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Hydro-Thermal-Wind Generation Scheduling Considering Economic and Environmental Factors Using Heuristic Algorithms

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Abstract: Hydro-thermal-wind generation scheduling (HTWGS) with economic and environmental factors is a multi-objective complex nonlinear power system optimization problem with many equality and inequality constraints. The objective of the problem is to generate an hour-by-hour optimum schedule of hydro-thermal-wind power plants to attain the least emission of pollutants from thermal plants and a reduced generation cost of thermal and wind plants for a 24-h period, satisfying the system constraints. The paper presents a detailed framework of the HTWGS problem and proposes a modified particle swarm optimization (MPSO) algorithm for evolving a solution. The competency of selected heuristic algorithms, representing different heuristic groups, *viz.* the binary coded genetic algorithm (BCGA), particle swarm optimization (PSO), improved harmony search (IHS), and JAYA algorithm, for searching for an optimal solution to HTWGS considering economic and environmental factors was investigated in a trial system consisting of a multi-stream cascaded system with four reservoirs, three thermal plants, and two wind plants. Appropriate mathematical models were used for representing the water discharge, generation cost, and pollutant emission of respective power plants incorporated in the system. Statistical analysis was performed to check the consistency and reliability of the proposed algorithm. The simulation results indicated that the proposed MPSO algorithm provided a better solution to the problem of HTWGS, with a reduced generation cost and the least emission, when compared with the other heuristic algorithms considered.

Keywords: hydrothermal scheduling; emission and economic dispatch; heuristic algorithms

1. Introduction

The role of optimal generation scheduling of a thermal-renewable power generation system aiming economic and environmental benefits is vital in the current scenario of increasing power demand, escalating the fuel price and high pollution rate. The optimal generation scheduling of a hydro-thermal-wind system aims to distribute the power demand among the generating plants in such a way that the net energy cost and emission of pollutants are minimised, while satisfying the various constraints of power plants. Earlier, the combined operation of hydro-thermal plants was successfully scheduled to reduce the fuel cost, as well as the emission of pollutants. Now, with the development and readiness of new and cost-effective technologies, the penetration of wind power plants in the energy sector has become significant, necessitating its inclusion in the scheduling process. But, research publications describing the optimal generation scheduling of such hybrid energy sources are scanty.

The HTWGS is a non-linear optimization problem with two conflicting objectives. The first approach for solving the HTWGS problem is adopting calculus-based solution techniques (conventional method) such as linear programming [1], dynamic non-linear programming [2], lagrangian relaxation [3], and differential dynamic programming [4], etc. These methods are iterative techniques, containing composite mathematical expressions and long computational steps. Also, they have a limited space to address discrete and non-differentiable problems. The second approach is to adopt heuristic optimization methods which mimic the natural behaviour of certain things or physical phenomena of certain items. This approach gained wide popularity due to the easiness of implementation, adaptability in searching for the best solution, and ability to address non-linear optimization problems. It can be broadly classified as, evolutionary algorithms, swarm intelligence based methods, and algorithms based on the principle of other natural phenomena.

A comprehensive review of short-term hydrothermal scheduling (STHTS) using different classes of heuristic algorithms has been elaborated in [5]. The Genetic Algorithm is applied to generate optimal generation scheduling of a short-term hydrothermal system in [6,7]. An evolutionary algorithm is employed for addressing STHTS in [8,9]. Following evolutionary algorithms, swarm intelligence-based optimisation algorithms received wide acceptance due to the lower number of computational steps and control variables involved. One popular algorithm in this category is particle swarm optimization (PSO). In [10], the PSO method was proposed for STHTS of the multi-reservoir cascaded system. The predator prey optimisation (PPO) technique, which is an extended version of PSO, was suggested in [11] as a solution for STHTS. There are several reports on the use of heuristic algorithms to optimize wind-thermal plant scheduling. An artificial bee colony optimization algorithm was employed for emission and economic dispatch on a wind–thermal system in [12]. A modified particle swarm optimization algorithm influenced by the gravitational search method was adopted to effect emission level reduction in [13]. Many other heuristic algorithms based on natural phenomena and the random optimization process such as Harmony search (HS) and JAYA algorithms have been reported. The HS algorithm [14] mimics the improvisation procedure of an orchestra. A solution to STHTS using the HS algorithm was also proposed in [15]. In [16], a newly introduced population-based heuristic algorithm (JAYA algorithm) was applied for optimal power flow solution. The optimal generation scheduling of a hybrid system consisting of hydro-thermal-wind plants has not often been reported in the literature. The intermittent behavior of wind power is the main hurdle in the massive incorporation of wind plants into the hydrothermal system. Many researchers have addressed the unpredictable nature of wind power using fuzzy logic, neural network, and time series analysis, etc. The Weibull distribution function [17] is suitable for modelling wind speed characteristics with minimum parameters. An incomplete gamma function term is used in [18] to illustrate the wind power impact. In [19], the stochastic wind power was considered as a constraint. The fluctuating nature of wind power can be considerably mitigated by the wind-hydro joint operation since hydropower can be altered rapidly. Some of the associated works on HTWGS were described in [20–24]. Security constrained hydrothermal generation scheduling accounting for the discontinuity and uncertainty of wind power is addressed in [20]. But, in this model, the emission of pollutants from the thermal plant is not accounted for. In [21], the NSGA-III technique is used for computing the optimal allocation load among the hydro-thermal-wind power units. In this paper, the thermal power is modelled as a quadratic polynomial where only limited generator constraints are considered. Reference [22] presents a bee colony optimization method for finding short-term economic/environmental HTWGS, incorporating wind power uncertainty, along with non-linear generator constraints, into the approach. A distributionally robust optimization method is proposed in [23] for solving the hydro-thermal-wind economic dispatch problem. In this paper, the S-lemma method is used to incorporate the wind power uncertainty within a confined set. In [24], the spinning reserve was considered and allocated between the hydro-thermal units to mitigate the challenges that occurred due to the uncertain nature of wind power during HTWGS.

This paper investigates the capability of selected algorithms representing different heuristic groups for searching for the optimal solution for HTWGS considering economic and environmental factors. Here, well accepted and suitable mathematical functions were chosen for addressing the generation cost, emission of pollutants, and water discharge. An improvement is proposed to conventional PSO, named as modified particle swarm optimization (MPSO), and employed to obtain hour-by-hour optimal generation scheduling of integrated hydro-thermal-wind power plants. An optimum solution was searched for using the proposed method (MPSO) and four other algorithms (BGA, PSO, IHS, and JAYA) with a trial system consisting of a multi-reservoir cascaded system with four hydro, three thermal, and two wind power plants. The two objective functions dealing within the problem, namely economic and emission, are of a conflicting nature. Therefore, a balanced optimal operating point was searched for by combining the two objectives and treating it as one function by means of a penalty factor. This approach reduced the computational burden and provided a better compromised solution. A comparison of the results obtained from the various algorithms used has been presented. Among the algorithms employed, the MPSO method exhibited a better performance and capability for searching for a more optimal solution in the test case.

The paper is organized as follows: Section 2 presents the modeling of hydro-thermal-wind generation scheduling considering economic and emission factors. Section 3 illustrates the outline of GA PSO, HS, and JAYA algorithms. Section 4 gives a short description of the MPSO method. Section 5 presents the computational steps of MPSO. The application of the proposed method in a test system and its results are discussed in Section 6. Section 7 summarizes the conclusions.

2. Hydro-Thermal-Wind Generation Scheduling Considering Economic and Environmental Factors

HTWGS deals with the optimal distribution of power demand among existing generation plants so as to reduce the overall generation cost and pollutant emission during the specified period, satisfying the power limit of plants and water constraint of hydro plants of the integrated generation system.

The total cost of generation comprises the coal cost of the thermal plant and rate of wind power only, since the hydro power cost is independent of generation output. Hence, the objective function to be minimized involves the generation cost of thermal and wind power plants and the emission of pollutants. This problem is basically a nonlinear constrained multi-objective optimization problem. The overall objective function is given by:

$$Minimize \quad C_T(F_T, W_T, E_T) \tag{1}$$

where C_T is the overall cost of the generation of thermal-wind plants, F_T is the total fuel cost of thermal plants, W_T is the wind power generation cost, and E_T is the net pollutant emission from thermal plants.

Subject to a number of equality and inequality constraints as follows:

a. *System active power balance:*

$$\sum_{j}^{N_T} P_{gj,\tau} + \sum_{m}^{N_H} P_{hm,\tau} + \sum_{l}^{N_W} w_{l,\tau} = P_{D,\tau} + P_{Loss,\tau} \qquad (\tau = 1, 2, \ldots, T) \tag{2}$$

where N_T, N_H, and N_W are number of thermal, hydro, and wind power plants, respectively; $P_{gj,\tau}$ is the power output of the jth thermal power plant; $P_{hm,\tau}$ is the power output of the mth hydro power plant; $w_{l,\tau}$ is the power output of the lth wind power plant in the sub-interval τ; $P_{D,\tau}$ is the load demand during the sub-interval τ; $P_{Loss,\tau}$ is the transmission loss in the sub-interval τ; and T is the scheduling period.

b. *The dynamic water balance in the reservoir:*

$$V_{hm,\tau} = V_{hm,\tau-1} + I_{hm,\tau} - Q_{hm,\tau} - S_{hm,\tau} + \sum_{l=1}^{R_{um}} \left(Q_{hl(\tau - t_{lm})} + S_{hl(\tau - t_{lm})} \right) \tag{3}$$

where $V_{hm,\tau}$ and $Q_{hm,\tau}$ are the storage volume and water discharge rate of the mth hydro plant in the sub-interval τ, respectively; $I_{hm,\tau}$ and $S_{hm,\tau}$ are the inflow rate and spillage of the mth hydro power plant in the sub-interval τ, respectively; R_{um} is the number of upstream hydro plants directly above the mth hydro power plant; and t_{lm} is the water transport delay from reservoir l to m.

c. *Initial and final reservoir storage volume:*

$$V_{hm,0} = V_{hm,begin} \tag{4}$$

$$V_{hm,T} = V_{hm,end} \tag{5}$$

where $V_{hm,begin}$ and $V_{hm,end}$ are the initial and final storage volume of mth hydro plant, respectively.

d. *Thermal power plant generation limit:*

$$P_{gj}^{\min} \le P_{gj} \le P_{gj}^{\max} \quad (j = 1, 2, \ldots, N_T) \tag{6}$$

where $P_{gj}^{\min}$ and $P_{gj}^{\max}$ are the minimum and maximum power output of the jth thermal power plant, respectively.

e. *Hydro power plant generation limit:*

$$P_{hm}^{\min} \le P_{hm} \le P_{hm}^{\max} \quad (m = 1, 2, \ldots, N_H) \tag{7}$$

where $P_{hm}^{\min}$ and $P_{hm}^{\max}$ are the minimum and maximum power output of the mth hydro power plant, respectively.

f. *Wind power plant generation limit:*

$$0 \le w_l \le w_{r,l} \quad (l = 1, 2, \ldots, N_W) \tag{8}$$

where w_{rl} is the rated power output of the lth wind power plant.

g. *Reservoir storage volume and discharge limit:*

$$V_{hm,\tau}^{\min} \le V_{hm,\tau} \le V_{hm,\tau}^{\max} \tag{9}$$

$$Q_{hm,\tau}^{\min} \le Q_{hm,\tau} \le Q_{hm,\tau}^{\max} \tag{10}$$

where $V_{hm,\tau}^{\min}$, $V_{hm,\tau}^{\max}$ and $Q_{hm,\tau}^{\min}$, $Q_{hm,\tau}^{\max}$ are the minimum and maximum reservoir volume and water discharge of the mth hydro plant, respectively.

The hydro units power output is expressed as a function of reservoir volume and head [25] given by:

$$P_{hm,\tau} = C_{1m} V_{hm,\tau}^2 + C_{2m} Q_{hm,\tau}^2 + C_{3m} V_{hm,\tau} Q_{hm,\tau} + C_{4m} V_{hm,\tau} + C_{5m} Q_{hm,\tau} + C_{6m} \tag{11}$$

where C_{1m}, C_{2m}, C_{3m}, C_{4m}, C_{5m}, and C_{6m}, are the generation coefficients of the mth hydro plant in the sub-interval τ.

In the present work, the multi-objective HTWGS considering economic and emission factors is modified into a single objective optimization problem using a penalty factor [26]. The penalty factor converts the emission to the indirect cost of emission and hence allows treating fuel costs and emission together. Thus, the total cost of the thermal system is the sum of the fuel cost and the indirect cost of emission. The penalty factor h_j is given by the equation:

$$h_j = \frac{F_j(P_{gj}^{\max})}{E_j(P_{gj}^{\max})} \qquad \$/lb \tag{12}$$

Thus, the objective function (1) can be modified as:

$$Minimize \quad C_T(F_T + h * E_T, W_T) \tag{13}$$

The fuel cost function of the thermal plant is expressed as a quadratic function of the real power output [27]. The valve-point effects are taken into account by incorporating a sinusoidal term in the cost function [28]. Consider a grid system with N_H hydro, N_T thermal, and N_W wind power plants. The objective of the problem is to reduce the energy cost of the hydro-thermal-wind system through optimal generation scheduling considering economic and emission factors. The fuel cost function of thermal power plant is denoted by:

$$F_T = \sum_{\tau=1}^{T}\sum_{j=1}^{N_T} F_j(P_{gj,\tau}) = \sum_{\tau=1}^{T}\sum_{j=1}^{N_T} a_j P_{gj,\tau}^2 + b_j P_{gj,\tau} + c_j + \left| e_j \sin(h_j(P_{gj}^{\min} - P_{gj,\tau})) \right| \tag{14}$$

where $F_j(P_{gj,\tau})$ is the fuel cost function of the jth thermal power plant in the sub-interval τ in \$/h. $P_{gi,\tau}$ is the power output of the jth thermal power plant in the sub-interval τ in MW. a_j, b_j, c_j are the fuel cost coefficients and h_j, e_j are the coefficients of the valve point effect of the jth power thermal plant. $P_{gj}^{\min}$ is the minimum power output of the jth thermal plant.

The pollutant emission from a coal-based power plant depends on the power output of that plant. The total emission of pollutant E can be expressed [22] as:

$$E_T = \sum_{\tau=1}^{T}\sum_{j=1}^{N_T} E_j(P_{gj,\tau}) = \sum_{\tau=1}^{T}\sum_{j=1}^{N_T} \alpha_j P_{gj,\tau}^2 + \beta_j P_{gj,\tau} + \gamma_j + \eta_j e^{\delta_j P_{gj,\tau}} \quad lb/h \tag{15}$$

where α_j, β_j, γ_j, η_j, and δ_j are the coefficients of emission of the jth thermal plant.

The total operating cost of a wind-powered generator consists of three components: (a) direct cost, (b) cost for not utilizing existing wind power (underestimation), and (c) overestimation cost [13]. The cost function of a wind generator is formulated as:

$$W_T = \sum_{\tau=1}^{T}\sum_{l=1}^{N_W}(C_{d,l}(w_{l,\tau}) + C_{u,l}(W_{l,avl} - w_{l,\tau}) + C_{o,l}(w_{l,\tau} - W_{l,avl})) \tag{16}$$

where $C_{d,l}$ is the direct cost function of the wind power plant l. $w_{l,\tau}$ is the scheduled wind power output of plant l in the sub-interval τ in MW. $C_{u,l}$ is the penalty cost function for underestimation and $C_{o,l}$ is the penalty cost function for overestimation of the lth wind power plant. $W_{l,avl}$ is the available power of the lth wind power plant.

Direct cost is involved when the utility is purchasing the power from the wind farm, which is expressed as a linear cost function of actual power usage.

$$C_{d,l}(w_{l,\tau}) = d_l w_{l,\tau} \qquad (l = 1, 2, \ldots, N_W; \quad \tau = 1, 2, \ldots, T) \tag{17}$$

where d_l is the coefficient of direct cost of the lth wind plant.

The underestimation and overestimation of wind power are mainly due to the uncertainty involved in the available wind power. The power output of a wind turbine depends on the blowing strength of the wind, which relies on many environmental parameters. Hence a reliable and accurate prediction of wind energy is difficult. In this paper, the uncertain nature of the wind generation is accounted for by a probability distribution function. The wind speed frequency distribution can supply a clear-cut picture about the wind speed pattern of a given location. Then, a proper statistical function can be fitted to express the wind speed distribution mathematically.

The penalty cost due to the underestimation of wind energy occurs when the available wind power is more than the predicted power (or actual wind power used), and the system operator should then pay a reasonable amount to the utility to compensate for the wastage of available wind power. Conversely, if the available wind power is less than the expected power (or actual wind power needed), then the system operator should purchase power from alternative sources or the load must be shut down.

The expression for penalty cost corresponding to underestimation and overestimation of wind power presented in [17] was used in this work. The penalty cost function for underestimation of the wind power plant l in the sub-interval τ is expressed as a linear relation showing the difference between available wind power and actual wind power, and is given by:

$$C_{u,l}(W_{l,avl} - w_{l,\tau}) = k_{u,l} \times \int_{w_{l,\tau}}^{w_{r,l,\tau}} (w - w_{l,\tau}) \times f_W(w)\, dw \tag{18}$$

where $k_{u,l}$ is the cost coefficient of underestimation of wind power plant l. $w_{r,l,\tau}$ is the rated wind power output of the unit l in the sub-interval τ. $f_W(w)$ is the probability density function (PDF) of wind power.

The penalty cost function for overestimation of the lth wind power plant in the sub-interval τ is given by:

$$C_{o,l}(w_{l,\tau} - W_{l,avl}) = k_{o,l} \times \int_{0}^{w_{l,\tau}} (w_{l,\tau} - w) \times f_W(w)\, dw \tag{19}$$

where $k_{o,l}$ is the cost coefficient of overestimation of the wind power plant l.

Modelling of Wind Speed and Power

The numerical value of the underestimation and overestimation cost is obtained only by assuming a proper statistical function for the wind power output. Weibull distribution is the most popular distribution function, which closely follows the wind speed profile [17,19]. The Weibull probability density function is expressed as:

$$f_v(v) = \left(\frac{\kappa}{c}\right) \times \left(\frac{v}{c}\right)^{(\kappa-1)} \times \exp^{-\left(\frac{v}{c}\right)^{(\kappa)}}, 0 < v < \infty \tag{20}$$

where v is the wind speed of the given location. κ and c are the shape parameter and scale parameter, respectively.

The wind turbine power output can be mathematically expressed [22] as:

$$w = \begin{cases} 0 & (v < v_{in} \text{ and } v > v_o) \\ w_r \times \frac{(v - v_{in})}{(v_r - v_{in})} & (v_{in} \le v \le v_r) \\ w_r & (v_r \le v \le v_o) \end{cases} \tag{21}$$

where w is the power output of the wind turbine (kW or MW); w_r is the rated wind power output; and v_{in}, v_r, and v_o are the cut-in, rated, and cut-out wind speed, respectively.

Thus, the wind turbine power output is a combination of discrete and continuous random variables, ie, wind turbine power output is a discrete random variable between v_r and v_o and also a continuous random variable between v_{in} and v_r.

The Weibull probability distribution function can be obtained for three portions of wind power output, described in Equation (23).

$$\begin{aligned} P(w = 0) &= P(v < v_{in}) + P(v > v_o) \\ &= F_V(v_{in}) + (1 - F_V(v_o)) \\ &= 1 - \exp^{-\left(\frac{v_{in}}{c}\right)^{(\kappa)}} + \exp^{-\left(\frac{v_o}{c}\right)^{(\kappa)}} \end{aligned} \tag{22}$$

and

$$\begin{aligned} P(w = w_r) &= P(v_r \leq v \leq v_o) \\ &= F_V(v_o) - F_V(v_r) \\ &= \exp^{-(\frac{v_r}{c})^{(\kappa)}} + \exp^{-(\frac{v_o}{c})^{(\kappa)}} \end{aligned} \tag{23}$$

The Weibull PDF for the continuous range of wind power output equation is expressed as:

$$f_W(w) = \frac{\kappa \sigma v_{in}}{w_r c} \left(\frac{(1 + \phi\sigma) \times v_{in}}{c} \right)^{(\kappa - 1)} \exp^{-(\frac{(1+\phi\sigma)\times v_{in}}{c})^{(\kappa)}} \tag{24}$$

where $\phi = \frac{w}{w_r}$ and $\sigma = \frac{(v_r - v_{in})}{v_{in}}$.

3. Outline of GA PSO, HS, and JAYA Algorithms

3.1. Genetic Algorithm (GA)

GA is an evolutionary-based computation technique that mimics the genetic evolution process. Initially, a set of chromosomes called a population, representing the encoded control parameters, are randomly generated within the search space. The chromosomes are evaluated based on the fitness value derived from the objective function and a new population is generated. The process is repeated until the global optimum point is reached.

3.2. PSO Algorithm

The PSO algorithm is the mathematical simulation of the social behavior of fish schooling or birds' flocking [26]. The particles constitute a swarm (or group), moving along the solution space searching for an optimal solution. Each particle knows its earlier position (x_k), and the best value (*pbest*) achieved so far. Among the best position of individuals, the optimal value is denoted as *gbest*. Each individual in the subsequent search attempts to improve the earlier status through the present speed, best position, and *gbest*.

The following equations are used to compute the new velocity and position of each particle.

$$v_k{}^{(r+1)} = C_f \left[wt\, v_k{}^{(r)} + c_1 rand_1 \left(pbest_k - x_k^{(r)} \right) + c_2 rand_2 \left(gbest_k - x_k^{(r)} \right) \right] \tag{25}$$

$$x_k{}^{(r+1)} = x_k^{(r)} + v_k{}^{(r+1)} \tag{26}$$

where C_f is the constriction factor; $rand_1$ and $rand_2$ are the random numbers between 0 and 1; $v_k^{(r)}$ and $x_k^{(r)}$ are the velocity and position of the *k*th particle at *r*th iteration, respectively; *wt* is the inertia weight; and c_1, c_2 are the learning factors.

The constriction factor is used to improve the search procedure [28], given by:

$$C_f = \frac{2}{\left| 2 - \psi - \sqrt{\psi - 4\psi} \right|} \tag{27}$$

where $\psi = c_1 + c_2$, $\psi > 4$.

In order to attain a balance among the local and global search, an inertia weight parameter is introduced, which is given by the equation:

$$wt = wt_{\max} - \frac{(wt_{\max} - wt_{\min}) \times r}{r_{\max}} \tag{28}$$

where r is the iteration count and $r_{\max}$ is the maximum number of iterations.

3.3. Harmony Search (HS) Algorithm

The HS algorithm simulates the improvisation procedure of music players to obtain better harmony among the instruments by adjusting the pitches of the instrument [29]. The harmony of instruments resembles the optimization of variables and the improvisation procedure of an orchestra is akin to the local and global search process. A harmony memory (*HM*) is initialized with randomly generated control variables within the search space. New *HM* (*NHM*) is created on the basis of the memory consideration rate (*HMCR*), pitch alteration (*PAR*), band width (*bw*), and random choice. The fitness of each *NHM* vector is evaluated on the basis of objective function and the corresponding *HM* vector is replaced, if improvement is exhibited in the *NHM* vector.

PAR and *bw* parameters are significant in refining the solution vectors and influence the convergence rate of the algorithm. The Improved Harmony Search algorithm uses a dynamically varying *PAR* and *bw* in the search process.

3.4. JAYA Algorithm

JAYA is a population-based optimization algorithm developed by Venkata Rao [30] in 2016. This algorithm does not involve any specific tuning parameters. The optimization process follows the procedure of solution search by shifting towards the optimum solution, avoiding the inferior solution. A population consisting of candidate solution vectors is randomly generated within the search space. The fitness of each candidate solution is evaluated, and the *best* and *worst* candidates are identified. Each candidate solution is updated based on the best and worst solutions using Equation (29).

$$X'_{j,i,k} = X_{j,i,k} + rand_1\left(X_{j,best,k} - \left|X_{j,i,k}\right|\right) - rand_2\left(X_{j,worst,k} - \left|X_{j,i,k}\right|\right) \tag{29}$$

where $X_{j,i,k}$ is the value of the jth variable for the ith candidate during the kth iteration; $X'_{j,i,k}$ is the updated value; $X_{j,best,k}$ and $X_{j,worst,k}$ are the best and worst solutions, respectively; and $rand_1$ and $rand_2$ are the two random numbers in the range [0, 1].

4. Modified Particle Swarm Optimization (MPSO)

The conventional PSO keeps the randomness of search by maintaining normal random values in the velocity computation equation of each particle. In this case, the velocity calculation of each particle assigns different random values. In the proposed modified particle swarm optimization algorithm, a unique random value is assigned to individual search (*pbest*) part of the velocity calculation for the population in one iteration. Also, in the global search (*gbest*) part of the velocity equation, each particle is assigned different random values. This modification shows improvement in the individual search process and is able to explore more optimal solutions compared with conventional PSO.

In MPSO, the equation to update velocity is modified as below.

$$v_k{}^{(r+1)} = C_f\left[wt\ v_i{}^{(r)} + c_1 rand^{(r)}\left(pbest_k - x_k^{(r)}\right) + c_2 rand_k^{(r)}\left(gbest_k - x_k^{(r)}\right)\right] \tag{30}$$

where $rand^{(r)}$ is a uniform random number between 0 and 1 for the rth iteration of the population. $rand_k{}^{(r)}$ is the random number of the kth particle in the rth iteration.

5. Solving HTWGS Considering Economic and Emission Factors Using MPSO

The solution technique begins with the illustration of the candidate solution (or decision variables) denoted as the particle. In this study, the decision variables in the optimization process are the thermal power output, the quantity of water discharged, and wind power output (i.e., $P_{gj,\tau}$, $q_{m,\tau}$, and $w_{n,\tau}$). Thus, each particle carries a solution to these variables and searches for optimal values in the subsequent iteration. Hence, for a scheduling period T, the kth particle x_k is expressed as:

$$x_k = \begin{bmatrix} P_{g1,1,j} & \cdots & P_{g1,N_T,j} & q_{1,1,m} & \cdots & q_{1,N_H,m} & w_{1,1,l} & \cdots & w_{1,N_W,l} \\ \vdots & P_{\tau,k,j} & \vdots & \vdots & q_{\tau,k,m} & \vdots & \vdots & w_{\tau,k,l} & \vdots \\ P_{gT,1,j} & \cdots & P_{gT,N_T,j} & q_{T,1,m} & \cdots & q_{T,N_H,m} & w_{T,1,l} & \cdots & w_{T,N_W,l} \end{bmatrix} \quad (31)$$

The computational steps of the proposed MPSO method are as follows, and the flow chart is shown in Figure 1.

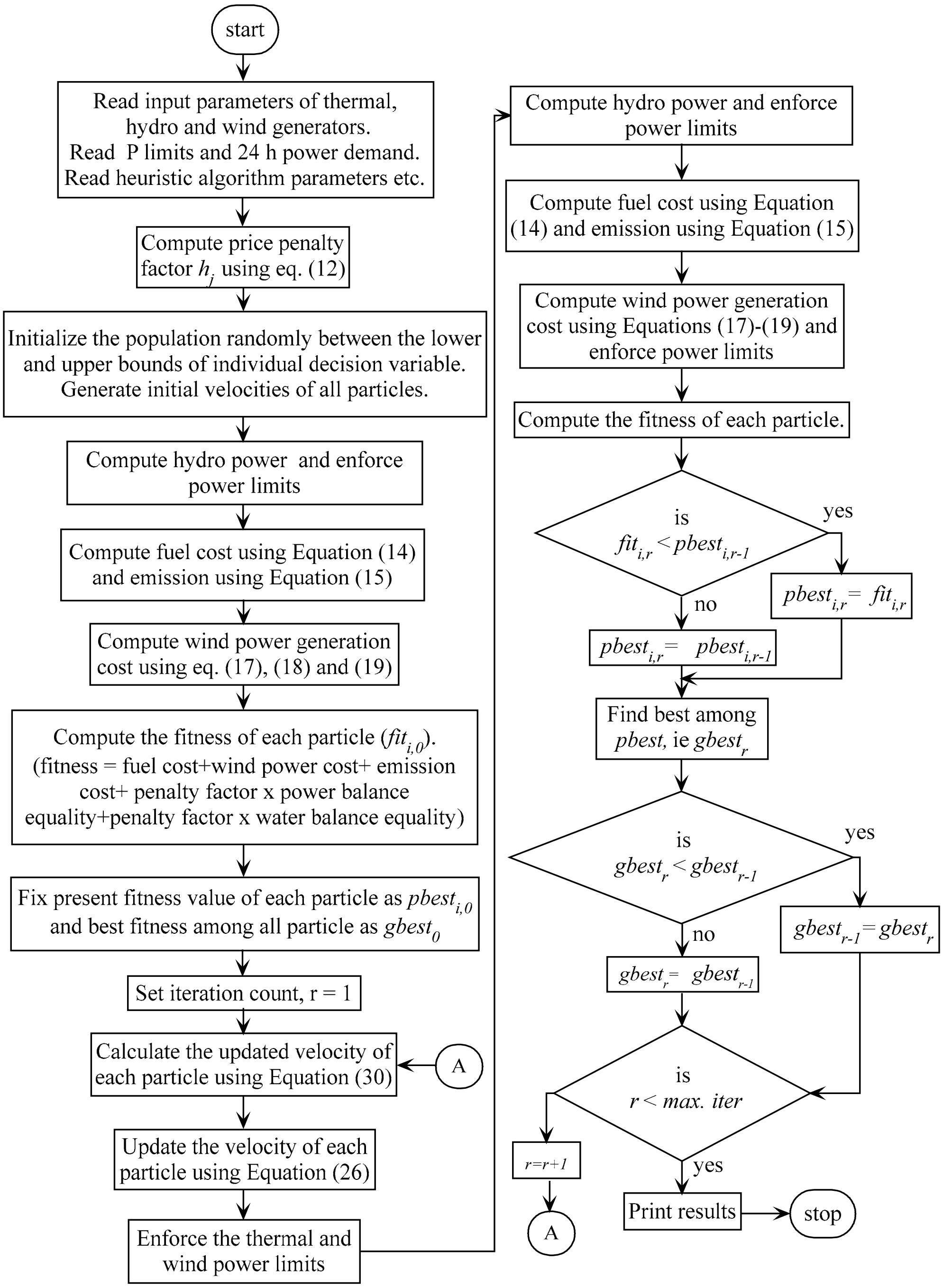

Figure 1. Flow chart of the proposed MPSO method.

Step 1: The algorithm starts with initialization of the particles. A uniform random value is chosen between the minimum and maximum limits of the individual decision variables. The initial velocities are also generated in the same way for all the particles.

Step 2: Compute penalty factor h_j for all thermal power plants using Equation (12). These values are constant and hence do not require modification in the iteration process

Step 3: Calculate the hydro power plant's output and apply the respective power inequality constraints. If any of the plants violate lower limits, fix the generation to the lower limit. In other words, if any of the plants violate upper limits, fix the generation to the upper limit.

Step 4: Compute the fuel cost and emission of thermal power plants using Equations (14) and (15).

Step 5: Compute the wind power generation cost by solving Equations (17)–(19).

Step 6: Calculate the fitness of the particles, considering all generation costs and equality constraints. Set the present value of each particle as its best position, *pbest*.

Step 7: Check for the lowest value of particle best position. Set the value as *gbest*.

Step 8: Calculate the updated velocity of each individual by Equation (30).

Step 9: Update each individual position by Equation (26).

Step 10: Calculate the new fitness value for each particle. Replace the old *pbest* value with new one, if the present value shows improvement over the previous value.

Step 11: Replace the *gbest* with the lowest value from the new *pbest*, if the present value shows improvement over the previous value.

Step 12: Repeat steps 8–11 until the equality constraints fall within a specified tolerance limit or maximum number of iterations reached.

The particle generates the latest *gbest*, giving the optimum schedule of generation.

6. Simulation Results

In this work, the two conflicting objectives are treated together using the penalty factor. The maximum penalty factor approach has been chosen for combining the fuel cost and emission; it offers an acceptable solution for the problem of emission and fuel cost.

The parameter setting is counted as the main limitation of any heuristic algorithm. Once the parameters are suitably chosen, the algorithm follows the logical pattern and converges to an optimal solution. In this study, the following values are assigned to the control parameters of each algorithm. The range of these parameter values is considered by observing similar published case studies, and the fine turning is done by a trial-and-error process.

MPSO and PSO parameters:

Swarm size (population) = 10
Learning factors, c_1, c_2 = 2.05
Maximum iterations = 500
wt_{min} = 0.4, wt_{max} = 0.9

Binary Coded GA parameters:

Size of Population = 60
Probability of crossover = 0.7
Probability of mutation = 0.1
Probability of elitism = 0.15
Maximum iterations = 500

Harmony Search parameters:

Harmony Memory Size (*HMS*) =10

Harmony Memory Consideration Rate (*HMCR*) = 0.85
Pitch Adjustment Rate (*PAR*): $PAR_{min} = 0.2$, $PAR_{max} = 2$
Bandwidth (bw): $bw_{min} = 0.45$, $bw_{max} = 0.9$

JAYA Algorithm parameters:

Size of Population = 10
Maximum iterations = 500

In this work, a test system consisting of a multi-stream cascaded hydro system with four hydro plants, three thermal plants, and two wind plants has been considered for investigating the feasibility and performance of the solution techniques. The schematic diagram of the hydro-thermal-wind test system is shown in Figure 2. The HTWGS considering economic and emission factors has been conducted by implementing the algorithm based on conventional PSO, MPSO, Binary Coded GA, IHS, and JAYA algorithms. The simulations were executed in MATLAB 2015a platform. The program was run 30 times for the test case and the results were analyzed on the basis of the best, average, and worst case with standard deviation. The proposed MPSO shows competency and effectiveness in terms of solution quality and consistency of results.

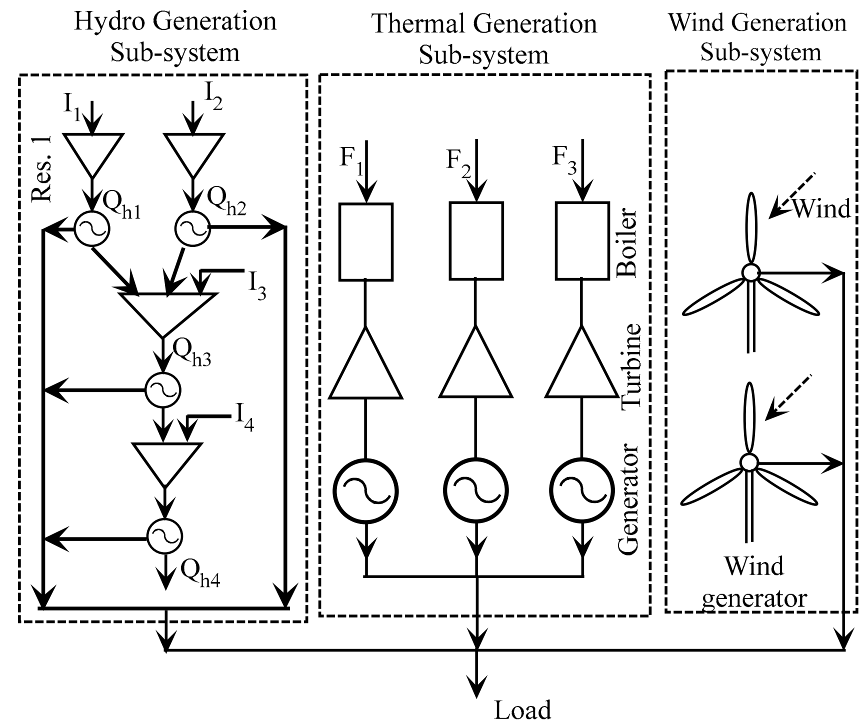

Figure 2. Schematic diagram of the hydro-thermal-wind test system.

Thermal system coefficients and constraints are taken from [31]. The hydro system data is taken from [25]. The scheduling period is taken as one-day, which is split into 24 numbers of a 1-h time span. Figure 3 shows the system power demand curve. The wind system parameters are taken from [18,22]. All the necessary data of the hydro-thermal-wind system are shown in Tables A1–A5 in Appendix A.

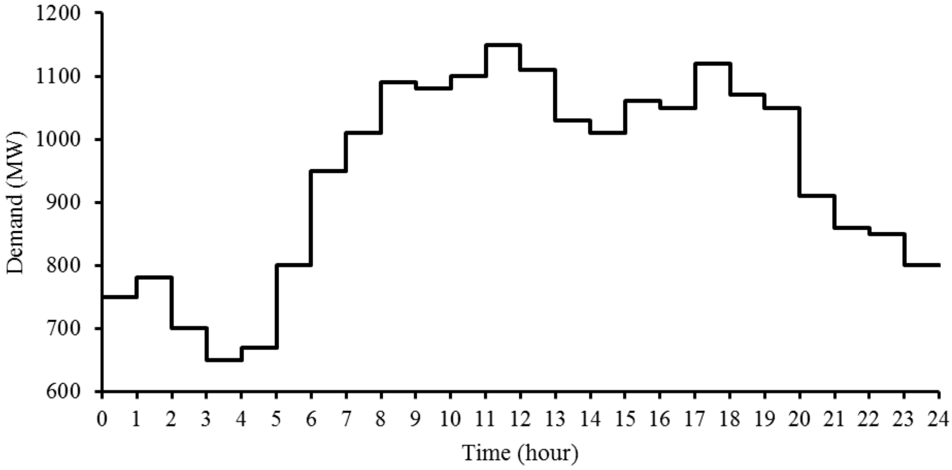

Figure 3. Load curve.

The optimal allocation of demand among the hydro-thermal-wind system and corresponding economic and emission values obtained from the best run are tabulated in the following tables. Table 1 shows the optimal hydro-thermal-wind generation scheduling of the test system accounting for economic and emission factors obtained from the MPSO method. Table 2 presents hourly water discharge and reservoir storage volume values. The storage volume satisfied the end conditions of each reservoir by adjusting the water discharge from each reservoir.

Table 1. Optimal generation schedule of the hydro-thermal-wind system obtained using the MPSO method.

Time Period	Load (MW)	Hydro Generation (MW)				Thermal Generation			Wind Generation	
		Ph1	Ph2	Ph3	Ph4	Pg1 (MW)	Pg2 (MW)	Pg3 (MW)	w1 (MW)	w2 (MW)
1	750	94.3446	64.6098	0	200.0937	97.0717	171.7155	81.1411	13.9578	27.0658
2	780	53.2168	54.7813	0	187.7553	111.0668	197.9873	108.9593	34.5615	31.6717
3	700	58.3977	71.3749	21.6249	173.7333	85.8489	173.7902	50	40.3164	24.9138
4	650	63.5595	74.6322	0	106.1287	75.7075	190.9036	75.6822	23.0245	40.3618
5	670	61.5147	60.4167	0	184.0039	125.9647	114.583	50	41.7498	31.7672
6	800	60.0718	75.4794	37.5928	201.273	93.3212	244.2375	50	10.6048	27.4194
7	950	80.0715	63.2057	43.6685	210.5434	175	235.3744	83.3197	25.4334	33.3833
8	1010	92.3268	57.3724	43.0301	230.708	152.4463	244.8935	122.4235	33.0502	33.7493
9	1090	91.6351	46.3783	46.5969	252.941	153.8851	285.6351	156.7121	35.1824	21.0341
10	1080	69.7957	50.5121	50.3702	247.5302	165.8896	275.2491	171.9534	30.1827	18.5171
11	1100	99.6658	59.3188	53.1227	243.5127	170.4439	246.0919	161.4542	31.5046	34.8855
12	1150	79.6106	64.5824	49.1105	238.7893	175	265.7111	195.7342	36.6807	44.7814
13	1110	80.4696	62.1875	56.265	250.6784	174.1035	264.8422	164.2855	33.7377	23.4305
14	1030	80.5697	45.0925	38.0304	233.5562	170.515	275.617	113.672	38.3423	34.6049
15	1010	54.8119	70.5269	57.8224	234.0562	173.1186	261.2254	90.5305	35.9323	31.9758
16	1060	89.5141	46.3464	57.8832	252.4703	174.9847	271.7981	125.0961	31.2084	10.6987
17	1050	76.2008	46.5497	2.6721	261.2708	174.9083	255.7756	128.4801	63.1456	40.997
18	1120	80.235	46.8197	56.4534	275.2267	175	288.7387	140.2839	26.3899	30.8527
19	1070	86.2937	58.1137	52.4138	253.7575	175	273.5513	139.2643	8.6983	22.9074
20	1050	84.4796	63.8071	59.096	240.8272	175	225.3728	111.6748	54.3708	35.3717
21	910	80.5451	50.8618	50.9588	253.8385	172.3393	191.1432	75.043	18.794	16.4763
22	860	55.3626	52.4023	57.7269	240.1722	134.3991	188.0448	56.6721	25.702	49.5181
23	850	69.213	71.3405	49.0087	238.0051	86.1625	168.4148	90.8949	33.4861	43.4744
24	800	68.3821	59.2113	56.7243	231.55	78.7156	166.8387	86.9736	12.052	39.5524

Table 2. Hourly water discharge and reservoir storage volume obtained using the MPSO method.

Time Period	Water Discharge ($\times 10^4$ m^3/h)				Reservoir Storage Volume ($\times 10^4$ m^3)			
	Qh1	Qh2	Qh3	Qh4	Vh1	Vh2	Vh3	Vh4
1	12.8199	8.51	28.4074	13	97.1801	79.49	149.6926	109.8
2	5.0551	6.7801	27.7573	13	101.125	80.7099	130.1352	99.2
3	5.6021	9.7487	21.4226	13	103.5229	79.9612	125.5325	87.8
4	6.2155	10.7139	26.0631	7.1202	104.3074	78.2473	115.0346	80.6798
5	5.9594	7.9081	29.3136	13	104.348	78.3392	101.1032	96.0872
6	5.7547	11.7759	15.0074	13	105.5933	73.5633	106.0601	110.8445
7	8.5738	9.4541	12.184	13	105.0196	70.1092	113.5494	119.2671
8	11.3008	8.5349	13.7926	13.8042	102.7188	68.5743	114.8546	131.526
9	11.2396	6.5382	10	14.669	101.4792	70.036	126.2042	146.1706
10	7.0032	6.9623	10.6834	13.9647	105.476	72.0738	137.1593	147.2132
11	14.5872	8.3606	11.0345	13.6862	102.8888	72.7132	146.8993	145.711
12	8.527	9.5876	16.4497	13	104.3618	71.1255	145.9911	147.8044
13	8.5607	9.2871	11.3302	14.756	106.801	69.8384	160.2103	143.0484
14	8.4356	6.0828	20.7956	13.1501	110.3654	72.7557	159.3023	140.5818
15	5	11.005	11.2636	13.4466	116.3654	70.7506	169.1871	138.1697
16	9.7486	6.2934	15.6133	15.424	116.6168	72.4572	173.2965	139.1953
17	7.5765	6.2518	26.3538	17.4795	118.0404	73.2054	160.0255	133.0461
18	8.1621	6.322	10	19.5147	117.8783	72.8834	172.7791	134.3269
19	9.2013	8.2817	17.8064	17.1321	115.677	71.6017	169.8426	128.4584
20	8.9984	9.5936	13.9034	15.3456	112.6786	70.0081	171.353	128.7261
21	8.3993	7.0267	18.356	15.5498	111.2793	71.9814	170.5203	139.5301
22	5.0791	7.0677	15.8161	14.4662	114.2002	73.9136	173.9843	135.0639
23	6.6747	11.2261	19.1923	13.7738	116.5255	70.6875	173.7849	139.0966
24	6.5255	8.6875	15.8907	13	120	70	170	140

Table 3 shows the total fuel cost, emission, and wind penalty cost of the optimal generation schedule of the test system. Statistical analysis and comparison of performance of the proposed method (MPSO) with other heuristic algorithms (conventional PSO, BCGA, IHS, and JAYA algorithm) in terms of total fuel cost and emission are presented in Table 4. The simulation results obtained using PSO, BCGA, IHS and JAYA methods are shown in Tables S1–S12 in the Supplementary Materials.

Table 3. Fuel cost, rate of pollutant emission, and wind generation penalty cost of the optimal generation schedule-MPSO method.

Time Period	Fuel Cost ($/h)	Emission (lb/h)	Wind Generation Penalty Cost ($/MWh)		
			Underestimation, $C_{u,i}$	Overestimation, $C_{o,i}$	Total Penalty Cost ($/MWh)
1	1611.884	0.3236	8836.2542	5046.1429	13,882.3971
2	2209.5646	0.5994	4337.2198	12,622.7566	16,959.9764
3	1304.4773	0.3265	4749.0639	13,058.5234	17,807.5873
4	1654.3548	0.4735	5092.8514	12,550.882	17,643.7334
5	1004.6594	0.1628	3468.7626	16,177.8374	19,646.6
6	1959.8535	2.0063	9556.4892	4730.2502	14,286.7394
7	2439.4743	1.6761	5522.8453	9957.0411	15,479.8865
8	3005.1477	2.1402	4247.5442	12,829.0308	17,076.575
9	4086.2278	7.3297	6102.0851	9540.1611	15,642.2462
10	4336.2812	5.3488	7335.8588	6940.0995	14,275.9583
11	3810.8999	2.2833	4318.4725	12,699.2466	17,017.7192
12	4821.5891	4.0622	2506.8309	20,009.3807	22,516.2116
13	4078.5391	3.9218	5838.5679	9529.7335	15,368.3015
14	3248.474	5.3733	3438.9994	15,590.3949	19,029.3943
15	2789.2418	3.4751	4110.1291	13,353.5198	17,463.6489
16	3395.4302	4.7982	8926.3287	6096.0134	15,022.3421
17	3280.1853	2.9839	1187.6681	35,464.4723	36,652.1403
18	3853.9937	8.1135	5727.5656	9242.6715	14,970.2372
19	3666.5457	5.0712	10,827.3697	3198.1782	14,025.5479
20	2706.8783	1.3052	2055.3136	25,747.1212	27,802.4348
21	1926.3172	0.6037	9842.2448	3251.1891	13,093.434
22	1610.3694	0.4959	3810.945	18,735.3378	22,546.2828
23	1679.3987	0.2983	3051.1934	17,836.4405	20,887.6339
24	1603.8759	0.2838	7505.4181	9991.1292	17,496.5473
Total	**66,083.6629**	**63.4563**	**132,396.0213**	**304,197.5537**	**436,593.5754**

Table 4. Statistical analysis of the heuristic algorithms in terms of total fuel cost and emission.

Method	Fuel Cost ($/h)				Emission (lb/h)			
	Best	Average	Worst	Std. Dev.	Best	Average	Worst	Std. Dev.
MPSO	66,083.6629	66,086.7462	66,089.3723	1.6586	63.4564	64.1998	64.9746	0.4732
PSO	68,646.8010	68,649.4948	68,652.1555	1.6634	65.7942	66.7107	67.4718	0.5176
GA	71,016.9724	71,021.0267	71,025.9314	2.8973	70.7457	71.9998	73.3102	0.7616
IHS	71,300.9716	71,305.7043	71,309.3033	2.5949	66.4630	67.6929	68.8929	0.7339
JAYA	85,394.0271	85,404.1629	85,414.3417	5.6383	79.0351	80.5991	82.3240	0.9574

The comparison of total fuel cost and emission shown in Table 4 indicates that the MPSO method is capable of providing the optimal generation schedule. Also, the MPSO solution maintains the lower value of standard deviation, representing the consistency in the results compared with conventional PSO, BCGA, IHS, and newly introduced JAYA algorithms. To show a quantitative measure, here the MPSO solution is compared with the next best performing algorithm (conventional PSO). The total fuel cost and emission of pollutants by the MPSO algorithm are $66,083.6629 and 63.4564 lb, respectively, whereas the PSO-based algorithm shows total fuel cost and emission values of $68,646.8010 and 65.7942 lb, respectively. In other words, over the specified time schedule and demands, the proposed MPSO-based method attains an average reduction of 109.7974 $/h in generation cost and 0.0974 lb/h in emission of pollutant compared with the PSO-based algorithm. This quantitative comparison exhibits the efficiency of the MPSO algorithm for providing the optimal generation schedule accounting for economic and emission factors, without being trapped in the local minima.

Figure 4 shows the optimal load allocation among hydro, thermal, and wind plants of the test system over the 24-h time span. The thermal generation shows dominancy from 8.0 h to 20.0 h, because of the increased power demand on the system. Figures 5 and 6 show the fuel cost and emission release of thermal plants over the scheduling period obtained by MPSO, PSO, BCGA, IHS, and JAYA algorithms. MPSO maintains a lower fuel cost and emission over the scheduling period.

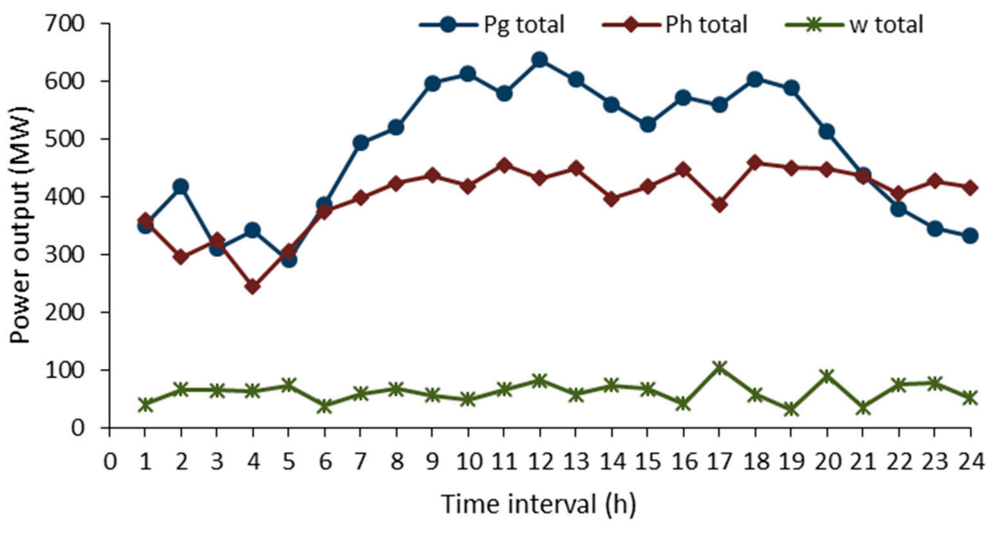

Figure 4. Optimal power generation schedules from the MPSO algorithm over 24 h time span.

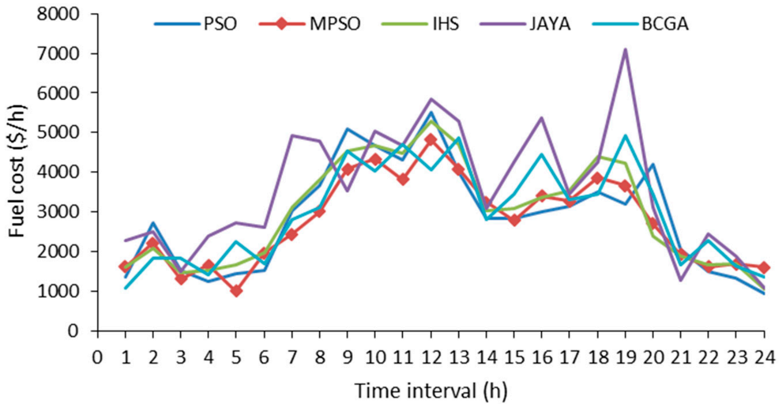

Figure 5. Fuel cost curve obtained from the MPSO, PSO, BCGA, IHS, and JAYA algorithms over the scheduling time.

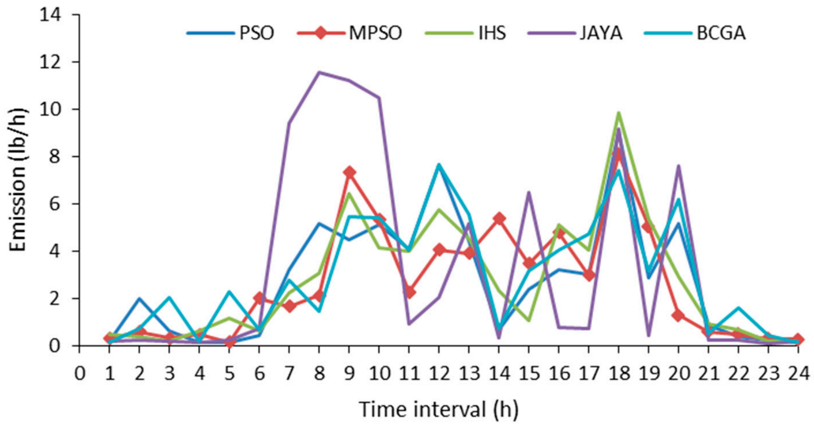

Figure 6. Emission curves obtained from MPSO, PSO, BCGA, IHS, and JAYA algorithms over the scheduling time.

Figures 7 and 8 show the hourly water discharge from the hydro plant and storage volume of reservoirs, respectively. The convergence characteristics of MPSO, conventional PSO, BCGA, IHS, and JAYA algorithms in terms of total fuel cost are shown in Figure 9. The JAYA method exhibits an almost constant fuel cost in the beginning stage. The MPSO, conventional PSO, BCGA, and IHS methods exhibit a similar curve, but MPSO shows the lowest position.

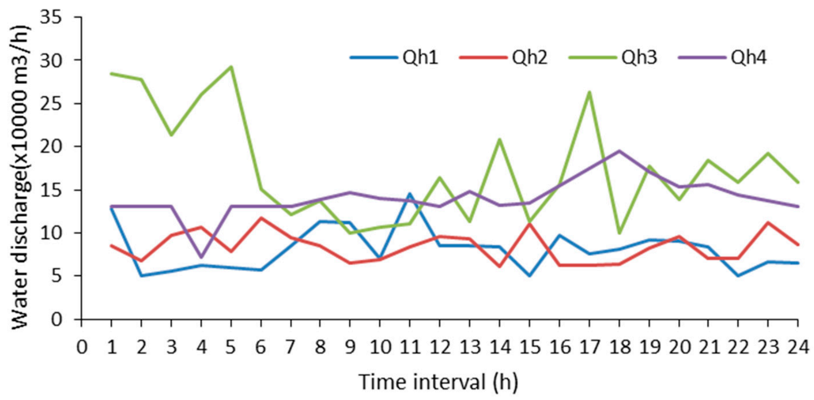

Figure 7. Hydro plant discharge curves.

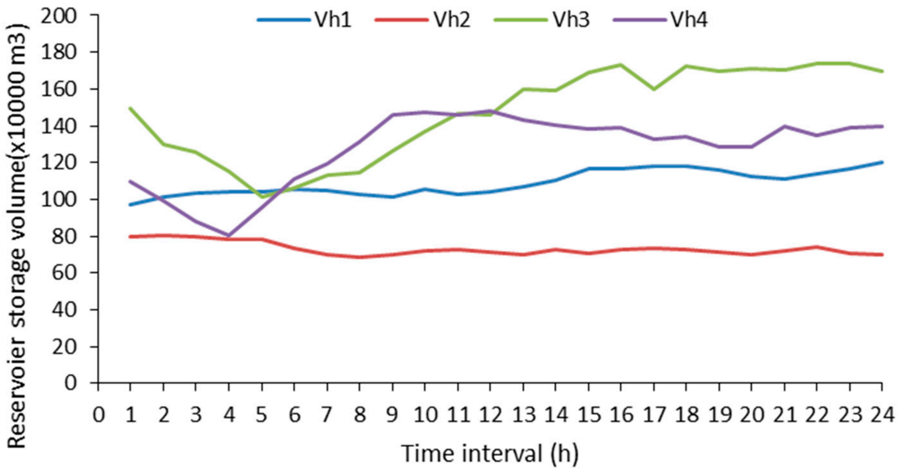

Figure 8. Hydro plant reservoir storage volume curves.

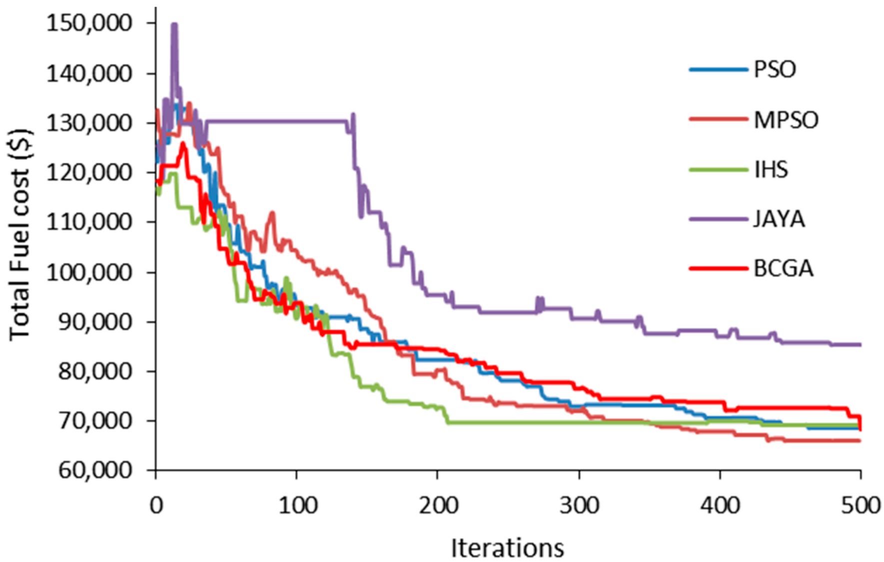

Figure 9. Convergence characteristics of MPSO, PSO, BCGA, IHS, and JAYA algorithms in terms of total fuel cost.

7. Conclusions

This paper investigated the competency of certain heuristic algorithms representing different heuristic groups, for searching for the optimal generation schedule of an HTW system considering economic and environmental factors. A modified particle swarm optimization (MPSO) method is suggested for the purpose. The proposed modification to the conventional PSO method improved the local search capability of the algorithm and hence delivered a solution with the minimum emission value and lowest overall operating cost. Here, the maximum penalty factor approach was used to transform the multi-objective economic and emission function into a single objective. The computational efficiency of the algorithm is illustrated with a test system consisting of three thermal plants, a multi stream reservoir with four hydro plants, and two wind plants. This algorithm offers a trade-off solution between the generation cost and quantity of emission. The proposed MPSO algorithm, conventional PSO, binary coded GA, IHS, and JAYA algorithm were executed 30 times with the test system and the solutions were compared and analyzed statistically on the basis of the best, average, and worst values, along with the standard deviation. The simulation results showed that MPSO demonstrated a better performance than the other selected algorithms in terms of quality solution and consistency. The salient features of the method are less computational steps and easiness of implementation, which makes the algorithm more suitable for accounting for large-scale hydro-thermal-wind optimal scheduling.

Supplementary Materials: The following are available online at www.mdpi.com/1996-1073/11/2/353/s1, Table S1: Optimal generation schedule of the hydro-thermal-wind system obtained using the PSO method, Table S2: Hourly water discharge and reservoir storage volume obtained using the PSO method, Table S3: Fuel cost, rate of pollutant emission, and wind generation penalty cost of the optimal generation schedule-PSO method, Table S4: Optimal generation schedule of the hydro-thermal-wind system obtained using the GA method, Table S5: Hourly water discharge and reservoir storage volume obtained using the GA method, Table S6: Fuel cost, rate of pollutant emission, and wind generation penalty cost of the optimal generation schedule-GA method, Table S7: Optimal generation schedule of the hydro-thermal-wind system obtained using the IHS method, Table S8: Hourly water discharge and reservoir storage volume obtained using the IHS method, Table S9: Fuel cost, rate of pollutant emission, and wind generation penalty cost of the optimal generation schedule-IHS method, Table S10: Optimal generation schedule of the hydro-thermal-wind system obtained using the JAYA method, Table S11: Hourly water discharge and reservoir storage volume obtained using the JAYA method, Table S12: Fuel cost, rate of pollutant emission, and wind generation penalty cost of the optimal generation schedule-JAYA method.

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Author Contributions: Suresh K. Damodaran completed the coding, execution of programs, compilation of results, and preparation of the paper. T. K. Sunil Kumar was involved in designing and conceptualizing the study.

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

Appendix

Table A1. Water inflow time delay between reservoirs.

Plant	1	2	3	4
R_u	0	0	2	1
τ_d	2	3	4	0

R_u: Number of upstream hydro plants; τ_d: Time delay to immediate downstream hydro plant.

Table A2. Hydro power generation coefficients.

Plant	C_1	C_2	C_3	C_4	C_5	C_6
1	−0.0042	−0.42	0.030	0.09	10.0	−50
2	−0.0040	−0.30	0.015	1.14	9.5	−70
3	−0.0016	−0.30	0.014	0.55	5.5	−40
4	−0.0030	−0.31	0.027	1.44	14.0	−90

Table A3. Reservoir storage, plant discharge, reservoir end conditions ($\times 10^4$ m^3), and hyro plant generation limits.

Plant	$V_h^{\min}$	$V_h^{\max}$	V_h^{begin}	V_h^{end}	$Q_h^{\min}$	$Q_h^{\max}$	$P_h^{\min}$	$P_h^{\max}$
1	80	150	100	120	5	15	0	500
2	60	120	80	70	6	15	0	500
3	100	240	170	170	10	30	0	500
4	70	160	120	140	13	25	0	500

Table A4. Reservoir inflows ($\times 10^4$ m^3).

Time Period	Reservoir				Time Period	Reservoir			
	1	2	3	4		1	2	3	4
1	10	8	8.1	2.8	13	11	8	4	0
2	9	8	8.1	2.4	14	12	9	3	0
3	8	9	4	1.6	15	11	9	3	0
4	7	9	2	0	16	10	8	2	0
5	6	8	3	0	17	9	7	2	0
6	7	7	4	0	18	8	6	2	0
7	8	6	3	0	19	7	7	1	0
8	9	7	2	0	20	6	8	1	0
9	10	8	1	0	21	7	9	2	0
10	11	9	1	0	22	8	9	2	0
11	12	9	1	0	23	9	8	1	0
12	10	8	2	0	24	10	8	0	0

Table A5. Wind speed data.

κ	c	v_{in}	v_r	v_o	$w_{r,1} = w_{r,2}$	$k_{u,1} = k_{u,2}$	$k_{o,1} = k_{o,2}$	$d_1 = d_2$
2.2	15	5	15	45	0.8	1583	500	0

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