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Optimal Scheduling of Large-Scale Wind-Hydro-Thermal Systems with Fixed-Head Short-Term Model

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Abstract: In this paper, a Modified Adaptive Selection Cuckoo Search Algorithm (MASCSA) is proposed for solving the Optimal Scheduling of Wind-Hydro-Thermal (OSWHT) systems problem. The main objective of the problem is to minimize the total fuel cost for generating the electricity of thermal power plants, where energy from hydropower plants and wind turbines is exploited absolutely. The fixed-head short-term model is taken into account, by supposing that the water head is constant during the operation time, while reservoir volume and water balance are constrained over the scheduled time period. The proposed MASCSA is compared to other implemented cuckoo search algorithms, such as the conventional Cuckoo Search Algorithm (CSA) and Snap-Drift Cuckoo Search Algorithm (SDCSA). Two large systems are used as study cases to test the real improvement of the proposed MASCSA over CSA and SDCSA. Among the two test systems, the wind-hydro-thermal system is a more complicated one, with two wind farms and four thermal power plants considering valve effects, and four hydropower plants scheduled in twenty-four one-hour intervals. The proposed MASCSA is more effective than CSA and SDCSA, since it can reach a higher success rate, better optimal solutions, and a faster convergence. The obtained results show that the proposed MASCSA is a very effective method for the hydrothermal system and wind-hydro-thermal systems.

Keywords: Cuckoo Search Algorithm (CSA); Fixed-Head Short-Term Model; Hydrothermal System; Optimal Scheduling of Wind-Hydro-Thermal System (OSWHTS)

1. Introduction

Short-term hydrothermal scheduling considers optimization horizon from one day to one week, involving the hour-by-hour generation planning of all generating units in the hydrothermal system, so that the total generation fuel cost of thermal units is minimized, while satisfying all constraints from hydropower plants, including hydroelectric power plant constraints, such as water discharge limits, volume reservoir limits, continuity water, generation limits, and thermal power plant constraints, including prohibited operating zone and generation limits. There is a fact that the load demand changes cyclically over one day or one week, and varies corresponding to the short-term scheduling horizon, which is in a range from one day to one week. A set of beginning conditions, consisting of initial and final reservoir volumes for the scheduling horizon, inflow into the reservoir, and the water amount to be used for the scheduling horizon, is assumed to be known. During the scheduling generation process, it is necessary to consider the capacity of the reservoir and inflow once they have significant impacts on the water head variations, and lead to being represented by different hydro models. In this paper, a fixed-head short-term hydrothermal scheduling with reservoir volume constraints is considered. The reservoir water head is supposed to be fixed during the scheduling horizon [1]. Therefore, the water discharge is still the second-order function of hydro generation and given coefficients. The total amount of water is not required to be calculated and constrained. However, the initial and final values of the Reservoir Volume Should Be met with the optimal operation of the hydrothermal system. The capacity of the reservoir to contain water during the operation must be observed and followed by the constrained values, such as minimum volume corresponding to the deadhead and maximum volume corresponding to the highest head. Moreover, the continuity of water is always constrained at each subinterval over the scheduling horizon. Other issues related to power transmission lines, such as power balance and power losses, are also taken into account for most test systems.

The problem has been studied so far and obtained many intentions from researchers. Several algorithms, such as Gradient Search Algorithm (GSA) [2], Newton–Raphson Method (NRM) [3], Hopfield Neural Networks (HNN) [4], Simulated Annealing Algorithm (SAA) [5], Evolutionary Programming Algorithm (EPA) [6–8], Genetic Algorithm (GA) [9], modified EPA (MEPA) [10], Fast Evolutionary Programming Algorithm (FEPA) [10], Improved FEPA (IFEPA) [10], Hybrid EPA (HEPA) [11], Particle Swarm Optimization (PSO) [12], Improved Bacterial Foraging Algorithm (IBFA) [13], Self-Organization Particle Swarm Optimization (SOPSO) [14], Running IFEPA (RIFEPA) [15], Improved Particle Swarm Optimization (IPSO) [16,17], Clonal Selection Optimization Algorithm (CSOA) [18], Full Information Particle Swarm Optimization (FIPSO) [19], One-Rank Cuckoo Search Algorithm with the applications of Cauchy (ORCSA-Cauchy) and Lévy distribution (ORCSA-Lévy) [20], Cuckoo Search Algorithm with the applications of Gaussian distribution (CSA-Gauss), Cauchy distribution (CSA-Cauchy), and Lévy distribution (CSA-Lévy) [21], Adaptive Cuckoo Search Algorithm (ACSA) [22], Improved Cuckoo Search Algorithm (ICSA) [23], Modified Cuckoo Search Algorithm (MCSA) [24], and Adaptive Selective Cuckoo Search Algorithm (ASCSA) [24] have been applied to solve the problem of hydrothermal scheduling. Almost all of the above-mentioned methods are mainly meta-heuristic algorithms, excluding GSA and NRM. Regarding the development history, GSA and NMR are the oldest methods, with the worst capabilities to deal with constraints and finding high-quality parameters of the problem, and they are applied for hydropower generation function with the piecewise linear form or polynomial approximation form. GSA cannot deal with the systems with complex constraints and also the systems with a large number of constraints and variables. NRM seems to be more effective than GSA when applied to systems where the approximation of the hydro generation cannot be performed. However, this method is fully dependent on the scale of the Jacobian matrix and the capability of taking the partial derivative of the Jacobian matrix with respect to each variable. On the contrary to GSA and NRM, population-based metaheuristic algorithms are successfully applied for solving the complicated problem. Among those methods, SAA and GA are the oldest methods and found low-quality solutions for hydropower plants and thermal power plants. Differently, PSO and EPA variants are more effective in reaching better solutions with faster speed. The improved versions of EPA are not verified, while they were claimed to be much better than conventional EPA. Only one-thermal and one-hydropower plant system and quadratic fuel cost function is employed as the case study for running those methods. In order to improve the conventional PSO successfully, weight factor [16] and constriction factor [17] are respectively used to update new velocity and new position. The improvement also leads to an optimal solution with shorter execution time, but the two research studies report an invalid optimal solution, since the water discharge violates the lower limit. In [19], the new version of the updated velocity of the FIPSO is proposed and tested on a system. However, the method reports an invalid solution violating the lower limit. IBFA [13] also shows an invalid optimal solution with more water than availability. CSOA is demonstrated to be stronger than GA, EP, and Differential Evolution (DE) for this problem. CSA variants [20–24] are developed for the problem and reached better results. Different distributions are tested to find the most appropriate one as compared to original distribution, which is Lévy distribution. Cauchy and Gaussian distributions also result in the same best solution for the system with four hydropower plants and one thermal power plant, but the two distributions cope with a low possibility of finding the best solution.

In recent years, wind energy has been considered as a power source, together with conventional power plants, to supply electricity to loads. The optimal scheduling of thermal power plants and wind turbines is successfully solved using the Artificial Bee Colony Algorithm (ABCA) [25] and Wait-And-See Algorithm (WASA) [26]. Then, the wind-thermal system is expanded by integrating one more conventional power source, which is a hydropower plant, leading to the wind-hydro-thermal system. The optimal scheduling of the wind-hydro-thermal system is performed using different metaheuristic algorithms, such as Nondominated Sorting Genetic Algorithm-III (NSGA-III) [27], Multi-Objective Bee Colony Optimization Algorithm (MOBCOA) [28], Distributionally Robust Hydro-Thermal-Wind Economic Dispatch (DR-HTW-ED) method [29], nonlinear and dynamic Optimal Power Flow (OPF) method [30], Modified Particle Swarm Optimization (MPSO) [31], Mixed Binary and Real Number Differential Evolution (MBRNDE) [32], Mixed-Integer Programming (MIP) [33], Two-Stage Stochastic Programming Model Method (TSSPM) [34], and Sine Cosine Algorithm (SCA) [35]. In general, almost all applied methods are meta-heuristic algorithms and the purpose of those studies is to demonstrate the highly successful constraint handling capability of the applied metaheuristic algorithms, rather than showing high-quality solution searching capability.

In this paper, wind farms, together with the hydrothermal system, are considered to supply electricity to loads, in which the fixed-head short-term hydrothermal system is investigated. The objective of the Optimal Scheduling of Wind-Hydro-Thermal System (OSWHTS) problem is to minimize total electricity generation fuel cost of thermal power plants in a day, subject to the wind farms, reservoirs, and thermal units' constraints. In the fixed-head short-term model, water discharge is a second-order equation, with respect to the power output of the hydropower plant. In addition, hydraulic constraints are discharge limits, reservoir volume limits, initial reservoir volume, and end reservoir volume. In order to solve the OSWHTS problem successfully and effectively, a Modified Adaptive Selection Cuckoo Search Algorithm (MASCSA) is proposed by applying two new modifications on the Adaptive Selection Cuckoo Search Algorithm (ASCSA), which was first developed in [24]. In addition, other metaheuristic algorithms are implemented for comparisons. The implemented algorithms are CSA [36] and SDCSA [37]. CSA was first introduced by Yang and Deb in 2009 [36], and it has been widely applied for different optimization problems in electrical engineering. However, CSA is indicated to be less effective for large and complicated problems [24,37]. Hence, SDCSA and ASCSA are proposed. SDCSA is applied only for benchmark functions, while ASCSA is more widely applied for three complicated hydrothermal scheduling problems. ASCSA is superior to many existing meta-heuristic algorithms, such as GA, DE, and other CSA variants. ASCSA is an improved version of CSA, by implementing two more modifications, including a new selection technique and an adaptive mutation mechanism. ASCSA can reach high performance, but it suffers from long simulation time, due to the selection of mutation factor and threshold. Thus, in this paper, two new modifications, including setting the mutation factor to one and proposing a new condition for replacing the threshold, are applied.

The novelties of the paper are the integration of wind turbines and the fixed-head short-term hydrothermal system and a proposed CSA, called MASCSA. Thanks to the novelties, the main contributions of the study are the most appropriate selection of control variables for the optimal scheduling of the wind-hydro-thermal system, the effective constraint handling method, and the high performance proposed MASCSA method.

The rest of the paper is organized as follows. The formulation of the OSWHTS problem is given in Section 2. The details of the proposed method are described in Section 3. The search process of

MASCSA for the OSWHTS problem is presented in Section 4. The comparison results of the two test systems are given in Section 5. Finally, the conclusions are summarized in Section 6.

2. Formulation of Optimal Scheduling of Wind-Hydro-Thermal System

In this section, the optimal scheduling problem of the wind-hydro-thermal system with the fixed-head short-term model of a hydropower plant is mathematically expressed considering the objective function and constraints. A typical wind-hydro-thermal system is shown in Figure 1. From the figure, N_h hydropower plants, N_t thermal power plants, and N_w turbines in a wind farm are generating and supplying electricity to loads via different buses. The purpose of the system is to minimize the total electricity generation cost of N_t thermal power plants, considering the available water in reservoirs and the intermittent nature of wind power. The cost of generated power by hydropower plants and the wind farm is neglected, but all constraints from the plants are supervised. The objective function and all constraints can be mathematically formulated as follows:

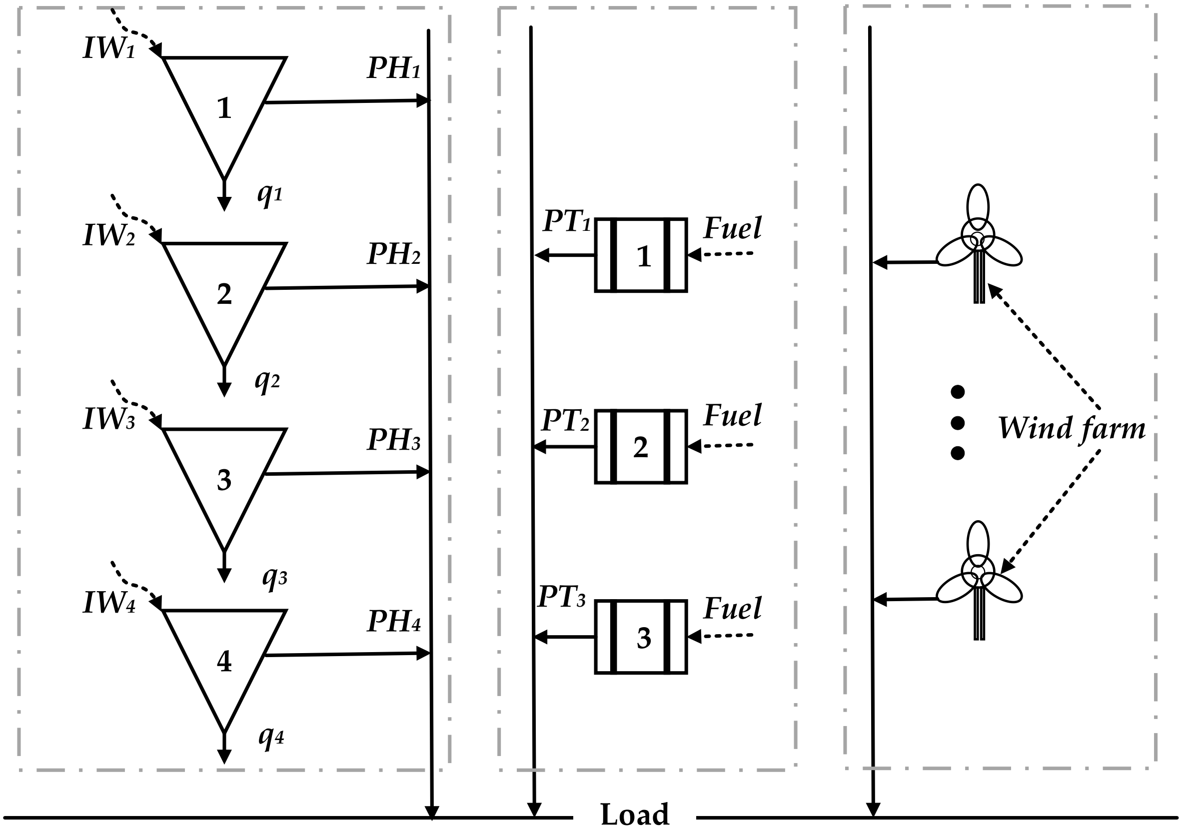

Figure 1. A typical wind-hydro-thermal system.

2.1. Total Electricity Generation Fuel Cost Reduction Objective

Total fuel cost for generating electricity from all thermal power plants is considered as a major part that needs to be minimized as much as possible. The objective is shown as follows:

$$TFC = \sum_{j=1}^{N_s} \sum_{tp=1}^{N_t} t_i \Big(k_{tp} + m_{tp} PT_{tp,i} + n_{tp,i} \big(PT_{tp,i} \big)^2 + \Big| \alpha_{tp} \times \sin\Big(\beta_{tp} \times \big(PT_{tp,min} - PT_{tp,i} \big) \Big) \Big| \Big) \quad (1)$$

2.2. Set of Constraints and Wind Model

2.2.1. Constraints from Hydropower Plants

Hydropower plants are constrained by limits of reservoirs, turbines, and generators. The detail is expressed as follows:

Water Balance Constraint: The reservoir volume at the i^{th} considered subinterval is always related to the volume of previous subinterval, water inflow, and water discharge. All the parameters must be supervised so that the following equality is exactly met.

$$RV_{hp,i-1} - RV_{hp,i} + WI_{hp,i} - Q_{hp,i} = 0,\ i = 1,\ 2, \ldots, N_s \tag{2}$$

Note that $RV_{hp,i-1}$ is equal to $V_{hp,0}$, if $i = 1$, and $RV_{hp,i}$ is equal to $RV_{hp,Ns}$, if $i = N_s$.

Initial and Final Volumes Constraints: $V_{hp,0}$ and $V_{hp,Ns}$ in constraint (2) should be equal to two given parameters, as shown in the model below.

$$RV_{hp,0} = RV_{hp,start} \tag{3}$$

$$RV_{hp,N_s} = V_{hp,end} \tag{4}$$

For each operating day, initial volume, $RV_{hp,start}$, and final volume, $RV_{hp,end}$, of each reservoir are required to be always exactly met.

Reservoir Operation Limits: Water volume of reservoirs must be within the upper and lower limits in order to assure that the water head is always in operation limits. Therefore, the following inequality is an important constraint.

$$RV_{hp,min} \leq RV_{hp,i} \leq RV_{hp,max}, \begin{cases} hp = 1,\ 2, \ldots,\ N_h \\ i = 1,\ 2, \ldots, N_s \end{cases} \tag{5}$$

Limits of Discharge Through Turbines: Turbines of each hydropower plant is safe, if the water discharge through them does not exceed the limits. Both upper and lower limits have a huge meaning for the safety and stable operation of turbines. Thus, the following constraints are considered.

$$q_{hp,min} \leq q_{hp,i} \leq q_{hp,max}, \begin{cases} hp = 1,\ 2, \ldots,\ N_h \\ i = 1,\ 2, \ldots, N_s \end{cases} \tag{6}$$

where $q_{hp,i}$ is determined as follows:

$$q_{hp,i} = x_{hp} + y_{hp}PH_{hp,i} + z_{hp}\left(PH_{hp,i}\right)^2 \tag{7}$$

In addition, the total discharge of each subinterval is determined as follows:

$$Q_{hp,i} = t_i q_{hp,i} \tag{8}$$

Limits of Hydropower Plant Generators: The power generation of each hydropower plant must follow the inequality below, to assure the safe operation of generators all the time.

$$PH_{hp,min} \leq PH_{hp,i} \leq PH_{hp,max}, \begin{cases} hp = 1,\ 2, \ldots,\ N_h \\ i = 1,\ 2, \ldots, N_s \end{cases} \tag{9}$$

2.2.2. Constraint of Thermal Power Plant

It is supposed that thermal power plants have plentiful fossil fuel and their energy is not constrained. However, thermal power plant generators have to satisfy physical limits similar to generators of hydropower plants. Namely, the power generation is limited as follows:

$$PT_{tp,min} \leq PT_{tp,i} \leq PT_{tp,max}, \begin{cases} tp = 1, 2, \ldots, N_t \\ i = 1, 2, \ldots, N_s \end{cases} \tag{10}$$

2.2.3. Constraints of Power Systems

Power systems require the balance between the generated and consumed power for the stable voltage and frequency in power systems [38–43]. The power generation of all hydropower plants and thermal power plants, and power consumed by load and lines must follow the equality below:

$$\sum_{tp=1}^{N_t} PT_{tp,i} \sum_{hp=1}^{N_h} PH_{hp,i} + \sum_{w=1}^{N_w} PW_{w,i} - P_{L,i} - P_{TL,i} = 0 \tag{11}$$

2.2.4. Modeling of Wind Uncertainty

Basically, electricity power from wind turbines is highly dependent on wind speed. The operation characteristics of a typical wind turbine are shown in Figure 2. For the figure, wind turbines cannot generate electricity when the wind speed is lower than WV_{in} and higher than WV_{out}. The generated power by wind turbines, shown in Figure 2, can be also formulated as follows [43,44]:

$$PW_w = \begin{cases} 0, & (WV_w < WV_{in} \text{ and } WV_w > WV_{out}) \\ \frac{(WV_w - WV_{in})}{(WV_r - WV_{in})} \times PW_{w,rate}, & (WV_{in} \leq WV_w \leq WV_r) \\ PW_{w,r}, & (WV_r \leq WV_w \leq WV_{out}) \end{cases} \tag{12}$$

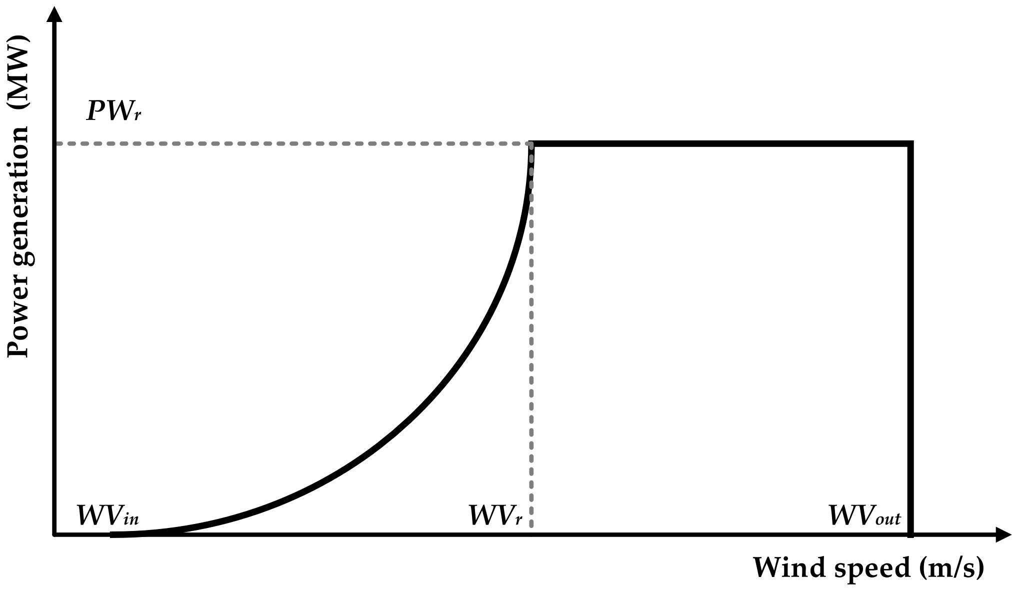

Figure 2. A typical wind turbine characteristic.

3. The Proposed Method

3.1. Conventional Cuckoo Search Algorithm (CSA)

CSA is comprised of two techniques for updating new solutions. The first technique is based on Lévy flights to expand searching space considering very large step sizes. On the contrary, the second technique narrows searching space nearby current solutions, using a mutation operation similar to that in the DE algorithm. Due to different strategies, the first technique is called the exploration phase, whereas the second technique is known as the exploitation phase. The exploration phase is mathematically expressed as follows:

$$So_s^{new} = So_s + \alpha \times (So_s - So_{Gbest}) \otimes \text{Lévy}(\beta) \quad (13)$$

where α is the positive scale factor, which can be selected within the range of 0 and 1; Lévy(β) is the Lévy distribution function [21], and So_{Gbest} is the best solution of the previous iteration.

The exploitation phase can be mathematically expressed as the following mutation technique:

$$So_s^{new} = \begin{cases} So_s + \delta \times (So_1 - So_2), & rd_s < MF \\ So_s, & otherwise \end{cases} \quad (14)$$

where So_1 and So_2 are two randomly generated solutions from the current solutions, rd_s is a randomly generated number within zero and 1, and MF is the mutation factor, which is selected within the range of 0 and 1.

In the exploitation phase, there is a possibility that new solutions cannot be updated, i.e., new solutions and old solutions can be the same. This is particularly the case, given that the mutation factor, MF, is selected to be close to zero, and therefore the possibility that the phenomenon happens is very high. Additionally, it is obvious that new solutions are absolutely updated, if MF is selected to be close to 1.0. Consequently, the searching performance of CSA is highly dependent on the most appropriate value of MF.

3.2. Modified Adaptive Selective Cuckoo Search Algorithm (MASCSA)

The main shortcomings of CSA are indicated in [24], by presenting and analyzing the selection mechanism and mutation mechanism. The two main shortcomings are to miss promising solutions due to the selection mechanism and generate new solutions with low quality, due to the same updated step size of the mutation mechanism. As a result, two modifications are proposed to be the new selection mechanism and the adaptive mutation mechanism. The selection mechanism and the adaptive mutation mechanism are presented in detail as follows:

3.2.1. New Selection Mechanism (NSM)

The selection mechanism in [24] is proposed to retain better solutions in the old and new solution sets. Thus, before implementing the selection between new and old solutions, the old and new solution sets with twice the population are grouped into one. Then, the fitness function is used to sort solutions from the best one to the worst one. Finally, the first population is retained and another one is abandoned.

3.2.2. Adaptive Mutation Mechanism (AMM)

AMM in [24] is applied to use two different sizes of the updated step. In Equation (14), only the step with the deviation between two random solutions is applied. Consequently, the mechanism applies two different sizes for each considered solution, in which the small step size is established by using two solutions, and the large step size is calculated by using four different solutions. The small size and the large size support the formation of new solutions, as shown in the following equations:

$$So_s^{new} = So_s + \delta \times (So_1 - So_2) \tag{15}$$

$$So_s^{new} = So_s + \delta \times (So_1 - So_2) + \delta \times (So_3 - So_4) \tag{16}$$

However, ASCSA has still applied the condition of the comparison between rd_s and MF, shown in Equation (14). Thus, either Equation (15) or Equation (16) is not used if rd_s is higher than MF. Clearly, there is a high possibility that new solutions are not generated if MF is set to close to zero. In order to avoid this shortcoming, MF is set to one in the proposed MASCSA method.

Furthermore, in order to determine the use of either Equation (15) or Equation (16), ASCSA has applied a condition much dependent on a high number of selections. A ratio of fitness function of each considered solution to the fitness function of the best solution is calculated and then the ratio is compared to a threshold, which is suggested to be 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, and 10^{-1}. If the ratio is less than the threshold, Equation (15) is used. Otherwise, Equation (16) is selected. Clearly, the condition is time-consuming, due to the selection of five values for the threshold. Consequently, in order to tackle the main disadvantage of ASCSA, a modified adaptive mutation mechanism is proposed and shown in the next section.

3.2.3. The Modified Adaptive Mutation Mechanism (MAMM)

In the MAMM, the adaptive mutation mechanism in [24] is applied, together with a proposed condition for determining the use of small size or large size in Equations (15) and (16). The fitness function of each solution is determined and defined as FF_s. The fitness function is used to calculate the effective index of each solution and the average effective index of the solutions. The effective index of the s^{th} solution, EI_s, and the average effective index of the whole population, EI_a, are calculated as follows:

$$EI_s = FF_{best}/FF_s \tag{17}$$

$$EI_a = FF_{best}/FF_a \tag{18}$$

where FF_{best} and FF_a are the fitness function of the best solution and the average fitness function of the whole population. In the case that the effective index of the s^{th} solution is less than that of the whole population, the s^{th} solution is still far from the so-far best solution and small size should be used for the s^{th} solution. On the contrary, the s^{th} solution may be close to the so-far best solution and the large size is preferred. In summary, the modified adaptive mutation mechanism can be implemented by the five following steps:

Step 1: Set mutation factor MF to one
Step 2: Calculate the fitness function of the s^{th} solution, FF_s and determine the lowest one, FF_{best}
Step 3: Calculate the mean fitness function of all current solutions, FF_a
Step 4: Calculate EI_s and EI_a using Equations (17) and (18)
Step 5: Compare EI_s and EI_a

If $EI_s < EI_a$, apply Equation (15) for the s^{th} solution.

Otherwise, apply Equation (16) for the s^{th} solution.

Using the AMM [34], ASCSA can jump to promising search zones with appropriate step size, as shown in Equations (15) and (16). However, the condition for applying either Equation (15) or Equation (16) is time-consuming, due to the many values of threshold, including 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, and 10^{-1}. In addition, the mutation factor is also set to the range from 0.1 to 1.0 with ten values. Therefore, it should try (5×10) = 50 values for the ASCSA. This becomes a serious issue of ASCSA in finding the best solution. Therefore, the application of the new condition can enable MASCSA to reach high performance, but the shortcomings of the time-consuming manner can be solved easily.

4. The Application of the Proposed MASCSA Method for OSWHT Problem

4.1. Decision Variables Selection

Solution methods can be applied for an optimization problem with the first step of determining decision variables, which are included in each candidate solution. In the problem, the decision variables are selected to be as follows:

1. Reservoir volume of all hydropower plants at the first subinterval to the $(N_s - 1)^{th}$ subinterval: $V_{hp,i}$, where $hp = 1, \ldots, N_h$ and $i = 1, \ldots, N_s$.
2. Power generation of the first $(N_t - 1)$ thermal power plants for all subinterval: $PT_{tp,i}$, where $tp = 1, \ldots, N_t - 1$ and $i = 1, \ldots, N_s$.

4.2. Handling Constraints of Hydropower Plants

From the constraint of water balance in Equation (2), the total discharge of each subinterval is obtained as follows:

$$Q_{hp,i} = V_{hp,i-1} - V_{hp,i} + WI_{hp,i},\ i = 1,\ 2, \ldots,\ N_s \tag{19}$$

Then, the discharge of each hour is determined using Equation (8), as follows:

$$q_{hp,i} = \frac{Q_{hp,i}}{t_i},\ \begin{cases} hp = 1,\ 2, \ldots,\ N_h \\ i = 1,\ 2, \ldots, N_s \end{cases} \tag{20}$$

As a result, the power generation of hydropower plants can be found using Equation (7).

4.3. Handling Power Balance Constraint

From the power balance constraint shown in (11), the power generation of the $N_t{}^{th}$ thermal power plant is determined as follows:

$$PT_{N_t,i} = P_{L,i} + P_{TL,i} - \sum_{tp=1}^{N_t-1} PT_{tp,i} - \sum_{hp=1}^{N_h} PH_{hp,i} - \sum_{w=1}^{N_w} PW_{w,i} \tag{21}$$

4.4. Fitness Function

The fitness function of each solution is determined to evaluate the quality of the solution. Therefore, the total electricity fuel cost of all thermal power plants and all constraints that have the possibility to be violated are the major terms of the fitness function. As shown in Section 4.1, reservoir volume and power generation of the first $(N_t - 1)$ thermal power plants are the decision variables. Hence, they never violate the limits. However, the discharge of each hour and power generation of hydropower plants, and the last thermal power plant, have a high possibility of violating both the upper and lower limits. Derived from the meaning, the solution quality evaluation function is established as follows:

$$FF_s = TFC + PF_1 \times \sum_{hp=1}^{N_h} \sum_{i=1}^{N_s} \Delta q_{hp,i}{}^2 + PF_2 \times \sum_{hp=1}^{N_h} \sum_{i=1}^{N_s} \Delta PH_{hp,i}{}^2 + PF_3 \times \sum_{i=1}^{N_S} \Delta PT_{N_t,i}{}^2 \tag{22}$$

where PF_1, PF_2, and PF_3 are the penalty factors corresponding to the violation of discharge, power generation of hydropower, and power generation of the last thermal power plant, respectively. $\Delta q_{hp,i}$, $\Delta PH_{hp,i}$, and $\Delta PT_{Nt,i}$ are the penalty terms of discharge, power generation of hydropower plants, and power generation of the last thermal power plants. The penalty terms in Equation (22) are determined as follows:

$$\Delta q_{hp,i} = \begin{cases} \left(q_{hp,i} - q_{hp,max}\right), & q_{hp,i} > q_{hp,max} \\ \left(q_{hp,min} - q_{hp,i}\right), & q_{hp,i} < q_{hp,min} \\ 0, & otherwise \end{cases} \tag{23}$$

$$\Delta PH_{hp,i} = \begin{cases} \left(PH_{h_p,i} - PH_{h_p,max}\right), & PH_{h_p,i} > PH_{h_p,max} \\ \left(PH_{h_p,min} - PH_{hp,i}\right), & PH_{h_p,i} < PH_{h_p,min} \\ 0, & otherwise \end{cases} \tag{24}$$

$$\Delta PT_{N_t,i} = \begin{cases} \left(PT_{N_t,i} - PT_{N_t,max}\right), & PT_{N_t,i} > PT_{N_t,max} \\ \left(PH_{N_t,min} - PT_{N_t,i}\right), & PT_{N_t,i} < PT_{N_t,min} \\ 0, & otherwise \end{cases} \tag{25}$$

4.5. The Whole Application Procedure of MASCSA for OSWHT Problem

The whole solution process of the optimal scheduling of the wind-hydro-thermal system with the fixed-head short-term model is described in Figure 3, as follows:

Step 1: Set values to P_s and $Iter^{max}$
Step 2: Randomly initialize So_s (s=1, … , P_s) within the lower and upper bounds
Step 3: Calculate $PW_{w,i}$ using Equation (12)
Step 4: Calculate $Q_{hp,i}$, $q_{hp,i}$ and $PH_{hp,i}$ using Equations (19), (20), and (7).
Step 5: Calculate $PT_{Nt,i}$ using Equation (21)
Step 6: Calculate the fitness function using Equations (22)–(25)
Step 7: Determine So_{Gbest} and set current iteration to 1 ($Iter$=1)
Step 8: Generate new solutions using Equation (13) and correct the solutions
Step 9: Calculate $Q_{hp,i}$, $q_{hp,i}$, and $PH_{hp,i}$ using Equation (19), (20), and (7).
Step 10: Calculate $PT_{Nt,i}$ using Equation (21)
Step 11: Calculate fitness function using Equations (22)–(25)
Step 12: Compare FF_s^{new} and FF_s to keep better solutions
Step 13: Generate new solutions using MAMM and correct the solutions
Step 14: Calculate $Q_{hp,i}$, $q_{hp,i}$, and $PH_{hp,i}$ using Equations (19), (20), and (7).
Step 15: Calculate $PT_{Nt,i}$ using Equation (21)
Step 16: Calculate fitness function using Equations (22)–(25)
Step 17: Apply NSM in Section 3.2.1.
Step 18: Determine So_{Gbest}
Step 19: If $Iter$= $Iter^{max}$, stop the solution searching algorithm. Otherwise, set $Iter$= $Iter$+1 and go back to Step 8

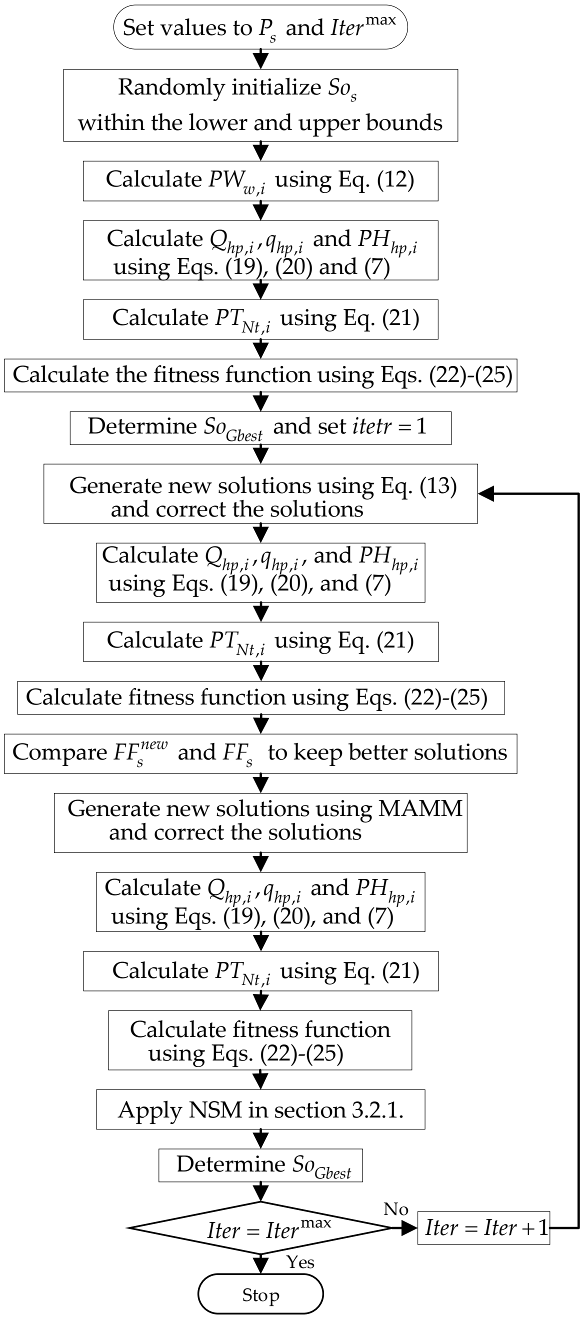

Figure 3. The flowchart for implementing MASCSA for OSWHT problem.

5. Numerical Results

In this section, the performance of the proposed MASCSA is investigated by comparing the results of the proposed method to those from other implemented methods, such as CSA and SDCSA. Two test systems are employed as follows:

1. Test System 1: Four hydropower plants and four thermal power plants with valve effects are optimally scheduled over one day with twenty-four one-hour subintervals. The data of the system are modified from Test System 1 in [7] and also reported in Tables A1–A3 in the Appendix A.
2. Test System 2: Four hydropower plants, four thermal power plants, and two wind farms with the rated power of 120 MW and 80 MW are optimally scheduled over one day with twenty-four

one-hour subintervals. The data of the hydrothermal system are taken from Test System 1 while wind data are taken from [45] and also reported in Table A3 in the Appendix A.

The implemented methods are coded on MATLAB and a personal computer with the CPU of Intel Core i7-2.4GHz, RAM 4GB for obtaining 50 successful runs. The optimal generations of two systems are reported in Tables A4 and A5 in the Appendix A.

5.1. Comparison Results on Test System 1

In this section, the MASCSA is tested on a large hydrothermal system with four hydropower plants and four thermal power plants, considering valve effects scheduled in twenty-four one-hour subintervals. In order to investigate the effectiveness of the MASCSA, CSA and SDCSA are implemented to compare the results. In the first simulation, P_s and $Iter^{max}$ are set to 200 and 5000 for all methods, respectively, but CSA cannot reach successful runs for each of the 50 trial runs. Meanwhile, SDCSA reaches a very low success rate. Then, $Iter^{max}$ is increased to 10,000 with a change of 1000 iterations. SDCSA and MASCSA can reach 100% successful runs at $Iter^{max}$ = 10,000, but CSA only reaches 50 successful runs over 70 trial runs. Results obtained by the implemented methods are summarized in Table 1.

It is noted that the results from CSA, SDCSA, and MASCSA are obtained at P_s = 200 and $Iter^{max}$ = 10,000, with the aim of reaching a higher number of successful runs for CSA and SDCSA. In order to check the powerful searchability of MASCSA over CSA and SDCSA, Figures 4 and 5 are plotted to present less cost and the corresponding level of improvement. Figure 4 indicates that the reduced cost that ASCSA can reach is significant and much increased for average cost and maximum cost. Accordingly, the level of improvement of the minimum cost, average cost, and maximum cost are respectively 0.54%, 1.3% and 2.81% as compared to CSA and 0.29%, 0.92% and 2.75% as compared to SDCSA. Similarly, the improvement of standard deviation is also high, corresponding to 23% and 27.12%, as compared to CSA and SDCSA. The indicated numbers lead to the conclusion that MASCSA is superior over CSA and SDCSA, in terms of finding the best solution and reaching a more stable search process.

In addition, the best run and the average run of 50 successful runs are also plotted in Figures 6 and 7 for search speed comparison. The two figures confirm that MASCSA is much faster than CSA and SDCSA for the best run and the average of all runs. In fact, in Figure 6, the best solution of MASCSA at the 5000th iteration is much better than CSA and SDCSA, and the best solution of MASCSA at the 7000th iteration is also better than that of CSA and SDCSA at the last iteration. This indicates that the speed of MASCSA can be nearly two times faster than CSA and SDCSA. In Figure 7, the average solution of 50 solutions found by MASCSA is also much more effective than that of CSA and SDCSA. The average solution of MASCSA at the 7000th iteration is also better than that of CSA and SDCSA at the last iteration. Clearly, the stability of MASCSA is also nearly twice as good as that of CSA and SDCSA. The whole view of the 50 solutions comparison can be seen by checking Figure 8. Many solutions of MASCSA have lower cost than that of CSA and SDCSA.

In summary, the proposed MASCSA is superior over CSA and SDCSA in finding optimal solutions and reaching a faster search speed for Test System 1. Hence, the proposed modifications of MASCSA are effective for large-scale power systems.

Table 1. Summary of results obtained by CSA, SDCSA, and MASCSA for Test System 1.

Method	CSA	SDCSA	MASCSA
Minimum Cost ($)	35640.09	35550.06	35447.25
Average Cost ($)	36835.21	36694.27	36355.55
Maximum Cost ($)	38616.82	38595.07	37533.4
Std. Dev. ($)	595.36	628.65	458.1301
Computation Time (s)	437.30	498.71	457.92
Success Rate	50/70	50/50	50/50

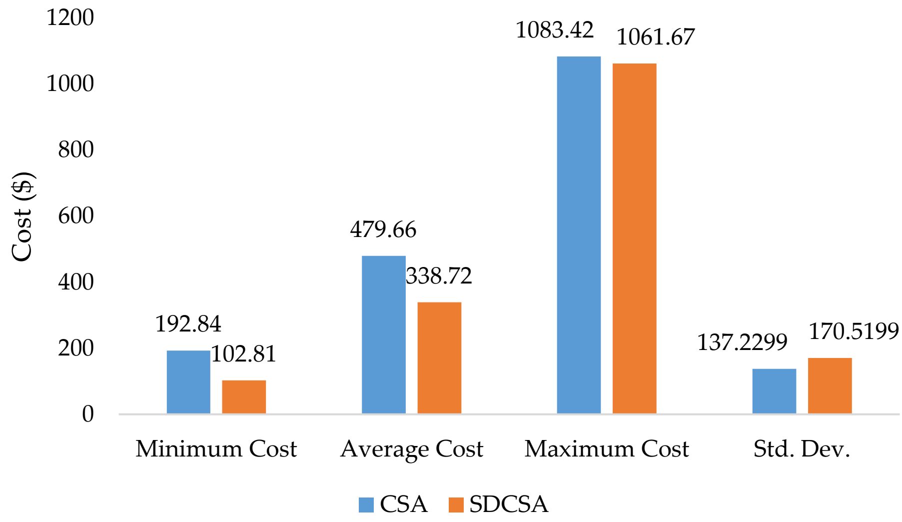

Figure 4. Better cost in $ obtained by MASCSA, compared to CSA and SDCSA, for Test System 1.

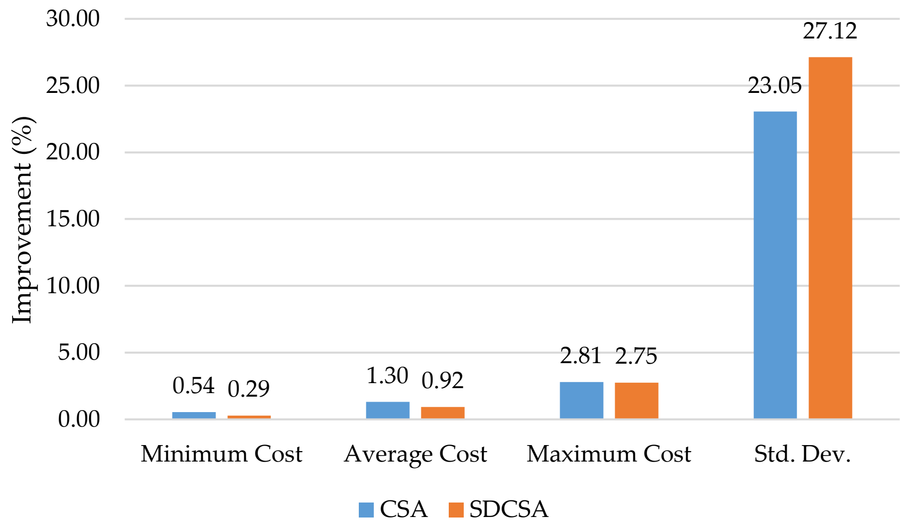

Figure 5. The level of improvement of MASCSA compared with CSA and SDCSA for Test System 1.

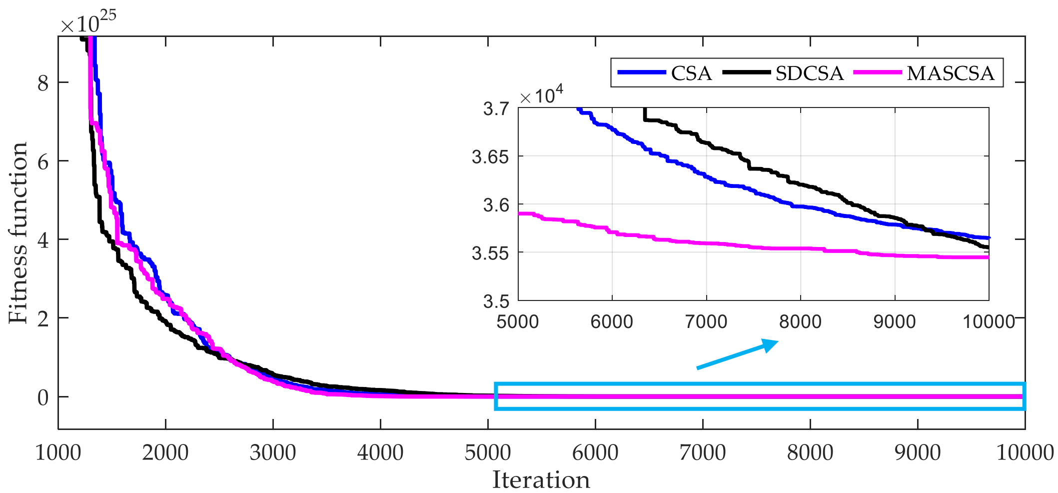

Figure 6. The best convergence characteristics obtained by implemented CSA methods for Test System 1.

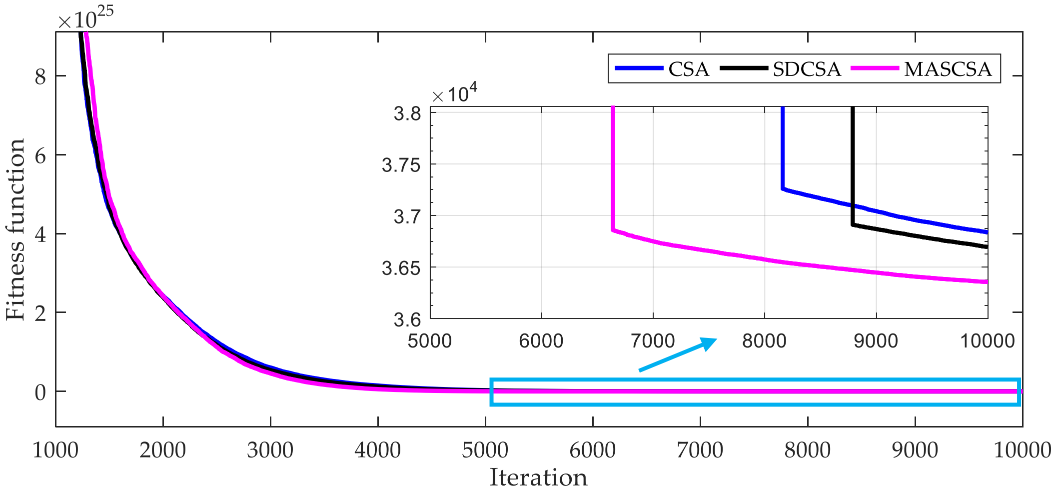

Figure 7. The mean convergence characteristics of 50 successful runs obtained by implemented CSA methods for Test System 1.

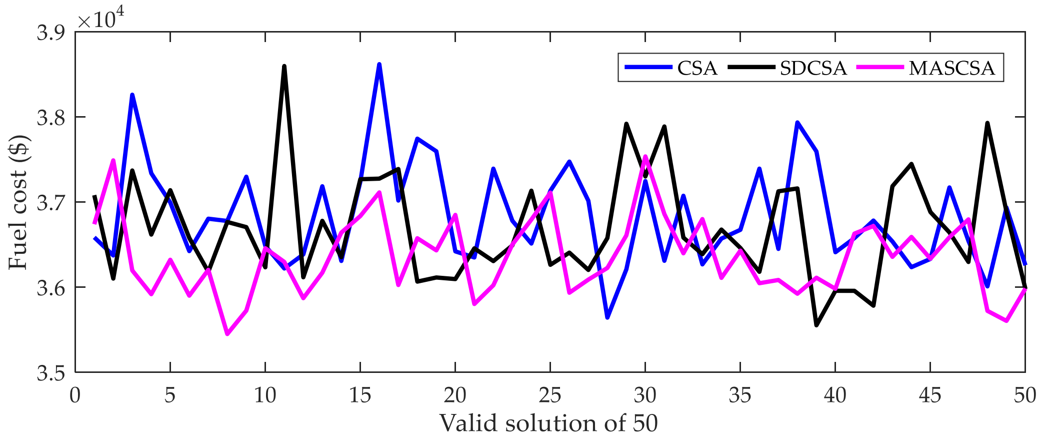

Figure 8. Fitness functions of 50 successful runs obtained by CSA methods for Test System 1.

5.2. Comparison Results on Test System 2

In this section, the implemented methods are tested on a wind-hydro-thermal system. The system is the combination of the hydrothermal system in Test System 1 and two wind farms. The system is optimally scheduled in twenty-four one-hour subintervals. Similar to Test System 1, three CSA methods, including CSA, SDCSA, and MASCSA, are successfully implemented considering all constraints of the system with the initial settings of P_s = 200 and $Iter^{max}$ = 10,000. Accordingly, Table 2 shows the obtained results by CSA, SDCSA, and MASCSA. The key information in this table is the success rate comparison. Meanwhile, the comparison of cost is shown in Figures 9 and 10 for reporting less cost and the corresponding level of improvement of MASCSA over CSA and SDCSA, respectively. It should be emphasized that MASCSA can reach 50 successful runs over 50 trial runs, but the number of trial runs for CSA and SDCSA is much higher, which is 72 runs for CSA and 65 runs for SDCSA. Obviously, the constraint solving performance of MASCSA is much better than CSA and SDCSA. Figure 9 shows the significant cost reduction that MASCSA can reach as compared to CSA and SDCSA. The exact calculation, as compared to CSA and SDCSA, of MASCSA can reduce minimum cost by $685.51 and $422.90, mean cost by $572.95 and $466.75, maximum cost by $447.48 and $291.97, and standard deviation by 49.53 and 72.62. As can be observed from Figure 10, the level of improvement is also high and can be up to 2.46% for minimum cost and 14.69% for standard deviation.

Table 2. Summary of results obtained by CSA, SDCSA, and MASCSA for Test System 2.

Method	CSA	SDCSA	MASCSA
Minimum Cost ($)	27890.67	27628.06	27205.16
Average Cost ($)	28682.37	28576.17	28109.42
Maximum Cost ($)	29793.52	29638.01	29346.04
Std. Dev.	471.41	494.50	421.88
Computation Time (s)	440.5	499. 1	462.4
Success Rate (%)	50/72	50/65	50/50

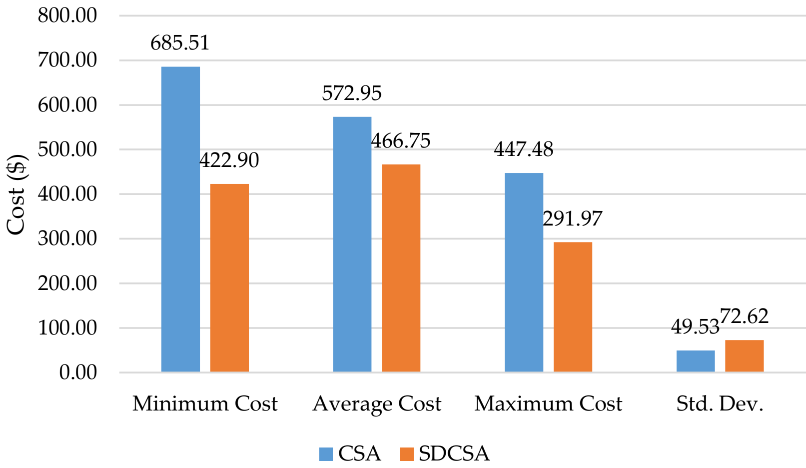

Figure 9. Better cost in $ obtained by MASCSA, compared to CSA and SDCSA for Test System 2.

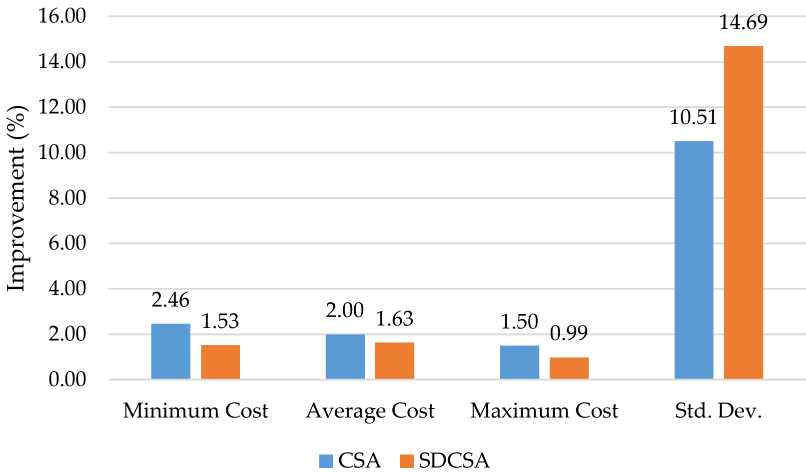

Figure 10. The level of improvement of MASCSA, compared to CSA and SDCSA for Test System 2.

Figures 11 and 12 illustrate the faster search performance of MASCSA than CSA and SDCSA for the best run and the whole search process of 50 successful runs. The pink curves of MASCSA in the two figures are always below the black and blue curves of CSA and SDCSA. The best solution and the mean solution of MASCSA are always more promising than those of CSA and SDCSA at each iteration. Namely, the best solution and the mean solution of MASCSA at the 7000th iteration have lower fitness functions than those of CSA and SDCSA at the 10,000th iteration. Fifty valid solutions shown in Figure 13 indicate that MASCSA can find a high number of better solutions than the best solution of CSA and SDCSA.

In summary, the proposed MASCSA can reach a higher success rate, better solutions, and faster speed than CSA and SDCSA for Test System 2. Consequently, the proposed MASCSA is really effective for the system.

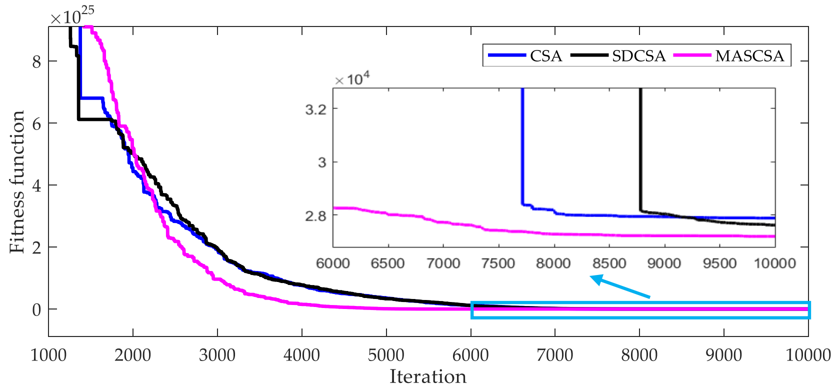

Figure 11. The best convergence characteristics obtained by implemented CSA methods for Test System 2.

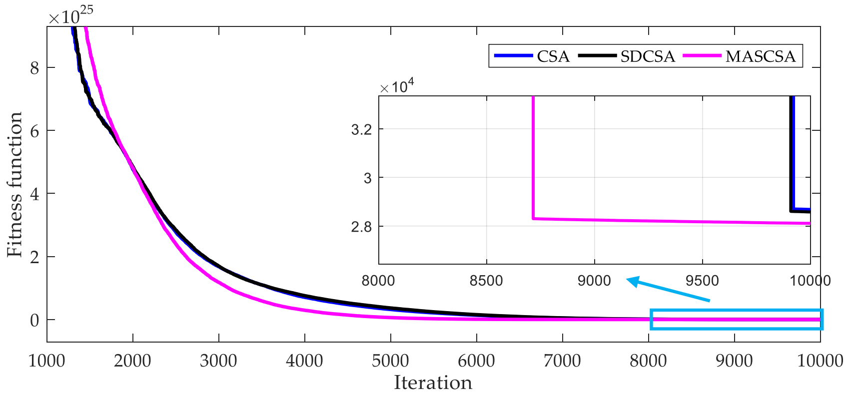

Figure 12. The mean convergence characteristics of 50 successful runs obtained by implemented CSA methods for Test System 2.

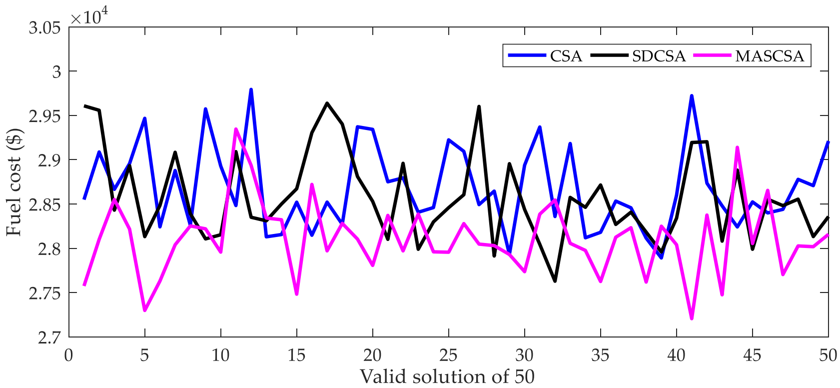

Figure 13. Fitness functions of 50 successful runs obtained by CSA methods for Test System 2.

6. Conclusions

In this paper, a Modified Adaptive Selection Cuckoo Search Algorithm (MASCSA) is implemented for determining the optimal operating parameters of a hydrothermal system and a wind-hydro-thermal system, to minimize the total electricity generation cost from all available thermal power plants. The fixed-head short-term model of hydropower plants is taken into consideration. All hydraulic constraints, such as initial and final reservoir volumes, the upper limit and lower limit of reservoir volume, and water balance of reservoir, are seriously considered. The proposed MASCSA competes with the conventional Cuckoo Search Algorithm (CSA) and Snap-Drift Cuckoo Search Algorithm (SDCSA). Two test systems are employed to run the proposed methods and those CSA methods.

The comparison results indicate that the proposed method is more powerful than CSA and SDCSA in searching for optimal solutions, with much faster convergence. The proposed method can deal with all constraints more successfully and reach much better results. The success rate of the proposed method is 100% for all test cases, while the success rates of the other CSA methods are 0% or much lower than 100%. Furthermore, the proposed method can reach a speed that is twice as fast as CSA and SDCSA. The improvement of the proposed method is significant compared to CSA methods, even when it is over 2%. Consequently, the proposed method is effective for complicated problems with a set of complicated constraints.

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Nomenclature

TFC	Total fuel cost for generating electricity of all thermal power plants
t_i	Number of hours for the i^{th} subinterval
k_{tp}, m_{tp}, n_{tp}, α_{tp}, β_{tp}	Coefficients of the fuel cost function of the ${t_p}^{th}$ thermal power plant
$PT_{tp,i}$	Power generation of the ${t_p}^{th}$ thermal power plant at the i^{th} subinterval
$PT_{tp,min}$	Minimum power generation of the ${t_p}^{th}$ thermal power plant
$PT_{tp,max}$	Maximum power generation of the ${t_p}^{th}$ thermal power plant
N_t	Number of thermal power plants
N_s	Number of subintervals
t_p	Thermal power plant index
h_p	Hydropower plant index
N_w	Number of wind turbines in a wind farm
N_h	Number of hydropower plants
$RV_{hp,i}$	Reservoir volume of the ${h_p}^{th}$ hydropower plant at the end of the i^{th} subinterval
$WI_{hp,i}$	Water inflow into the reservoir of the ${h_p}^{th}$ hydropower plant at the i^{th} subinterval
$Q_{hp,i}$	Total water discharge through turbines of the ${h_p}^{th}$ hydropower plant over the i^{th} subinterval
$RV_{hp,start}$	Available reservoir volume of the ${h_p}^{th}$ hydropower plant before optimal scheduling
$RV_{hp,end}$	Final reservoir volume of the ${h_p}^{th}$ hydropower plant at the end of optimal scheduling
$RV_{hp,Ns}$	Reservoir volume of the ${h_p}^{th}$ hydropower plant at the end of the ${N_s}^{th}$ subinterval
$RV_{hp,min}$	Minimum reservoir volume of the ${h_p}^{th}$ hydropower plant
$RV_{hp,max}$	Maximum reservoir volume of the ${h_p}^{th}$ hydropower plant
$q_{hp,min}$	Minimum discharge per hour through turbines of the ${h_p}^{th}$ hydropower plant
$q_{hp,max}$	Maximum discharge per hour through turbines of the ${h_p}^{th}$ hydropower plant
$q_{hp,i}$	Discharge per hour through turbines of the ${h_p}^{th}$ hydropower plant over the i^{th} subinterval
x_{hp}, y_{hp}, z_{hp}	Discharge function coefficients of the ${h_p}^{th}$ hydropower plant
$PH_{hp,min}$	Minimum power generation of the ${h_p}^{th}$ hydropower plant
$PH_{hp,max}$	Maximum power generation of the ${h_p}^{th}$ hydropower plant
$PT_{tp,max}$	Maximum power generation of the ${t_p}^{th}$ thermal power plant
w	Wind turbine index in the wind farm
$PW_{w,i}$	Power output of the w^{th} wind turbine at the i^{th} subinterval
N_w	Number of wind turbines in a wind farm
PW_w	Power generation of the w^{th} wind turbine
$P_{TL,i}$	Total power loss at the i^{th} subinterval
$P_{L,i}$	Power of load at the i^{th} subinterval
$PW_{w,r}$	Rated generation of the w^{th} turbine
WV_w	Wind speed flowing into the wind turbine
WV_{in}	Cut-in wind speed

WV_r	Rated wind speed
WV_{out}	Cut-out wind speed
$So_s{}^{new}$	The s^{th} new solution
So_s	The s^{th} solution
δ	Randomly generated number within 0 and 1
P_S	Population size
$Iter^{max}$	Maximum number of iterations
FF_s	Fitness function of the s^{th} solution
$FF_s{}^{new}$	Fitness function of the s^{th} new solution

Appendix A

Table A1. Data of thermal units for Test Systems 1 and 2.

Thermal Plant (tp)	k_{tp} ($/h)	m_{tp} ($/MWh)	n_{tp} ($/MW^{2}h)	α_{tp} ($/h)	β_{tp} (rad/MW)	$PT_{tp,\min}$ (MW)	$PT_{tp,\max}$ (MW)
1	60	1.8	0.0011	14	0.04	10	500
2	100	2.1	0.0012	16	0.038	10	675
3	120	1.7	0.0013	18	0.037	10	550
4	40	1.5	0.0014	20	0.035	10	500

Table A2. The data of hydropower plants of Test Systems 1 and 2.

Hydro Plant	x_{hp}	y_{hp}	z_{hp}	$PH_{hp,\min}$ (MW)	$PH_{hp,\max}$ (MW)	$RV_{hp,start}$ (acre-ft)	$RV_{hp,end}$ (acre-ft)	$RV_{hp,min}$ (acre-ft)	$RV_{hp,max}$ (acre-ft)
1	330	4.97	0.0001	0	1000	100,000	80,000	60,000	120,000
2	350	5.20	0.0001	0	1000	100,000	90,000	60,000	120,000
3	280	5.00	0.00011	0	1000	100,000	85,000	60,000	120,000
4	300	4.80	0.00011	0	1000	100,000	85,000	60,000	120,000

Table A3. Load demand and water inflows of Test Systems 1 and 2, and wind speed of Test System 2.

i	$P_{L,i}$ (MW)	$WI_{1,i}$ (acre-ft/h)	$WI_{2,i}$ (acre-ft/h)	$WI_{3,i}$ (acre-ft/h)	$WI_{4,i}$ (acre-ft/h)	$WV_{1,i}$ (m/s)	$WV_{2,i}$ (m/s)
1	1200	1000	800	800	600	13.2500	11.8000
2	1500	600	500	600	600	14.0000	12.0000
3	1100	700	500	700	700	12.7500	12.2000
4	1800	900	700	900	900	11.9000	12.4000
5	1200	900	700	900	900	12.5000	12.5000
6	1300	800	1000	800	800	13.9000	14.0000
7	1200	800	800	800	800	11.8000	15.0000
8	1500	700	800	700	700	12.7500	14.5000
9	1100	500	800	500	500	12.9000	13.0000
10	1800	500	800	500	500	12.2000	13.7500
11	1200	500	1000	500	500	15.0000	13.4000
12	1300	500	500	500	500	13.2500	13.4000
13	1200	800	500	700	800	14.3000	12.8000
14	1500	900	600	500	900	14.1000	12.2500
15	1100	600	600	600	600	14.2500	11.4000
16	1800	500	500	500	900	11.7500	11.5000
17	1200	950	950	950	900	13.7500	11.0000
18	1300	650	650	650	900	12.6000	11.2500
19	1200	550	550	550	700	11.5000	11.1000
20	1500	600	800	600	600	11.9000	11.0000
21	1100	600	800	600	600	14.5000	11.4500
22	1800	350	800	350	700	16.0000	11.8000
23	1200	600	1000	600	600	12.7000	11.7500
24	1300	400	400	800	800	13.0000	12.2500

Table A4. Optimal generations obtained by MASCSA for Test System 1.

i	$PH_{1,i}$ (MW)	$PH_{2,i}$ (MW)	$PH_{3,i}$ (MW)	$PH_{4,i}$ (MW)	$PT_{1,i}$ (MW)	$PT_{2,i}$ (MW)	$PT_{3,i}$ (MW)	$PT_{4,i}$ (MW)
1	44.80801	14.16502	490.1285	87.41643	89.3452	12.62116	88.98154	372.5341
2	609.7317	143.2493	12.82028	307.1734	23.53235	230.9884	137.2026	35.30191
3	109.6465	37.35409	2.452622	124.6044	28.81944	257.5346	262.3531	277.2352
4	118.6829	209.1928	666.0213	297.5565	12.51122	258.6675	166.9801	70.38769
5	56.98094	45.39613	206.5053	160.3263	78.1622	171.7098	110.8455	370.0738
6	503.2596	29.56263	129.0674	139.9014	22.80823	14.94842	269.5132	190.939
7	36.86074	25.08108	68.49895	347.292	94.01591	54.25231	265.6672	308.3319
8	354.087	119.3664	422.4064	22.18463	10.79384	40.37366	317.7927	212.9954
9	144.103	61.76661	44.56178	516.3614	25.04571	33.71163	15.01317	259.4367
10	655.2274	16.59057	91.88618	456.164	18.12036	176.5345	92.90249	292.5745
11	278.88	388.1928	55.58513	137.1538	91.58185	54.79326	122.1367	71.67637
12	139.7707	155.1218	691.5244	9.54121	32.3046	26.83425	147.7469	97.15622
13	303.2588	157.3504	313.9772	31.71765	83.83766	57.62889	109.2016	143.0277
14	10.34539	272.7907	410.6611	120.8436	18.08671	88.22264	305.0479	274.0019
15	88.28575	72.00485	91.75589	3.615984	125.1402	258.6483	264.4204	196.1286
16	202.7669	355.5148	124.7267	413.8378	21.4753	38.13277	185.3267	458.2191
17	405.6118	173.3598	65.81836	191.381	172.3582	81.61249	16.90782	92.95048
18	53.41923	578.2875	32.04454	36.24217	14.19755	206.3252	17.42234	362.0615
19	25.19439	55.43374	107.4736	606.1157	10.38145	17.65185	349.2747	28.47448
20	113.4698	387.7457	218.9941	476.7102	36.44216	61.98075	94.40057	110.2567
21	21.36867	45.56289	68.42235	0.01089	83.52566	176.4324	517.9546	186.7225
22	781.8121	182.5285	84.45162	206.7152	12.23156	10.00549	152.9166	369.3391
23	32.86834	39.96427	319.6729	24.81205	163.4837	28.45411	231.0542	359.6904
24	488.9518	0.799135	14.99782	405.5991	13.56384	100.0802	197.855	78.15313

Table A5. Optimal generations obtained by MASCSA for Test System 2.

i	$PH_{1,i}$ (MW)	$PH_{2,i}$ (MW)	$PH_{3,i}$ (MW)	$PH_{4,i}$ (MW)	$PT_{1,i}$ (MW)	$PT_{2,i}$ (MW)	$PT_{3,i}$ (MW)	$PT_{4,i}$ (MW)	$PW_{1,i}$ (MW)	$PW_{2,i}$ (MW)
1	16.85933	229.55	0.134587	148.8408	159.2501	36.35852	424.1347	31.472	99	54.4
2	109.9363	124.1835	450.167	129.3755	19.29588	30.2673	195.5862	277.1883	108	56
3	156.1532	89.33193	29.22211	424.3342	40.3847	18.70972	82.69941	108.5647	93	57.6
4	513.1342	271.1357	94.45502	420.9233	72.21183	249.6429	19.60898	16.88815	82.8	59.2
5	51.90915	130.3908	245.2019	379.6717	14.69276	115.6292	98.70234	13.80215	90	60
6	294.8739	11.9783	196.5268	34.98355	93.87338	35.32824	182.5234	271.1124	106.8	72
7	416.6924	85.92395	8.473279	179.9067	101.4721	22.10531	97.93109	125.8952	81.6	80
8	351.3595	155.4003	202.7161	240.5383	12.53609	48.06011	38.52946	281.8602	93	76
9	389.9609	30.64644	54.04259	10.0147	102.4636	86.01121	77.38582	190.6748	94.8	64
10	720.8998	144.4804	329.3808	181.5187	93.46645	33.37868	10.59862	129.8766	86.4	70
11	240.2481	189.7078	86.89813	349.9913	24.03108	13.15772	96.695	12.07097	120	67.2
12	244.4353	271.5002	395.8987	77.36695	41.96806	47.50929	45.08705	10.03442	99	67.2
13	168.0087	16.65194	56.36502	475.7266	11.10658	12.34142	73.02665	212.7731	111.6	62.4
14	388.4088	216.0905	196.185	6.14652	29.35371	72.20059	179.7867	244.6281	109.2	58
15	56.27707	87.74482	73.2046	34.60997	52.19771	161.4649	181.1577	291.1432	111	51.2
16	69.37554	645.5049	83.869	471.2085	10.57164	87.95043	180.7956	117.7243	81	52
17	24.40547	27.2146	408.8432	236.6929	27.55716	134.5309	146.7204	41.03535	105	48
18	402.7853	12.41216	333.9288	4.44101	33.34047	169.246	103.3128	99.33338	91.2	50
19	64.22907	202.1967	35.74582	90.85649	14.28666	246.1285	98.05939	321.6974	78	48.8
20	295.1399	75.00936	206.4338	254.5644	83.71423	100.8545	186.706	166.7778	82.8	48
21	36.08288	120.2875	402.702	24.58846	64.47947	139.7841	41.62437	104.8512	114	51.6
22	0.695207	18.65639	438.5363	708.044	58.3994	75.50154	141.1705	184.5967	120	54.4
23	178.9307	341.9207	198.9793	80.87282	22.25196	29.93504	10.96953	189.7399	92.4	54
24	396.5688	69.67454	216.289	157.7857	27.38508	154.2192	88.0156	36.06202	96	58

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