NSTLBO-Based Approach for Optimal Scheduling of Hydrothermal Generating Units in Regulated Environment

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Abstract This research paper benevolence is a technique for short-term hydrothermal generation scheduling (STHTGS) power plant using a non-dominant sorting teaching learning-based optimization (NSTLBO) algorithm. It involves the deployment of thermal power plants in optimum operating conditions to reduce fuel costs and optimize the cost of hydroelectric power plants. The electrical energy considered in this study is assumed to be efficient. The NSTLBO algorithm has been found suitable for this problem as it reaches the minimum cost in the shortest time compared with the previous methods.

Keywords Hydro · Thermal · Economic dispatch · Valve point loading effect · NSTLBO algorithm

1 Introduction

Hydrothermal scheduling will optimize the timing of hydroelectric and thermal power plants toward diminishing the fuel costs of thermal power plants [1]. It is an important part of the energy industry and economy that provides electrical and heat

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energy within this system [2, 3]. The increasing cost of thermal power plants and the intersection of renewable energy further emphasize the importance of hydrothermal propulsion [4].

In the short-term transmission problem, some limitations such as the capacity of the hydraulic unit, the demand of the load, the hydraulic input, the flow restriction of the reservoir and the reservoir capacity should be known [5]. The stability of a hydroelectric power plant depends on the balance between thermal and hydroelectric power generation and load demand. However, generators are difficult to operate and deliver in industry due to hydraulic constraints and the need to meet load requirements [6]. Many techniques, such as Lagrangian multipliers, gradient search methods, evolutionary programming, rapid evolutionary programming, mixed evolutionary programming, simulated annealing, genetic algorithms and particle swarm optimization have been used to solve short-term problems [7–14].

However, the aforementioned algorithms all have their own limitations. For example, the Lagrange multiplier method will face the problem that the binary solution is not possible, the simulated annealing convergence speed is slow, and the problem is not easy, and the evolutionary algorithm will face the problem of slow convergence speed in multimodal optimization. Additionally, genetic algorithms may have poor search results [15], while optimization of the particle swarm may suffer from premature intersections [10, 16–19]. To solve these problems in short-term hydrothermal scheduling, this article proposes to use the non-dominant sequence-based learning-based optimization (NSTLBO) algorithm [20–22]. This optimization process was inspired by the teaching-to-learn behavior and outperforms the advanced know-how, especially in the execution period.

This method differs from other algorithms in that it does not rely on standard optimization parameters. The algorithm reduces the costs associated with thermal power plants by dividing energy consumption by hydrothermal generation. To evaluate the effectiveness of the NSTLBO method, we apply it to extensive experiments and compare the simulation results with those obtained by further approaches.

2 Problematic Construction

2.1 The Cost Minimization

$$F_1 = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{j_s} f_s(P_s) \right\} \tag{1}$$

In the formulary, F_1 is the total operating cost of the thermal power unit.

The number of electric generators is j_s, respectively.

T is the timer for the generator. The productivity power of the thermal unit is P_s, respectively.

After delightful into account the valve point load effect, the fuel cost of the thermal unit at time T is shown as follows:

$$f_{it}(P_{sit}) = \min \sum_{t=1}^{T} \sum_{i=1}^{j_s} \left\{ a_i + b_i P_{si} + c_i P_{si}^2 + \left| d_i \sin\left[e_i \left(P_{si}^{\min} - P_{si} \right) \right] \right| \right\} \quad (2)$$

where a_i, b_i, c_i, d_i and e_i are the cost coefficients of the thermal unit and $P_{si}^{\min}$ is the slightest power generation limit of the thermal unit.

2.2 Constraints

The STHTGS problem would gratify the subsequent equality and inequality.

Equal to the Energy Limit

$$\sum_{i=1}^{j_s} P_{si} + \sum_{g=1}^{r_h} P_{hg} + \sum_{k=1}^{l_w} P_{wk} + \sum_{m=1}^{n_{pvm}} P_{pv} - P_L = P_D \quad (3)$$

Power generation of hydro entities can be expressed as

$$\begin{aligned} P_{hg} = {} & C_{1g}\left(V_{hg}\right)^2 + C_{2g}\left(Q_{hg}\right)^2 + C_{3g} V_{hg} Q_{hg} + C_{4g} V_{hg} \\ & + C_{5g} Q_{hg} + C_{6g} \quad g \in N_h, t \in T \end{aligned} \quad (4)$$

Water Balance Constraint

$$V_{hj}^{t} = V_{hj}^{t-1} + I_{hj}^{t} - Q_{hj}^{t} - S_{hj}^{t} + \sum_{l=1}^{R_{uj}} \left(Q_{hl}^{t-d_{lj}} + S_{hl}^{t-d_{lj}} \right) \quad j \in N_h, t \in T \quad (5)$$

Limited Storage Capacity and Initial and Final Discharge Rate of the Reservoir

$$V_{hj}^{\min} \leq V_{hj}^{t} \leq V_{hj}^{\max} \quad j \in N_{h,}, t \in T \quad (6)$$

$$Q_{hj}^{\min} \leq Q_{hj}^{t} \leq Q_{hj}^{\max} \quad j \in N_h, t \in T \quad (7)$$

Power Generation Limits

$$P_{hj}^{\min} \leq P_{hj}^{t} \leq P_{hj}^{\max} \quad j \in N_h, t \in T \quad (8)$$

$$P_{si}^{\min} \leq P_{si}^{t} \leq P_{si}^{\max} \quad i \in N_s, t \in T \quad (9)$$

3 Elucidation Procedure

3.1 Non-dominated Sorting TLBO Algorithm

The NSTLBO procedure is an improvement of the TLBO procedure, which provides a unique way to generate Pareto optimal results for multi-objective optimization difficulties. Similar to the TLBO algorithm, it uses a grading algorithm combined with the teacher–student level to manage multiple objectives. The NSTLBO algorithm uses a non-critical permutation technique and mass distance measurement to more efficiently search for space and continuously select the optimal solution along the Pareto front. With its bottleneck-free working time, it enables teachers to be selected from a wide search area and prevents premature convergence to the best locale.

The NSTLBO algorithm combines the teacher's instruction and the learning level of the TLBO algorithm, so the student can use it quickly. Finding good solutions to individual optimization problems is easy, but it becomes more difficult when there are multiple conflicting goals. In this case, finding the best solution in the problem solving process is not an easy task. The algorithm solves this problem by comparing the solution sequences based on the congestion distance values and the non-dominant strategies to novelty the optimum solution. The process starts with startup.

The algorithm starts with an initialization step that creates an N $\times$ D matrix containing the values generated in the search space, where N represents the total size (often called 'room size') and D represents the size of the problem being solved given all parameters. The algorithm remains designed toward work aimed at 'g' iterations. At the beginning of each iteration, the value of the jth parameter of the ith vector is calculated using the following equation:

$$x_{(i,j)}^{1} = x_j^{\min} + \mathrm{rand}_{(i,j)} \times \left(x_j^{\max} - x_j^{\min}\right) \tag{10}$$

where $\mathrm{rand}_{(i,j)}$ signifies a consistently disseminated arbitrary variable within the limit (0,1). The workings of the ith vector for the generation 'g' is shown by

$$X_i^g = \left\lfloor x_{(i,1)}^g, x_{(i,2)}^g, \ldots, x_{(i,j)}^g, \ldots, x_{(i,D)}^g \right\rfloor \tag{11}$$

In this two-objective problem, the line vector represents the main target for a generation. Line vectors correspond to two objective functions in thought. The two-objective problem defined as (a and b) can be framed as follows.

$$\left[\frac{Y_{a_i^g}}{Y_{b_i^g}}\right] = \begin{bmatrix} fa\left(X_{(i)}^g\right) \\ fb\left(X_{(i)}^g\right) \end{bmatrix} \tag{12}$$

where $i = 1, 2,\ldots,N$; $j = 1, 2,\ldots,D$ and $g = 1, 2,\ldots,G$.

Teacher Phase

The mean trajectory is computed by taking the average of the learners' values for each subject in the class. So the mean vector μ is shown as

$$M^g = \begin{bmatrix} \text{mean}([x^g_{(1,1)}, \ldots, x^g_{(i,1)}, \ldots, x^g_{(N,1)} \\ \text{mean}([x^g_{(1,j)}, \ldots, x^g_{(i,j)}, \ldots, x^g_{(N,j)} \\ \text{mean}([x^g_{(1,D)}, \ldots, x^g_{(i,D)}, \ldots, x^g_{(N,D)} \end{bmatrix}^T \tag{13}$$

Then

$$M^g = m^g_1, m^g_2, \ldots, m^g_j, \ldots, m^g_D \tag{14}$$

The vector with the lowest objective value is determined as the best vector and is chosen by way of the teacher for this recapitulation. The algorithm makes development by replacing the student's average by that of the teacher. This is done by combining the current mean vector with the potential mean vector in the student population, resulting in improved student level.

$$X\text{new}^g_{(i)} = X^g_{(i)} + \text{rand}^g \times \left(X^g_{\text{Teacher}} - T_F M^g\right) \tag{15}$$

Henceforth T_F is the teaching inspiration in the course of recapitulation which may be either 1 or 2.

The supplementary expert students in the matrix X_{new} relocate the inferior learners in matrix S by the non-dominated sorting algorithm.

Learner Phase

This stage is enthusiastic to interface between learners. The repetition of interface leads to the improvement of learner's expertise. Each learner works randomly with other learners, speeding up knowledge sharing. A precise student $\left(X^g_{(i)}\right)$ and the other learner $\left(X^g_{(r)}\right)$ has remained arbitrarily chosen ($i \neq r$). Lastly the ith vector of the matrix X_{new} in the learner phase seems

$$Xnew^g_{(i)} = \left\{ \begin{array}{c} X^g_{(i)} + \text{rand}^g_{(i)} \times \left(X^g_{(i)} - X^g_{(r)}\right)\text{if}\left(Y^g_i < Y^g_r\right) \\ X^g_{(i)} + \text{rand}^g_{(i)} \times \left(X^g_{(r)} - X^g_{(i)}\right) \text{ otherwise} \end{array} \right\} \tag{16}$$

There is an opportunity of manifold X_{new} conditions in the learner phase. Consequently cutting-edge circumstance of a bi-objective problem of the presentation of learner phase might have preparation as

$$Xnew^g_{(i)} = \left\{ \begin{array}{c} X^g_{(i)} + \text{rand}^g_{(i)} \times \left(X^g_{(i)} - X^g_{(r)}\right)\text{if}\left(Ya^g_i < Ya^g_r\right) \\ X^g_{(i)} + \text{rand}^g_{(i)} \times \left(X^g_{(r)} - X^g_{(i)}\right) \text{ otherwise} \end{array} \right\} \tag{17}$$

$$Xnew_{(i)}^{g} = \left\{ \begin{array}{c} X_{(i)}^{g} + \text{rand}_{(i)}^{g} \times \left(X_{(i)}^{g} - X_{(r)}^{g}\right)\text{if}\left(Yb_{i}^{g} < Yb_{r}^{g}\right) \\ X_{(i)}^{g} + \text{rand}_{(i)}^{g} \times \left(X_{(r)}^{g} - X_{(i)}^{g}\right) \text{ otherwise} \end{array} \right\} \quad (18)$$

Lastly, the X matrix and the X_{new} matrices are treated in organized manner in the NSTLBO, which devise the 'N' best learners for the confirming iteration. The algorithm will be finished afterward 'G' number of iteration is over.

Fuzzy Membership Function

The main goal of the systems cause is to resolve the conflict by fulfilling the constraints. In many cases, the results, limitations and benefits of the proposed methods cannot be accurately predicted. Most bugs are unreachable. This may be because of confusion, inaccurate or unclear information. When we look at the decision-making process, we see that they can replace all their business goals with vague or negative ones. Fuzzy crowds are determined by equations called membership. These properties are allocated standards between 0 and 1. Through setting least and extreme performance targets and cost of ownership, the decision-maker has to make a decision. The membership function $\mu(j_i)$ in a constructive manner.

It remains measured that $\mu\left(j_g\right)$ occurred to be a linear declining and unremitting purpose and is expressed as

$$\mu\left(j_g\right) = \begin{cases} 1 & j_g \le j_g^{\min} \\ \frac{j_g^{\max} - j_g}{j_g^{\max} - j_g^{\min}} & j_g^{\min} \le j_g \le j_g^{\max}\ (g = 1, 2, \ldots, N_{ob}) \\ 0 & j_g \le j_g^{\max} \end{cases} \quad (19)$$

where $j_g^{\min}$ and $j_g^{\max}$ remain the least and extreme standards of impartial role anywhere in the solution to be property-owning.

N_{ob} denotes the number of impartial purpose in the problem.

Regularized association values μ^k for each non-dominated resolution is intended by the subsequent equation.

$$\mu^k = \frac{\sum_{i=1}^{Nobj} \mu_i^k}{\sum_{k=1}^{M_{nds}} \sum_{i=1}^{Nobj} \mu_i^k} \quad (20)$$

where M_{nds} remains the amount of non-dominated solutions. Indicate the best contain explanation that is consuming the utmost value of μ^k.

4 Implementation

Figure 1 shows the flowchart for STHTGS problem and implementation of NSTLBO algorithm.

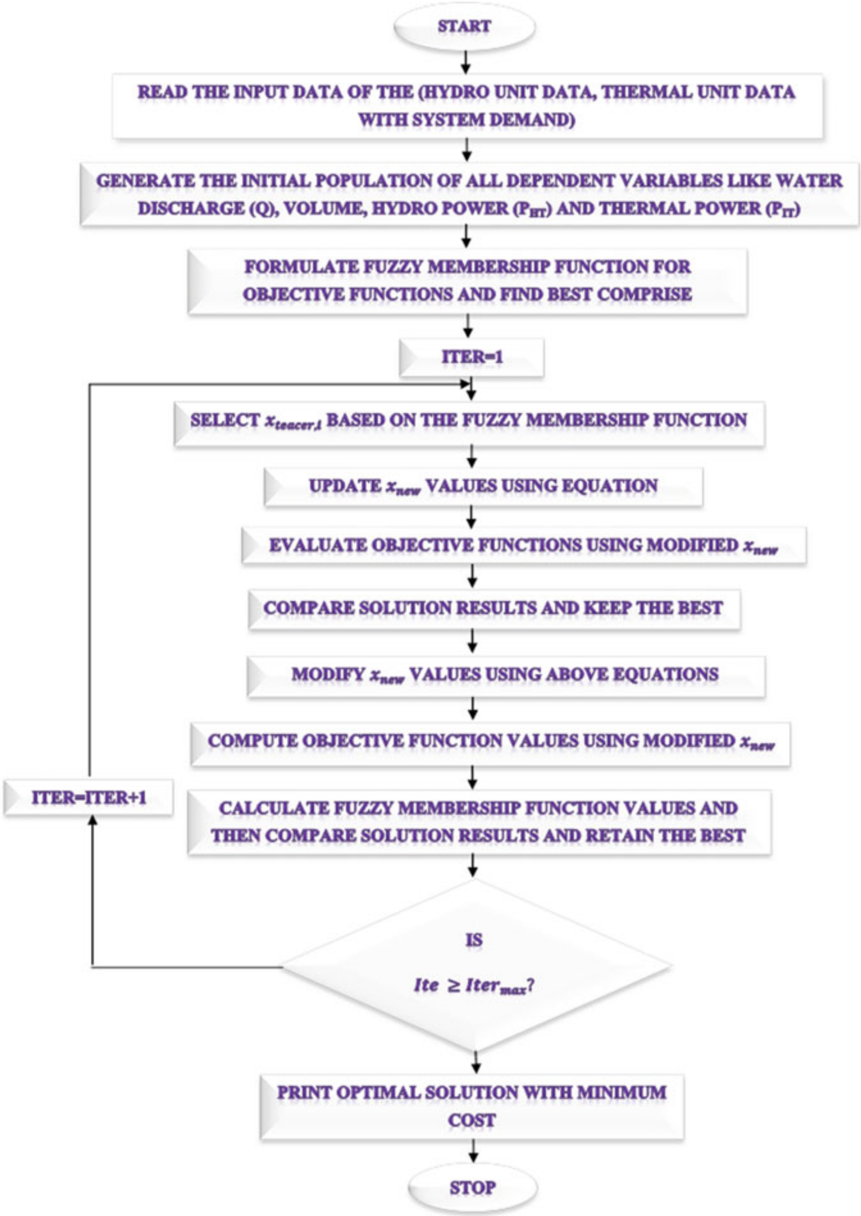

Fig. 1 Implementation of NSTLBO for STHTGS problem

5 Results and Discussion

Apply the NSTLBO algorithm to the test procedure, confirm the viability and efficacy of the NSTLBO algorithm and elucidate the STHTGS problem. The test system consists of four hydro generators and three thermal generators to achieve the best solution of the STHTGS problem, with and without the valve loading effect. The main objective of the process is the operating cost of the electric generator, captivating into explanation the effect of the valve loading point. Also, the hydraulic network of these machines is shown in Fig. 2. Total scheduling time is 24 h. The test procedure is explained in detail and the results are described below.

Test System

In this system, the best solution of the STHTGS problem is obtained by using the NSTLBO algorithm, taking into account the valve point load effect of the thermal power plant. All the input information of the hydrothermal system is taken in [21] and the NSTLBO algorithm effectively solves the STHTGS problem by finding the minimum fuel cost of the thermal unit with effectiveness, the slightest value that the NSTLBO algorithm can find. Table 1 demonstrates the hydraulic discharge for a period of 24 h in an optimal manner and also it is shown in Fig. 3.

Optimum power generation of hydro, thermal and total load demand are given in Table 2. The optimum power generation of water, steam and power demand is shown in Fig. 4 with an optimal manner.

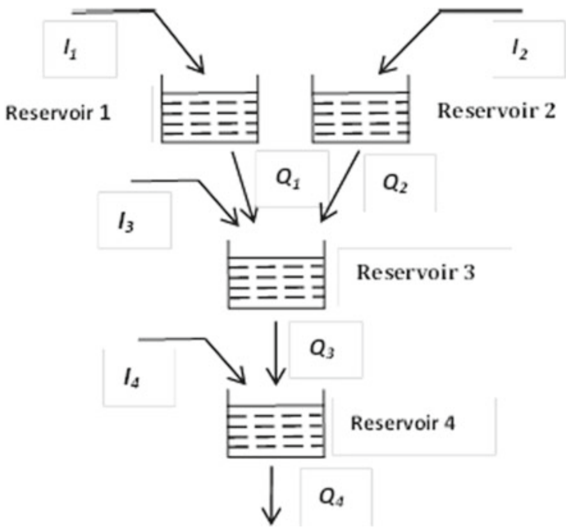

Fig. 2 Hydraulic network

Table 1 Optimal generation of water discharge for four hydro units

Hours	Water discharge				Hours	Water discharge			
	Q_1	Q_2	Q_3	Q_4		Q_1	Q_2	Q_3	Q_4
1	12.781	14.880	17.828	11.041	13	8.5450	6.8000	24.331	18.210
2	6.1990	6.8820	22.875	17.815	14	13.379	13.734	11.177	24.123
3	14.702	14.392	12.188	23.912	15	6.1500	11.524	11.342	23.784
4	15.452	14.352	28.339	24.836	16	14.999	14.999	15.127	24.872
5	6.7224	14.981	26.521	16.567	17	14.489	12.011	17.359	24.999
6	14.999	14.553	10.780	24.748	18	14.999	15.790	10.703	21.025
7	14.961	14.363	23.672	24.989	19	12.688	10.284	28.725	24.983
8	14.574	8.8940	29.754	24.582	20	14.671	7.5870	12.842	24.791
9	14.951	12.924	11.446	14.913	21	6.9730	14.969	29.999	24.984
10	12.968	14.793	23.551	17.260	22	14.999	14.759	13.385	18.617
11	11.849	13.681	29.978	23.335	23	9.8850	10.594	10.815	23.297
12	13.859	14.548	13.527	24.069	24	11.775	14.999	17.560	24.925

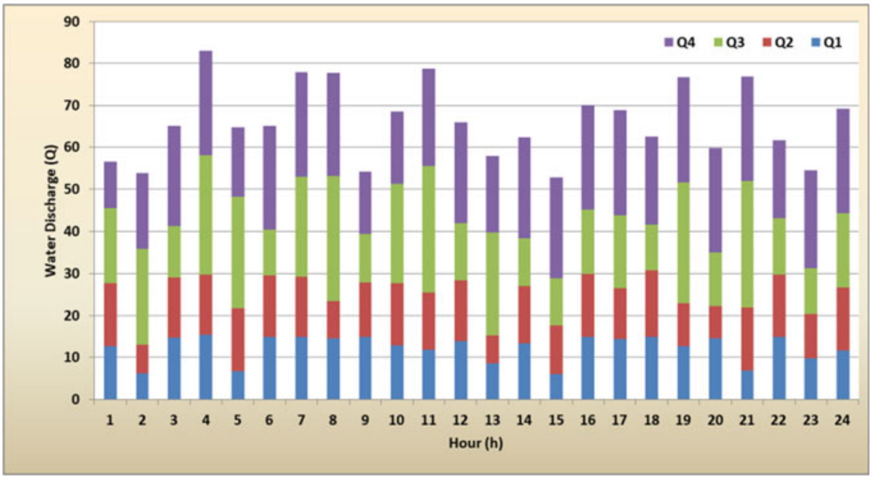

Fig. 3 Optimal generation of water discharge of four hydro units

Table 2 Optimal generation of four units of hydro, three units of thermal power and total load demand

Hour	Hydro				Thermal			Total load demand
	Ph1	Ph2	Ph3	Ph4	Ps1	Ps2	Ps3	
1	93.270	83.227	29.869	178.58	102.274	123.614	139.166	750
2	56.383	47.315	5.1850	216.99	101.77	123.887	228.47	780
3	96.363	77.525	39.374	208.17	20.910	206.958	50.700	700
4	92.260	75.829	0.0000	199.13	102.97	40.001	139.81	650
5	56.870	71.903	0.0000	259.45	102.767	40.000	139.01	670
6	86.053	70.088	37.770	325.32	99.590	40.809	140.37	800
7	87.337	71.486	0.0000	327.82	21.047	124.83	317.48	950
8	87.047	49.339	0.0000	326.61	20.904	208.53	317.57	1010
9	86.628	66.798	39.204	262.91	102.67	125.69	406.10	1090
10	84.497	72.197	0.0000	283.37	103.52	39.626	496.79	1080
11	82.018	68.992	0.0000	320.47	101.55	209.60	317.37	1100
12	86.179	71.816	44.005	323.40	102.70	292.70	229.20	1150
13	67.785	37.885	0.0000	290.68	103.17	293.19	317.29	1110
14	87.053	69.127	39.061	323.61	153.81	40.369	316.97	1030
15	52.563	61.833	39.154	321.88	101.56	292.53	140.48	1010
16	89.021	72.499	36.803	311.89	20.007	209.81	319.97	1060
17	86.612	63.69	31.388	327.84	102.63	209.64	228.20	1050
18	86.622	73.286	38.752	309.06	172.35	210.72	229.21	1120
19	83.831	56.459	0.0000	327.80	165.23	210.16	226.52	1070
20	86.640	42.486	43.407	327.24	100.67	39.827	409.73	1050
21	56.218	72.457	0.0000	327.80	21.105	292.67	139.75	910
22	87.023	71.517	38.953	293.64	101.66	39.807	227.40	860
23	73.535	57.885	38.799	320.31	102.55	206.6	50.321	850
24	96.651	80.948	55.537	302.37	173.89	39.81	50.794	800

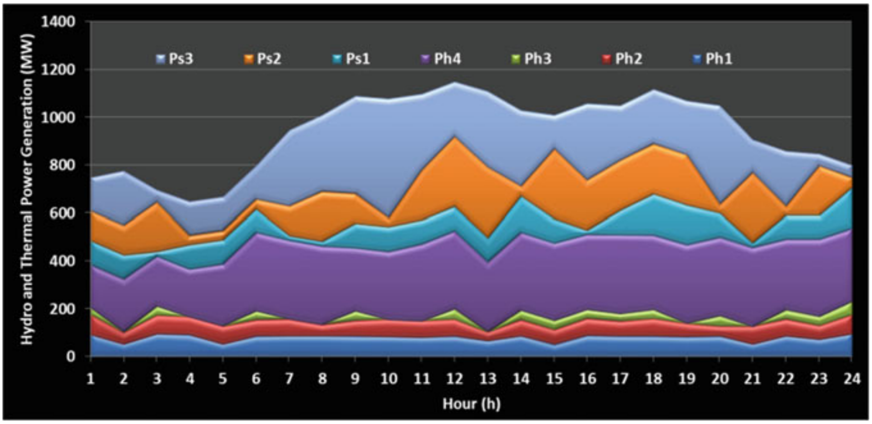

Fig. 4 Optimal generation of four hydro, three thermal units

6 Conclusion

This study presents a short-term hydrothermal power generation distribution by means of the NSTLBO algorithm. Toward verifying the efficacy of the future method, this experiment includes several consecutive hydroelectric chains and different thermal power plants to analyze and solve the STHTGS problem. The simulation outcomes of the NSTLBO technique demonstrate the validity then pre-eminence of the technique. In the future, different efficient and state-of-the-art multi-objective optimization algorithms will be considered for uncertain short-term hydrothermal production scheduling decisions.

References

1. Hossain SM, Shiblee MSAAF (2017) A short review study on problems during hydro-thermal optimal scheduling. Int J Adv Technol Eng Explor 4(34):142–147
2. Tahir MF, Haoyong C, Mehmood K, Ali N, Bhutto JA (2019) Integrated energy system modeling of China for 2020 by incorporating demand response, heat pump and thermal storage. IEEE Access 7:40095–40108
3. Tahir MF, Haoyong C, Khan A, Javed MS, Laraik NA, Mehmood K (2019) Optimizing size of variable renewable energy sources by incorporating energy storage and demand response. IEEE Access 7:103115–103126
4. Padmini S, Jegatheesan R, Thayyil DF (2015) A novel method for solving multi-objective hydrothermal unit commitment and sheduling for GENCO using hybrid LR-EP technique. Procedia Comput Sci 57:258–268
5. Das S, Bhattacharya A, Chakraborty AK (2018) Solution of short-term hydrothermal scheduling problem using quasi-reflected symbiotic organisms search algorithm considering multi-fuel cost characteristics of thermal generator. Arab J Sci Eng 43:2931–2960
6. Naversen CØ, Helseth A, Li B, Parvania M, Farahmand H, Catalão JP (2020) Hydrothermal scheduling in the continuous-time framework. Electr Power Syst Res 189:106787

7. Allen WOOD, Wollenberg BF (1984) Power generation, operation, and control. Wiley
8. Rodrigues RN, da Silva EL, Finardi EC, Takigawa FY (2012) Solving the short-term scheduling problem of hydrothermal systems via Lagrangian relaxation and augmented Lagrangian. Math Probl Eng
9. Zhang H, Yue D, Xie X, Dou C, Sun F (2017) Gradient decent based multi-objective cultural differential evolution for short-term hydrothermal optimal scheduling of economic emission with integrating wind power and photovoltaic power. Energy 122:748–766
10. Sinha N, Lai LL (2006) Meta heuristic search algorithms for short-term hydrothermal scheduling. In: 2006 international conference on machine learning and cybernetics. IEEE, pp 4050–4056
11. Hota PK, Chakrabarti R, Chattopadhyay PK (1999) Short-term hydrothermal scheduling through evolutionary programming technique. Electr Power Syst Res 52(2):189–196
12. Sinha N, Chakrabarti R, Chattopadhyay PK (2003) Fast evolutionary programming techniques for short-term hydrothermal scheduling. IEEE Trans Power Syst 18(1):214–220
13. Türkay B, Mecitoğlu F, Baran S (2011) Application of a fast evolutionary algorithm to short-term hydro-thermal generation scheduling. Energy Sources Part B Econ Plann Policy 6(4):395–405
14. Nallasivan C, Suman DS, Henry J, Ravichandran S (2006) A novel approach for short-term hydrothermal scheduling using hybrid technique. In: 2006 IEEE power India conference. IEEE, p 5
15. Fang N, Zhou J, Zhang R, Liu Y, Zhang Y (2014) A hybrid of real coded genetic algorithm and artificial fish swarm algorithm for short-term optimal hydrothermal scheduling. Int J Electr Power Energy Syst 62:617–629
16. Wong KP, Wong YW (1994) Short-term hydrothermal scheduling part. I. Simulated annealing approach. In: IEE Proc Gener Transm Distrib 141(5):497–501
17. Wong SYW (2001) Hybrid simulated annealing/genetic algorithm approach to short-term hydro-thermal scheduling with multiple thermal plants. Int J Electr Power Energy Syst 23(7):565–575
18. Kumar VS, Mohan MR (2011) A genetic algorithm solution to the optimal short-term hydrothermal scheduling. Int J Electr Power Energy Syst 33(4):827–835
19. Samudi C, Das GP, Ojha PC, Sreeni TS, Cherian S (2008) Hydro thermal scheduling using particle swarm optimization. In: 2008 IEEE/PES transmission and distribution conference and exposition. IEEE, pp 1–5
20. Yu B, Yuan X, Wang J (2007) Short-term hydro-thermal scheduling using particle swarm optimization method. Energy Convers Manage 48(7):1902–1908
21. Pasupulati B, Kumar A, Asokan K (2018) Optimal scheduling of hydrothermal system considering different environmental emissions using NSTLBO approach. Int J Renew Energy Res (IJRER) 8(4):1913–1925
22. Pasupulati B, Kumar RA, Asokan K (2020) A novel approach of non-dominated sorting TLBO for multi objective short-term generation scheduling of hydrothermal-wind integrated system. In: Emerging trends in electrical, communications, and information technologies: proceedings of ICECIT-2018. Springer, Singapore, pp 411–428