FIXED HEAD SHORT TERM SCHEDULING IN PRESENCE OF SOLAR AND WIND POWER

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Abstract:

A probabilistic short-term hydro-thermal-wind-photovoltaic scheduling based on point estimate method (PEM) is proposed in this project. To model the uncertainties related with wind and solar power, point estimate method is applied. The Weibull and Beta distributions are employed to handle the uncertain input variables. The average generation cost of the system is optimized based on optimization algorithm named Whale optimization algorithm (WOA). Three test systems have been considered, the first system is having only hydro and thermal units, and rest of the two systems are based on wind and solar including hydro and thermal units to investigate the effect of renewable energy sources in the selected test systems. Furthermore, under and over estimation of available wind power has also been included in the problem. The simulation results show that when the penetration of renewable energy sources increases, the average generation cost decreases. The results obtained by WOA have been compared with other well-known methods. Moreover, the accurate distribution of generation cost for the next day ahead can be found out using Gram Charlier series expansion.

Introduction:

Being a large and complex network, power system must deal with generation, transmission, and distribution of power. The power system is expected to supply the changing load demand of the consumer at an economical way. Thus, the importance of short-term hydrothermal scheduling (SHTS) problem has increased in recent years. The primary goal of SHTS problem is to minimize the generation cost of the thermal unit within a specified time interval by utilizing the available water of the hydro reservoir in an optimum manner. The reservoirs are basically connected in a cascaded way. The present SHTS problem has certain equality and inequality constraints which makes the problem complex and very interesting for power system engineers.

To solve SHTS problem, different approaches have been taken by the researchers so far. At the beginning some classical techniques like Linear programming (LP), Lagrange relaxation (LR), mixed integer programming (MIP), Gradient search (GS), Dynamic programming (DP), etc. were used. But all these methods have their own advantages and disadvantages. Later on, evolutionary algorithms have been extensively used and became popular due to their flexibility and robustness to find the optimal solution. Many evolutionary algorithms applied to solve the SHTS problem are: Simulated annealing (SA), Evolutionary programming (EP), Differential evolution (DE), Genetic algorithm (GE), Particle swarm optimization (PSO), and some other PSO based algorithms. Later on, some other population-based optimization techniques like Artificial immune system (AIS), real coded chemical reaction-based optimization (RCCRO), Teaching learning-based optimization (TLBO), Cuckoo search algorithm (CSA), Disruption based gravitational search algorithm (DGSA) and Symbiotic organisms search (SOS) algorithm have been successfully implemented to solve SHTS problem. In 2017 Esmaeily et al. proposed MILP to solve hydrothermal self-scheduling problem considering price uncertainty and forced outage rate to maximize the expected profit. An improved harmony search (IHS) optimization algorithm has been successfully applied by Nazari-Heris et al. in 2018 to solve short-term hydrothermal scheduling problem. Two test systems have been considered to justify the performance of IHS algorithm. Feng et al. proposed multi-objective quantum-behaved particle swarm optimization (MOQPSO) algorithm to solve the HTS problem. In this article, the authors have taken a multi-objective problem to minimize cost as well as emission. A real-coded genetic algorithm based on improved Muhlenbein mutation (RCGA-IMM) algorithm has been successfully applied by Nazari-heris et al. to solve short-term HTS problem considering valve-point loading effect and transmission loss. The result obtained demonstrate better performance by the proposed method. A time varying acceleration coefficient particle swarm optimization with mutation strategies (TVAC-PSO-MS) has been proposed by Patwal et al. to solve generation scheduling problem considering pump storage hydrothermal system combining solar units.

Renewable energy sources in power generation are continuously increasing and have reached a value of 2.8% of global energy consumption in 2015 as compared to 0.8% a decade ago. The global solar power generation had increased to 28.1% by year end with the inclusion of 50GW in 2015 as compared to the amount generated by the end of 2014. In the last four years solar power generation capacity has increased more than three times. Besides solar power, wind power generation has also been upscale by 16.9% and reached 435GW with the addition of 63GW wind power in 2015. In India, renewable energy sector has emerged as an important energy sector in grid connected power system. The government of India has setup an aim for renewable power capacity of 175GW by the year 2022 including 100GW from solar and 60GW from wind. Power system has witnessed over 20% growth of power generation through renewable sources in recent years. In 2009, the total renewable power capacity was 14,400MW which increased to 38,822MW at the end of December 2015.

Renewable energy sources like wind and solar are gaining more attention in most part of the world as these sources are very cost effective as well as eco-friendly. For this purpose, renewable energy sources have been incorporated with hydro and thermal units to solve SHTS problem. Banerjee et al. solved SHTS problem considering the wind energy using PSO. A multi-objective hydrothermal wind scheduling has been solved by Yuan et al. considering the wind speed uncertainty as well as overestimation and underestimation cost of wind energy. One test system consisting of four hydro, six thermal and two wind units has been taken for the study. The same approach has been taken in Ref. to solve SHTS problem taking both cost and emission considering uncertainty of wind power with different test systems and algorithm. Liang et al. solved short-term generation scheduling considering the uncertainties of load demand, available water in reservoir, wind speed and solar irradiation. The study comprises of one test system having ten thermal, seven hydro, one wind and one solar unit. In 2016, Dubey et al. solved hydro-thermal-wind scheduling considering the reserve and penalty cost-coefficient of wind generator. The objective was to minimize the generation cost, loss and emission simultaneously using novel ant lion optimization algorithm (ALO). To analyse the impact of renewable sources like large-scale rooftop solar-PV in a hydrothermal system, Singh et al. applied an algorithm consisting of two stage formulation using dynamic programming and linear programming techniques to solve SHTS problem. In 2017 wang et al. developed a multi objective model to analyse the coordinated operation of Hydro-wind-solar system. In that article the authors have applied non-dominated sorting genetic algorithm (NSGA-II) to maximize the total power generation as well as to minimize the output fluctuation. A short-term hydrothermal scheduling problem considering the intermittent energy sources like wind and solar has been solved by Zhang et al. in the year of 2017. To solve this, gradient based multi-objective cultural differential evolution (GDMOCDE) method has been proposed to minimize the generation cost and emission. To tackle the probability density functions, a probability constraint handling procedure has also been considered. Reza Hemmati successfully solved an optimal cogeneration and scheduling problem of hydro-thermal-wind-solar system including energy storage systems to reduce the fluctuations associated with renewable sources. The optimization model was implemented in GAMS software and solved as a mixed integer linear programming. Somma et al. in 2018 proposed a stochastic optimization model for optimal scheduling of distributed energy resource (DER) system considering both economic and environmental aspects. A hydro-thermal-wind scheduling problem has been solved by Damodaran et al. using modified particle swarm optimization (MPSO) and compared with other heuristic algorithms like binary coded genetic algorithm (BCGA), improved harmony search (IHS) and particle swarm optimization (PSO). The objective function has been taken as a multi objective considering different economic and environmental factors.

To deal with uncertainties of renewable energy sources, several techniques have been developed. Among them the three main probabilistic approaches are Monte Carlo Simulation, Analytical techniques, and approximate methods. Monte Carlo simulation is widely used in power system problems. But this simulation-based technique has a drawback, as it requires large simulation time to converge. It also follows deterministic procedures to solve the problem. In case of analytical techniques, it takes some mathematical assumption to simplify the problem. On the other hand, approximate methods provide an approximate description of statistical properties of the output random variables. It also makes a balance between computational efficiency and accuracy. First-order second moment method and point estimate method (PEM) are well known approximate methods. Among these, PEM is one of the popular approaches to solve probabilistic problems. It has certain advantages such as: it uses deterministic routines to solve probabilistic problems and has less computational burden than simulation methods. One more advantage is that, after the end of the solution, average value and standard deviation is computed which is much more informative and realistic than other methods. So, it is better to use average value rather than best values when uncertainties of renewable energy like wind velocity, solar irradiation are considered in a problem. PEM was first established by Rosenbleuth in the year of 1975. But due to high number of input random variables associated with practical power system problems, it takes more simulation time than Monte Carlo simulation. Even modern PEM is not an appropriate approach to solve the problems. But in case of PEM developed by Hong, the simulation grows linearly with the number of input random variables. Based on Hong's PEM method, various problems have been solved till now. Some of them are probabilistic load flow problems, probabilistic multi objective VAR control at distribution network, Modelling of wind and PV in distribution network, Optimal operation in micro grid, wind-thermal economic emission dispatch. But considering PEM method none of the work has been carried out in hydrothermal scheduling considering uncertainty of renewable sources.

In this article author solved short-term hydrothermal scheduling problem considering the uncertainty behaviour of renewable energy sources. To model the uncertainty of wind speed and solar irradiation, Hong's 2m PEM method has been implemented. Furthermore, Gram-Charlier expression has been adopted for proper distribution of output random variables. Lastly Whale optimization algorithm (WOA) is used to minimize the total cost generation cost. The results have been compared with CSA, Moth flame optimization (MFO) algorithm and Dragonfly algorithm (DA). The main contributions of the paper are as follows:

- Fixed head hydrothermal scheduling has been done in presence of both wind and photovoltaic power.
- A 2m point estimate method is proposed to model the uncertain behaviour of wind and photovoltaic energy more accurately. This method has not been used to model the uncertainty related with renewable sources in case hydrothermal scheduling problem in presence of wind and solar power till now.
- A new efficient optimization algorithm named Whale optimization algorithm has been proposed for the first time to solve HTS problem.

The organization of the paper is as follows:

Section 2 deals with the problem formulation part.

Section 3 explains the uncertain behaviour of wind and solar energy and their modelling using PEM method.

Whale optimization algorithm and its application to solve HTS problem has been stated in **section 4**.

Section 5 represents the case study and simulation results.

Effect of tuning parameter of WOA and conclusion part has been present in **section 6** and **section 7** respectively.

Problem Formulation:

In this project short-term hydro-thermal-wind-photovoltaic scheduling has been done. Being an unpredictable nature, wind and photovoltaic (PV) sources make the scheduling problem quite complex. Apart from the constraints of hydro and thermal units, constraints associated with wind and PV unit are also considered.

2.1. OBJECTIVE FUNCTION

As the hydro generation cost is negligible, the total generation cost includes cost of thermal, wind and solar. The goal of this article is to minimize the total generation cost satisfying all the constraints considered for scheduling. The objective function can be formulated as follows

$$\text{Min}\ldots\text{Cost}=\sum_{t=1}^{TL}[\sum_{j=1}^{Nt} Tp(j,t) + [\sum_{m=1}^{Nw} Wp(m,t) * Cw(m) + OEC(m,t) + UEC(m,t)] + \sum_{t=1}^{Ns} Sp(l,t) * Bid(l)] \quad (2.1.1)$$

Thermal power generation cost including valve point loading effect can be formulated as follows:

$$Tp(j,t) = [\alpha j + \beta j\ Tp(j,t) + XjTp2(j,t) + [\delta j \sin(\varepsilon j(Tp_{min}(j) - Tp(j,t))] \quad (2.1.2)$$

2.2. CONSTARINTS

The constraints related to this problem are generator operating limits, reservoir storage volume and discharge limits, water balance constraints and power balance constraints etc.

2.2.1. Hydraulic continuity equation

$$V_h(i,t) = V_h(i,t-1) + Ih(i,t) - D_h(i,t) + \sum_{u \in Ru(i)} D_h(u, t - \zeta u) \quad (2.2.1.1)$$

2.2.2. Hydro reservoir storage volume and discharge limits

$$Vh^{min}(i) \le Vh(i,t) \le Vh^{max}(i) \quad (2.2.2.1)$$

Dh^{min} (i) $\leq Dh(i,t) \leq Dh^{max}$ (i)
(2.2.2.2)

2.2.3. Initial and terminal reservoir storage volume limits

V_h(i,0)= $Vh^{begin(i)}$
(2.2.3.1)

V_h (i,T)= $Vh^{end(i)}$
(2.2.3.2)

2.2.4. Generation limits

Tp^{min} (j) $\leq Tp(j,t) \leq Tp^{max}$ (j)
(2.2.4.1)

j ∈ N_t; t ∈ TI

Hp^{min} (i) $\leq Hp(i,t) \leq Hp^{max}$ (i)
(2.2.4.2)

The hydro power generation is a function of water discharge and storage volume and may be represented as follow:

Hp(i, t) = $j_{1i}.Vh^2$(i, t) +j_{2i}. Dh^2(i, t) +j_{3i}. V_h (i,t). D_h (i,t)+ j_{4i}. V_h (i,t)+ j_{5i}. D_h (i,t)+ j_{6i} (2.2.4.3)

2.2.5. Power balance constraint

The total generation of hydro, thermal, wind and solar power must satisfy the total load demand and transmission IOS of each interval

$\sum_{j=1}^{nt} Tp(j,t) + \sum_{j=1}^{Nh} Hp(i,t) + \sum_{j=1}^{NW} Wp(j,t) + \sum_{j=1}^{Ns} Sp(l,t) +$ = Fb(t)+Ploss(t); t ∈ TI; k ∈ Nw; l ∈Ns (2.2.5.1)

RESULTS:

Test system consists of four hydro plants and six thermal plants. Here valve point loading effect of thermal generators is considered, but transmission loss is not considered. Scheduling period has been taken as one day and divided into 24 intervals. The system data have been taken outputs are represented in Fig. 3. WOA takes 30.4s to converge and the convergence characteristics of DA, MFO, CSA and WOA have been demonstrated in Fig. 2. The optimal values of hydro discharges are depicted in Table 5.1. The output of thermal power plant has been illustrated in Table 2. The optimal cost achieved by WOA is 395228.0714 $ which is less than DA (396580.0333$), MFO (395407.345 $) and CSA (395285.4697 $). The comparison of results among DA, MFO, CSA and WOA is depicted in Table 5.3. Table 5.3 also reveals that, the cost (9395228.0714 $) and computational time (30.4 s) achieved by CSA is less than the other algorithm mentioned above. After 20 trails run it has been observed that CSA consistently hit the minimum solution 19 times compare to CSA (18 times), MFO (18 times) and DA (18 times). Moreover, the standard deviation of CSA (6.0944) is also less than CSA (17.9247), MFO (41.6264) and DA (63.7036) and that signifies the robustness of this algorithm. A bar chart representation of the minimum cost and standard deviation of WOA, CSA, MFO and DA has been illustrated in Fig. 2.

Fig.2: Hydro reservoir discharges for 24 hours for test system 1

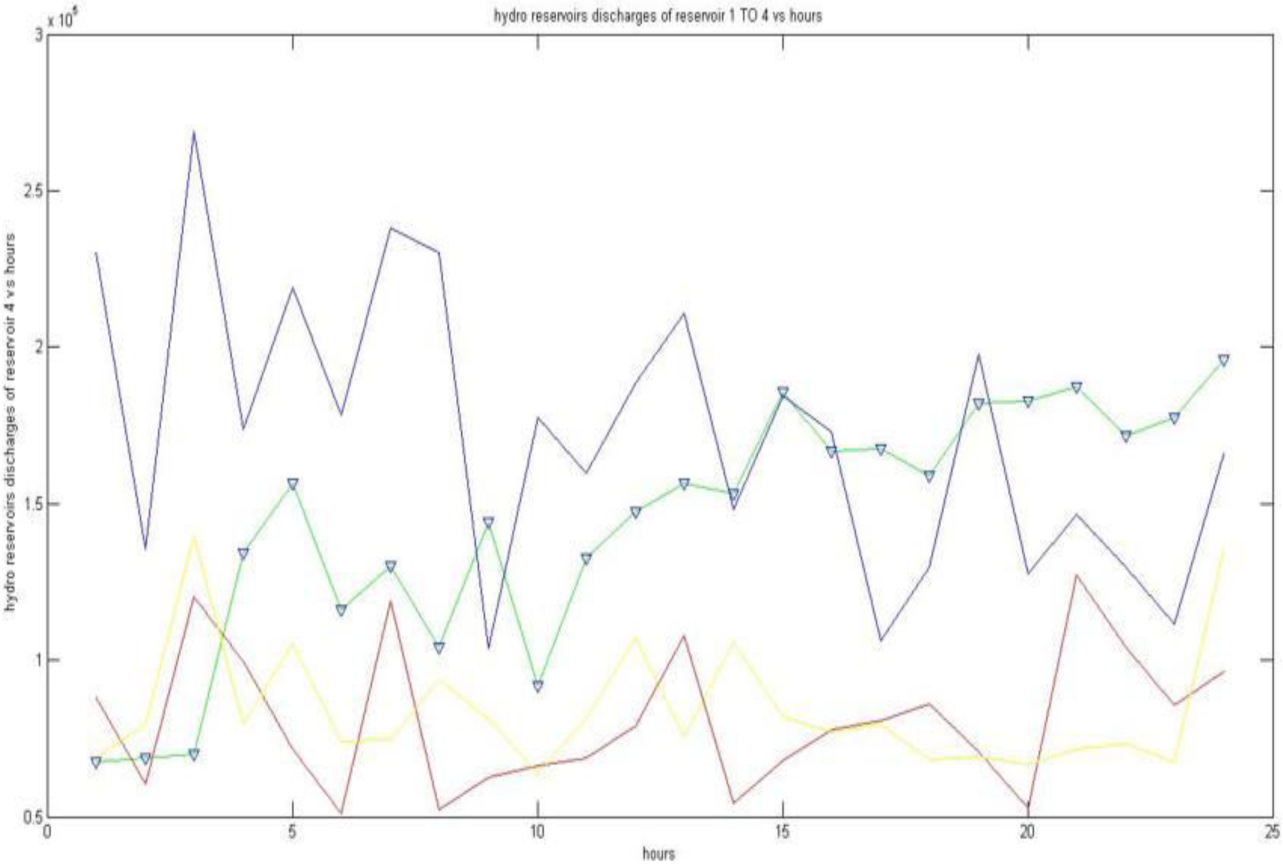
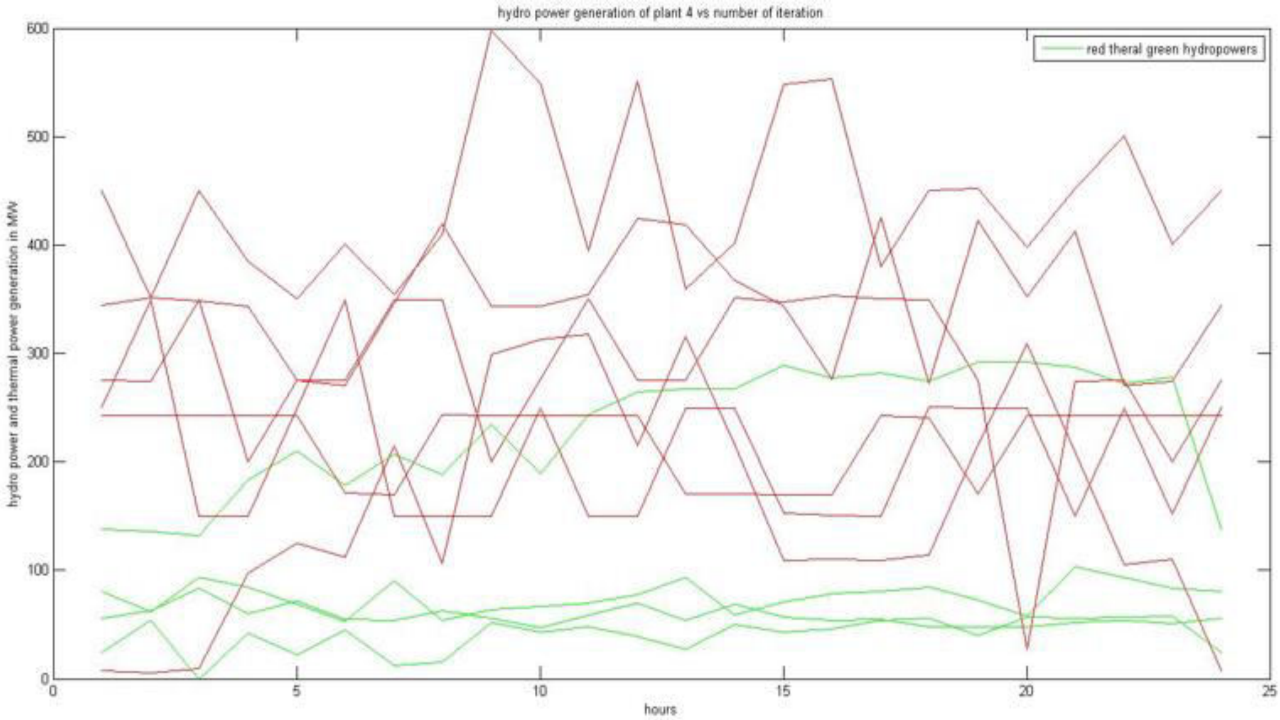


Fig.3: Power generation of plants(1-10) Vs number of iterations



Convergence Characteristics

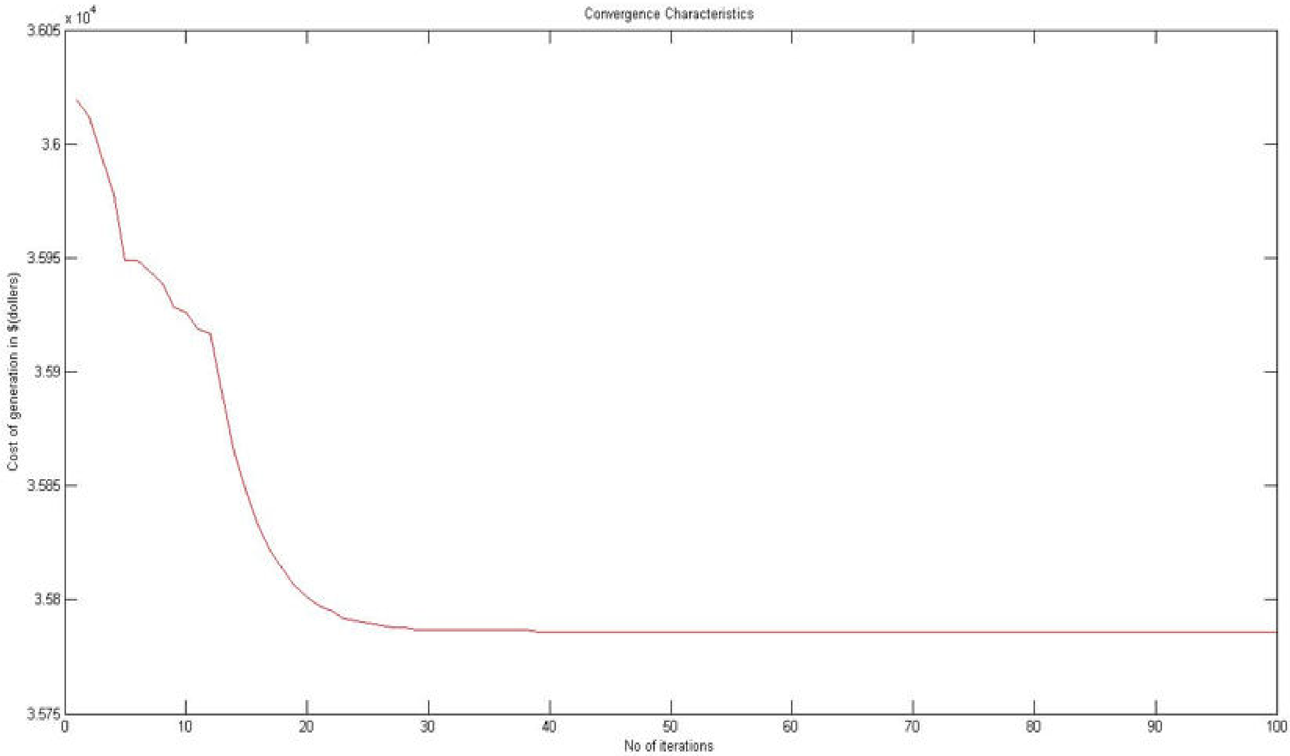


Table 5.1

Optimal values of hydro reservoir discharges in case of test system1.

Hour	Q1	Q2	Q3	Q4
1	88085.3157	69160.9029	230353.8390	67537.4075
2	60574.0714	79604.2659	135513.7543	68612.4831
3	120036.2948	139719.5420	268883.6230	69922.7220
4	99813.8971	79243.2528	173751.7667	134127.4493
5	71427.9656	105337.6108	219156.0044	156462.4994
6	51069.1739	73993.4829	178226.2877	116063.6402
7	119102.2589	74683.7870	237949.2924	130171.1335
8	52347.6310	93772.1559	230249.5439	103972.1371
9	62684.6291	81227.7547	103655.1918	144272.8452
10	66158.8844	63685.0946	177608.1351	91629.4241
11	68883.5612	81622.3700	159921.6375	132777.2959
12	78841.0468	107007.9120	188480.4212	147490.5886
13	107699.0551	75443.5117	210697.8683	156285.2807
14	54528.4732	105933.4627	148423.0720	153329.5707
15	67755.2675	82042.69169	184528.1491	185814.9671
16	77650.1403	76951.8333	172791.5936	166611.2550
17	80657.4251	79447.0536	106350.2293	167729.1869
18	85994.2671	68171.0801	129593.3656	159015.3247
19	70603.5668	69052.8590	197556.6882	182060.2642
20	52524.9301	66612.2427	127741.0587	182974.5278
21	127426.3998	71449.3186	146784.8004	187193.9892
22	104348.3708	73097.9174	129842.9451	171872.4788
23	85582.5444	67489.6250	111424.6899	177345.9745
24	96204.8291	135250.2718	165890.8550	196159.0762

Table 5.3

Result obtained by WOA algorithm in case of Test system 1 after 20 trails run.

Methods	Minimum cost ($)	Average cost ($)	Maximum Cost($)	Simulation(Time)	Standard deviation ($)	No of hits to minimum
DA	396580.0333	396600.7320	396787.0020	85.20	63.7036	18
MFO	395407.345	395420.8691	395542.5864	52	41.6264	18
CSA	395285.4697	395291.2933	395343.7060	26.11	17.9247	18
WOA	395228.0714	395229.4341	395255.3262	21.25	6.0944	19

Conclusions:

The article presents a solution methodology to deal with the uncertain behaviour of wind and PV energy sources, to solve hydrothermal wind-photovoltaic scheduling problems with an objective of minimizing the total generation cost. A point estimate method is used to model the uncertainty related to PV power and wind power. A new metaheuristic algorithm Whale optimization algorithm is used to tackle with the optimization problem. Three test systems considering different generating units have been taken in analysing the effect of renewable generating sources in HTS problem. Results show that as the number of renewable sources has increased, the cost has reduced. It has been observed that 13.84% total generation cost has reduced in case of test system 3 as compared to test system 2. Furthermore, the contribution of thermal power has also been reduced by 5.49%. A comparative study among WOA, CSA, DA and MFO also been done. The simulation results also indicate that WOA algorithm performs better than CSA, DA and MFO. The cost obtained by WOA also reduced by a percentage of 0.56, 3.94 and 5.62 as compared to CSA, the next best performed algorithm in case test systems 1, 2 and 3 respectively. The authors have performed the study considering only active power, so the effect of reactive power on the system in presence of renewable energy sources and load uncertainty may also be taken as future work in continuation of the present work. Moreover, the underestimation cost and overestimation cost of solar power is not considered in this article. That can be considered for further study.

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