8.424	9.199	10.298	19.987	83.520	77.592	57.383	301.828	1793.597	2240
20	10.474	11.904	27.516	19.607	96.000	88.807	6.038145	301.595	1674.858	2280
21	14.459	14.871	10.000	19.888	109.205	94.848	55.758	305.331	1645.757	2240
22	8.381	14.998	27.296	19.993	82.343	91.135	0.747	300.017	1387.038	2120
23	8.425	14.996	26.778	19.399	82.203	86.813	2.930	291.016	1096.580	1850
24	15.000	6.721	13.133	19.190	107.020	47.557	59.005	279.837	1058.625	1590

Table 4. Comparisons of simulation results for test system1, case 2.

Optimization Method	Min. Cost ($)
QEA [25]	930,647.96
DE [25]	928,662.84
RCGA-AFSA [34]	927,899.872
RQEA [25]	926,068.33
DRQEA [25]	925,485.21
CRQEA [25]	925,403.1
RCCRO [41]	925,214.20
ACDE [42]	924,661.53
MAPSO [36]	924,636
TLBO [37]	924,550.78
RCGA [34]	923,966.285
RQEA [25]	923,634.53
DE [25]	923,234.56
MDE [33]	922,556.38
DRQEA [25]	922,526.73
HCRO-DE [35]	922,444.79
MAPSO [36]	922,421.66
MDNLPSO [15]	923,961
IDE [40]	923,016.29
TLBO [37]	922,373.39
RCGA-AFSA [34]	922,339.625
SPPSO [33]	922,336.31
SOHPSO_TVAC [38]	922,018.24
PSO [39]	921,920
Improved DE [40]	917,250.1
IDE [40]	917,237.7
FAPSO [39]	914,660.00
Proposed method	901,191.9735

4.2. Test System 2

This test system consists of four cascaded hydro power plants and three thermal plants. Valve-point loading effect of thermal plants and transmission losses are considered in this test system. Data of hydro and thermal generation units are adopted from [42]. Coefficients of transmission loss for this system are given as the following:

$$B = \begin{pmatrix} 0.34 & 0.13 & 0.09 & -0.10 & -0.08 & -0.01 & -0.02 \\ 0.13 & 0.14 & 0.10 & 0.01 & -0.05 & -0.02 & -0.01 \\ 0.09 & 0.10 & 0.31 & 0.00 & -0.11 & -0.07 & -0.05 \\ -0.01 & 0.01 & 0.00 & 0.24 & -0.08 & -0.04 & -0.07 \\ -0.08 & -0.05 & -0.11 & -0.08 & 1.92 & 0.27 & -0.02 \\ -0.01 & -0.02 & -0.07 & -0.04 & 0.27 & 0.32 & 0.00 \\ -0.02 & -0.01 & -0.05 & -0.07 & -0.02 & 0.00 & 1.35 \end{pmatrix} \times 10^{-4}\mathrm{MW}^{-1} \quad (10)$$
$$B_0 = [-0.75 - 0.06\ 0.70 - 0.03\ 0.27 - 0.77 - 0.01] \times 10^{-6}$$
$$B_{00} = 0.55\,\mathrm{MW}$$

4.2.1. Test System 2, Case 1: Quadratic Cost without Valve-Point Loading Effect

This test system consists of four cascades hydro plants and three thermal plants considering valve-point loading effect for all thermal units. In this case, transmission loss is not considered. The optimal hydro discharges and hydro power generation of four hydro units are provided in Table 5. Moreover, power generations of three thermal plants are reported in this table. According to Table 5, the sum of power generation of four hydro units and three thermal plants meets the load demand during the scheduling time of the STHS problem.

Table 5. Optimal discharges and power output for test system 2 case 1.

Hour	Hydro Plant Discharges (10^4 m^3)				Hydro Power Output (MW)				Thermal Power Output (MW)		
	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant 3
1	5.940	6.000	11.919	15.335	59.103	45.317	54.084	224.158	102.673	124.908	139.758
2	6.699	7.766	14.024	20.000	65.989	58.072	52.592	236.005	102.673	124.908	139.760
3	6.864	6.002	16.358	13.099	67.796	46.733	48.618	169.512	102.673	124.908	139.760
4	5.000	6.000	20.251	12.102	53.000	48.545	34.952	146.162	102.673	124.908	139.760
5	5.000	6.000	19.354	7.486	53.361	50.298	36.816	162.185	102.673	124.908	139.760
6	5.562	6.000	18.081	20.000	58.435	51.426	41.026	281.773	102.673	124.908	139.760
7	8.717	7.235	10.050	9.521	81.434	60.381	48.532	189.953	175.000	165.181	229.519
8	6.793	6.000	10.000	12.002	68.402	51.295	49.484	226.483	175.000	209.816	229.520
9	8.278	6.984	10.000	17.853	79.131	58.617	50.361	287.556	175.000	209.816	229.520
10	9.721	6.901	10.000	15.166	87.819	58.640	51.683	267.523	175.000	209.816	229.520
11	9.980	7.651	10.000	16.174	89.468	64.626	52.759	278.812	175.000	209.816	229.519
12	11.526	9.682	12.521	19.991	96.739	76.822	56.159	305.945	175.000	209.816	229.519
13	8.830	8.827	18.363	19.431	83.318	71.352	48.797	292.197	175.000	209.816	229.519
14	8.337	6.894	17.750	12.235	80.723	59.110	51.359	224.472	175.000	209.816	229.519
15	7.791	6.297	19.374	13.639	77.682	56.137	47.225	236.017	175.000	209.812	208.126
16	5.474	7.836	10.000	17.345	59.431	67.731	56.316	262.186	175.000	209.816	229.519
17	8.555	7.625	10.000	12.243	83.821	66.503	57.468	227.928	174.999	209.816	229.465
18	9.628	9.144	10.000	17.593	90.452	75.044	58.138	282.031	175.000	209.816	229.519
19	8.801	8.764	10.000	12.800	85.273	71.213	58.453	240.726	175.000	209.816	229.520
20	5.000	8.951	21.305	14.379	55.099	71.229	46.410	262.927	175.000	209.816	229.520
21	7.167	12.825	25.403	8.680	73.741	87.127	22.093	197.616	175.000	124.903	229.520
22	10.381	13.611	26.991	19.652	94.074	86.783	8.525	303.277	102.673	124.908	139.760
23	9.956	15.000	26.187	19.731	91.469	86.389	11.133	293.668	102.673	124.908	139.760
24	7.979	7.656	13.143	14.001	79.296	53.388	59.005	240.969	102.673	124.908	139.760

Proposed method provided the minimum fuel cost of $41,101.738, which is compared with simulated annealing (SA) [25], DE [11], chaotic artificial bee colony (CABC) [26], adaptive differential evolution (ADE) [23], RCGA [13], DE [10], SPPSO [12], RQEA [10], PSO [27], chaotic differential evolution (CDE) [23], clonal selection algorithm (CSA) [28], TLBO [29], TLBO [18], improved quantum-behaved particle swarm optimization (IQPSO) [30], quasi-oppositional teaching learning based optimization (QTLBO) [29], Improved differential evolution (IDE) [21], adaptive chaotic differential evolution (ACDE) [23], real coded chemical reaction based optimization (RCCRO) [22], differential real-coded quantum-inspired evolutionary algorithm (DRQEA) [10], and adaptive chaotic artificial bee colony algorithm (ACABC) [26], quasi-oppositional group search optimization (QOGSO), as shown in Table 6. Results show that proposed method is better than previous methods used in the test system 2, case 1. As it can be seen, the minimum obtained cost is $41,274.42 which is related to ACABC [43] compare to $41,101.738 obtained by proposed method.

Table 6. Comparison of obtained optimal costs for test system 2 case 1.

Optimization Method	Min. Cost	Mean. Cost	Max. Cost
SA [44]	45,466	-	-
DE [32]	44,526.11	-	-
CABC [43]	43,362.68	-	-
ADE [43]	43,222.41	-	-
RCGA [34]	42,886.352	43,261.912	43,032.334
DE [25]	42 801.04	-	-
SPPSO [33]	42,740.23	43,622.14	44,346.97
RQEA [25]	42 715.69	-	-
PSO [45]	42,474.00	-	-
CDE [42]	42,452.99	-	-
CSA [46]	42,440.574	-	-
TLBO [47]	42,386.13	42,407.23	42,441.36
TLBO [33]	42,385.88	42,407.23	42,441.36
IQPSO [48]	42,359.00	-	-
GSO [49]	42,316.39	42,339.35	42,379.18
QTLBO [47]	42,187.49	42,193.46	42,202.75
QOGSO [49]	42,120.02	42,130.15	42,145.37
IDE [40]	41,856.5	-	-
ACDE [42]	41,593.48	-	-
RCCRO [41]	41,497.85	41,498.21	41,502.36
DRQEA [25]	41,435.76	-	-
ACABC [43]	41,274.42	-	-
Proposed method	41,101.738	-	-

4.2.2. Test System 2 Case 2: Quadratic Cost Function with Valve-Point Loading

The valve-point effects and transmission losses are considered in this case, which make the problem more complex. The optimal result obtained by OQNLP is reported in Table 7. The hourly discharge of four hydro plants and the power generation of the hydro units are prepared in this table. In addition, power generation of three thermal plants are reported in Table 7. The power transmission loss of the hydrothermal system by applying Equation (13) during 24-h scheduling time interval is also reported in this table. In this case, considering Table 7, total generation of four hydro units and three thermal plants meets total load demand and power transmission loss of the system.

Table 7. Hourly plant discharges, power outputs and total thermal generation for test system 2 case 2.

Hour	Hydro Plant Discharge, 10^4 m^3				Hydro Plant Generation (MW)				Thermal Plant Generation (MW)			Loss MW	Total Generation, MW
	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant 3	Plant 4	Plant 1	Plant 2	Plant 3		
1	6.224	7.064	12.991	6.797	61.232	52.277	56.939	130.234	102.511	124.322	229.518	7.033	757.033
2	7.280	8.237	13.107	19.956	69.961	59.942	55.806	237.968	102.673	124.908	139.759	11.017	791.017
3	5.092	6.000	12.818	5.327	53.354	45.533	55.918	188.300	102.674	122.365	139.760	7.903	707.903
4	5.000	6.000	14.572	18.111	53.119	47.349	55.882	184.839	95.539	80.854	139.759	7.341	657.341
5	5.000	6.000	11.545	6.000	53.470	49.149	56.573	149.761	102.657	124.908	139.760	6.278	676.278
6	5.000	6.000	15.314	16.648	53.632	50.309	56.596	280.372	102.674	124.908	145.345	13.836	813.836
7	5.393	6.000	16.445	17.907	57.420	50.877	54.608	291.657	157.940	124.907	229.519	16.928	966.928
8	5.981	6.000	10.000	18.064	62.814	50.877	54.961	292.422	175.000	162.192	229.520	17.786	1027.786
9	8.635	6.213	16.133	19.707	82.533	52.949	55.354	304.242	175.000	209.815	229.520	19.413	1109.413
10	8.277	6.156	17.258	18.833	80.533	53.535	51.892	298.668	175.000	209.816	229.519	18.963	1098.963
11	9.990	7.668	10.111	18.233	91.041	65.154	54.262	294.077	175.000	209.816	229.519	18.870	1118.870
12	14.072	11.849	13.399	20.000	105.690	86.772	57.662	306.000	175.000	209.815	229.520	20.458	1170.458
13	9.023	6.013	20.356	13.234	85.283	52.690	42.348	246.964	175.000	294.724	229.520	16.529	1126.529
14	7.224	7.208	18.028	18.421	73.582	61.938	50.867	295.082	175.000	162.205	229.519	18.193	1048.193
15	8.031	7.651	16.110	18.682	79.963	65.732	57.051	295.698	175.000	124.908	229.519	17.872	1027.872
16	8.314	8.539	19.347	20.000	82.214	71.786	50.242	294.907	175.000	209.816	194.414	18.379	1078.379
17	9.238	9.661	25.080	16.986	88.314	77.558	18.529	268.360	175.000	209.815	229.520	17.097	1067.097
18	10.245	11.054	10.689	20.000	93.953	82.465	57.043	291.376	175.000	209.816	229.519	19.172	1139.172
19	8.849	9.962	10.000	15.111	85.629	74.482	56.903	254.959	175.000	209.815	229.519	16.308	1086.308
20	8.546	9.668	21.651	15.281	83.461	71.185	41.508	257.413	175.000	208.174	229.519	16.260	1066.260
21	7.029	9.978	23.588	20.000	72.399	71.584	30.674	294.843	102.674	124.908	229.520	16.601	926.601
22	6.077	11.227	26.324	15.162	64.681	76.310	11.250	265.100	102.673	124.907	229.520	14.442	874.442
23	11.224	13.406	24.422	20.000	97.745	81.821	23.040	295.500	102.673	124.908	139.760	15.448	865.448
24	15.000	15.000	13.133	9.594	107.020	80.950	59.005	194.843	102.674	124.907	139.757	9.157	809.157

Comparisons of simulation results for this case study are accomplished in Table 8. It can be observed that the obtained result using the proposed method outperform the results of QEA [25], ABC [43], DE [32], SPPSO [50], RQEA [25], DNLPSO [15], PSO [51], CSA [44], TLBO [33], SA-MOCDE [37], GSA [52], QOTLBO [33], MOCA-PSO [53], SHPSO-TAC [51], IDE [40], RCGA-AFSA [34], QABDEVT [16], ACDE [54]. Taking into account transmission losses and valve-point effects, the best reported solution is related to ACDE [54], which obtained total cost of $41,593.48. However, the proposed method provided the optimal solution with the total operational cost of $41,350.5574 which is better than other methods.

Table 8. Comparisons of simulation results for test system 2 case 2.

Optimization Method	Min. Cost
QEA [25]	44,686.31
ABC [43]	43,362.00
QOGSO [49]	43,560.35
DE [32]	42,801.04
SPPSO [50]	42,740.23
RQEA [25]	42,715.69
DNLPSO [15]	42,645
PSO [51]	42,474.00
CSA [44]	42,440.574
TLBO [33]	42,386.13
SA-MOCDE [37]	42,038.00
GSA [52]	42,032.35
QOTLBO [33]	42,187.49
MOCA-PSO [53]	42,001.00
SHPSO-TAC [51]	41,983.00
IDE [40]	41,856.5
RCGA-AFSA [34]	41,818.42
QABDEVT [16]	41,762.00
ACDE [54]	41,593.48
Proposed method	41,350.5574

5. Conclusions

In this study, dynamic non-linear programming is introduced to obtain optimal scheduling of a hydrothermal system. The valve-point loading impact of conventional thermal units and system power transmission loss are considered in finding the optimal solution of the short-term hydro-thermal scheduling problem by studying two test systems. Optimal solutions are reported and analyzed, and are compared with those provided in recent papers. Results showed the capability of the proposed method to obtain better solutions in terms of total operational cost in comparison with other heuristic algorithms. Test system 1 includes four cascaded hydro units and one equivalent thermal plant, in which daily savings are $29,926.035 and $13,468.026 in comparison with previously reported solutions for both cases 1 and 2, respectively. In addition, for test system 2, which contains four cascaded hydro units and three thermal plants, daily savings are $172.682 and $242.9226 in comparison with reported solutions in previous studies for both cases 1 and 2, respectively. The optimal solutions show that the proposed method is an effective and high-performance technique to solve short-term hydro-thermal scheduling problem considering transmission losses and valve-point loading effects. The future research trends in the area of short-term hydro-thermal scheduling can be concentrated on consideration of limitations of AC network constraints. In addition, the unit commitment problem of hydrothermal systems, considering the start-up cost, minimum uptime, and minimum downtime of the generation units can be considered as another research topic in this area. Moreover, the unavailability of the generation units and consideration of renewable energy sources such as wind power are other exciting subjects to be investigated. Also, middle and long-term scheduling of hydro-thermal system, considering the installation and maintenance cost of hydro and thermal plants, may be introduced as interesting subject in the area of hydro-thermal systems.

Author Contributions: All authors have contributed equally work.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

Indexes	
t	Time interval of planning
N_s	The number of thermal plants
N_h	The number of hydro units
Constants	
a_i, b_i and c_i	Cost coefficients of ith thermal plant
e_i and f_i	Valve-point coefficients of cost function of thermal unit i
$P_i^{\min}$	Minimum power generation of thermal unit i
$P_i^{\max}$	Maximum power generation of thermal unit i
$V_j^{\min}$	Lower of operating volume of reservoir of ith hydro unit
$V_j^{\max}$	Upper bounds of operating volume of reservoir of ith hydro unit
$Q_j^{\min}$	Minimum release of water reservoir of the *i*th hydro plant
$Q_j^{\max}$	Maximum release of water reservoir of the *i*th hydro plant
V_j^{begin}	Elementary volume of reservoir
V_j^{end}	Final volume of reservoir
P_D^t	Load demand at time t
$C_{1,j}$, $C_{2,j}$, $C_{3,j}$, $C_{4,j}$, $C_{5,j}$, and $C_{6,j}$	Hydro power generation coefficients
ϕ_j	Set of instant upstream hydro plants of *j*th
Variables	
P_i^t	Power generated by the *i*th thermal plant at time t
P_j^t	Generation of hydro units
P_L^t	Total transmission loss at time t
V_j^t	The storage volume of reservoir
Q_j^t	The water discharge amount
I_j^t	The inflow rate of the reservoir
Acronyms	
STHTS	Short-term hydro-thermal scheduling

DNLP	Dynamic non-linear programming
MGS	Micro-grids
DGS	Distributed generations
DSM	Direct search method
ED	Economic dispatch
MABC	Modified artificial bee colony
DE	Differential evolution
MDNLPSO	Modified dynamic neighborhood learning based particle swarm optimization
QADEVT	Quadratic approximation based on differential evolution with valuable trade-off
PPO	Predator prey optimization
PSO	Particle swarm optimization
RCGA	Real coded genetic algorithm
LR	Lagrangian relaxation
MIP	Mixed integer programming
IMO	Improved merit order
ALHN	Augmented Lagrangian hopfield network
UC	Unit commitment
BFPSO	Bacterial foraging oriented by particle swarm optimization
DNLP	Dynamic non-linear programming
GAMS	General algebraic modeling system
LP	Linear programming
NLP	Nonlinear programming
MILP	Mixed-integer linear programming
MINLP	Mixed-integer nonlinear programming
DNLP	Dynamic nonlinear programming
QEA	Quantum-inspired evolutionary algorithm
WDA	Whole distribution algorithm
SPSO	Small population-based particle swarm optimization
RQEA	Real-coded quantum-inspired evolutionary algorithm
MDE	Modified differential evolution
DRQEA	Differential real-coded quantum-inspired evolutionary algorithm
DNLPSO	Dynamic neighborhood learning based particle swarm optimization
HCRO	Hybrid chemical reaction optimization
MAPSO	Modified adaptive particle swarm optimization
RCGA-AFSA	Real coded genetic algorithm and artificial fish swarm algorithm
TLBO	Teaching learning-based optimization
SOHPSO_TVAC	Self-organizing hierarchical particle swarm optimization technique with time-varying acceleration coefficients
IDE	Improved differential evolution
FAPSO	Fuzzy adaptive particle swarm optimization
ACDE	Adaptive chaotic differential evolution
CABC	Adaptive chaotic artificial bee colony
CSA	Clonal selection algorithm
IQPSO	Improved quantum-behaved particle swarm optimization
GSO	Group search optimization
ACDE	Adaptive chaotic differential evolution algorithm

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