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Introducing Adaptive Machine Learning Technique for Solving Short-Term Hydrothermal Scheduling with Prohibited Discharge Zones

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Abstract: The short-term hydrothermal scheduling (STHTS) problem has paramount importance in an interconnected power system. Owing to an operational research problem, it has been a basic concern of power companies to minimize fuel costs. To solve STHTS, a cascaded topology of four hydel generators with one equivalent thermal generator is considered. The problem is complex and non-linear and has equality and inequality constraints, including water discharge rate constraint, power generation constraint of hydel and thermal power generators, power balance constraint, reservoir storage constraint, initial and end volume constraint of water reservoirs, and hydraulic continuity constraint. The time delays in the transport of water from one reservoir to the other are also considered. A supervised machine learning (ML) model is developed that takes the solution of the STHTS problem without PDZ, by any metaheuristic technique, as input and outputs an optimized solution to STHTS with PDZ and valve point loading (VPL) effect. The results are quite promising and better compared to the literature. The versatility and effectiveness of the proposed approach are tested by applying it to the previous works and comparing the cost of power generation given by this model with those in the literature. A comparison of results and the monetary savings that could be achieved by using this approach instead of using only metaheuristic algorithms for PDZ and VPL are also given. The slipups in the VPL case in the literature are also addressed.

Keywords: hydrothermal scheduling; supervised machine learning model; empirical loss minimization; prohibited discharge zones; valve point loading

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1. Introduction

Without any iota of untruth, the increased power demand has made the power system complex in its structure and operation. Hydropower projects are not merely to generate electricity but are also used for the irrigation of land. The economic operation and control of the electrical power system demand the optimal scheduling of hydro- and thermal power plants. The hydrothermal scheduling problem is a complex, dynamic, non-linear, multi-model, and constrained optimization problem that involves the quadratic modeling of production costs of hydro- and thermal power generations. Hydrothermal scheduling can be classified based on scheduling periods as short-term hydrothermal scheduling and long-term hydrothermal scheduling. In this paper, short-term hydrothermal scheduling (STHTS) is considered with a scheduling horizon of 24 h. The hydro reservoirs are hydraulically connected with each other. The constraints include the water and power balance constraint, physical limitations of the reservoirs, and loading limits of both thermal and hydropower plants. In a cascaded reservoir system, a time delay is introduced in moving water from one reservoir to another, which acts as a constraint in solving the STHTS problem.

To solve this type of complex optimization problem, good computational tools are required. The scheduling problem has been investigated by classical optimization techniques, including non-linear programming [1], gradient search algorithm [2], Lagrange multiplier method [3], Lagrange relaxation method [4], dynamic programming [5], network flow and linear programming [6], mixed integer programming [7], and evolutionary computation [8].

Orero et al. [9] used the genetic algorithm to solve the STHTS problem considering the cascaded reservoirs with a non-linear relationship between water discharge rate and net head. Their research work also included the water transport delay from one reservoir to another. Researchers also worked on differential evolution (DE) [10], and Hopfield Neural Network (HNN) [11]. Rubiales et al. [12] proposed the novel decomposition approach. They modeled the transmission network at a high level of detail, considering AC power flow to avoid post-dispatch corrections. They used the generalized benders decomposition (GBD) with bundle methods. A symbiotic search algorithm was employed by Das et al. [13] to solve the short-term hydrothermal scheduling problem and computational efficiency was calculated. To solve the STHTS problem, a parallel differential evolution approach was adopted by Zhang et al. [14]. The research work divided the whole population into subpopulations, independently searching for optimal solutions synchronously.

The teaching-learning-based optimization (TBLO) algorithm was used by Roy [15]. The algorithm was tested on three test cases: without prohibited discharge zones, with prohibited discharge zones, and with prohibited discharge zones and valve point loading effect. The cuckoo search algorithm (CSA) was employed by Dubey et al. [16] and tested for the aforementioned three test cases. An improved version of CSA was applied by Nguyen et al. [17]. The clustered adaptive teaching-learning-based optimization (CATLBO) algorithm was utilized by Salkuti [18] to solve STHTS. Haroon et al. [19] applied the evaporation rate-based water cycle algorithm (ERWCA) to hydrothermal coordination problems and compared the results with other techniques. Ghosh et al. [20] applied the hybrid bat algorithm (BA) with an artificial bee colony (ABC) to solve the STHTS problem. This hybridization comprises agents' exchange policy between the two algorithms. The worst agents of bat algorithms are replaced by better agents of ABC and, on the other hand, the poor agents of ABC are replaced by good agents of BA. Yan et al. [21] used the improved proximal bundle method (IPBM) within the framework of Lagrangian relaxation for STHTS, which incorporates the expert system (ES) technique into the proximal bundle method (PBM). Alshammari et al. [22] utilized the non-dominated sorting particle swarm optimization technique to solve the economic dispatch problem with wind power integration. An improved teaching-learning-based optimization (ITBLO) was used by Thiagarajan et al. [23] to solve short-term scheduling problems. Balachander et al. [24] solved the STHTS problem with three thermal generators using particle swarm optimization and the improved bacterial foraging (PSO-IBF) algorithm. The hydro spillage model was proposed by Sakthivel et al. to solve the problem at hand by the quasi-oppositional turbulent water-flow-based optimization (QOTWFO) algorithm [25].

This research is intended to develop and embed an adaptive machine learning model with any meta-heuristic algorithm for the solution of the STHTS problem with prohibited discharge zones. A meta-heuristic technique is used to solve the STHTS without PDZ. The "sub-optimal" solution just obtained is fed as an input to a machine learning (ML) model that outputs an optimal solution with PDZ and VPL effect. Firstly, the model is trained on a data set. Once trained, it can be applied to the solution of any meta-heuristic algorithm without PDZ. The execution time is negligible, as once the model is trained it gives the results within no time. In the past, no such amalgam was made and applied to solve the STHTS problem at hand. A drastic improvement in the results is observed and is discussed in the subsequent sections.

2. Problem Formulation

A short-term hydrothermal scheduling problem is a mixture of linear and non-linear constraints and dynamic network flow. The details of the objective function and the linear and non-linear constraints are discussed in the following subsections. The test system is taken from [9], which has become a benchmark (details are given in the Appendix A Section). The hydrothermal power system under study is depicted in Figure 1.

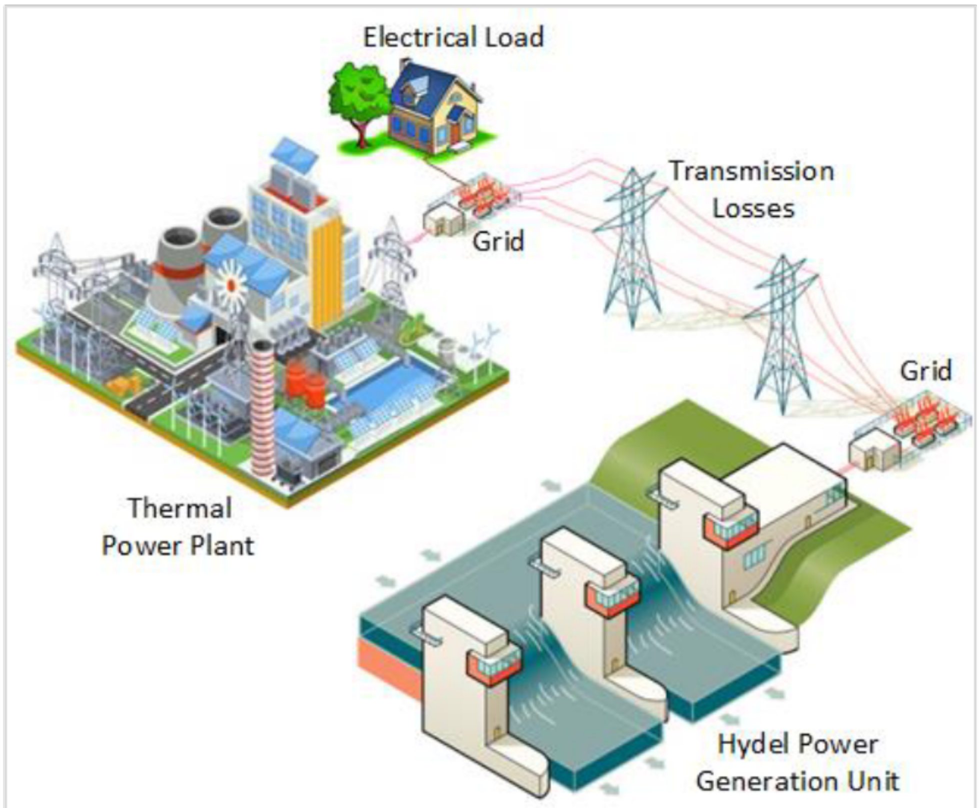


Figure 1. Typical hydrothermal power system under study.

The STHTS problem is a non-linear, multi-model, and NP-hard problem. Therefore, the best results cannot be guaranteed in this area. However, the metaheuristic algorithms give the results with some deviation when repeatedly applied to this problem. This is due to the randomness present in it.

2.1. Objective Function

The objective of STHTS is to optimize the fuel cost of the generation of electrical power satisfying the various constraints. The overall cost of the hydrothermal system is the cost of fuel for the thermal power plants [26]. Equation (1) describes the objective function [27]:

$$F = min \sum_{t=0}^{T} \sum_{i=1}^{N_s} f_i\left(P_{si}^t\right) \quad (1)$$

where N_s is the total number of thermal power plants. T is the scheduling period. Here, T is taken as 24 h considering per day scheduling of the hydrothermal power system. ${P_{si}}^t$ is the electrical power generated by the equivalent thermal power plant in the time instant t.

The fuel cost function of the thermal power generation is taken as a quadratic function of the power generated by the thermal plant given by [9]:

$$f_i\left(P_{si}^t\right) = a_{si} + b_{si} \cdot P_{si}^t + c_{si} \cdot \left(P_{si}^t\right)^2 \quad (2)$$

The above equation shows the fuel cost of a single thermal power generator. If multiple generators are considered, then the above equation is repeated, as discussed in [28]. However, in this research work, an equivalent thermal power plant is considered. In thermal power plants, valves control the steam entering the turbine. These valves are opened in sequence to obtain maximum efficiency at any given output. The result is a rippled efficiency curve. To incorporate these effects, an additional term is added to Equation (2) [27], which incorporates the effect of the valve point on the fuel cost of the thermal generators. The updated equation for the valve point loading effect is as follows:

$$f_i\left(P_{si}^t\right) = a_{si} + b_{si} \cdot P_{si}^t + c_{si} \cdot \left(P_{si}^t\right)^2 + \left|d_{si} \cdot \sin\left(e_{si}\left(P_{si,min} - P_{si}^t \right)\right) \right| \quad (3)$$

where a_{si}, b_{si}, and c_{si} are the coefficients for the ith generator's cost and d_{si} and e_{si} are its valve point effect coefficients. $P_{si,min}$ is the minimum power generated by the ith generator.

2.2. Hydel Power Generation Characteristics

The power generated by the hydel power plants has been modeled by many methods [9]. In general, the generated hydel power is a function of the net head, reservoir volume, and rate of discharge of water. The power generation characteristics of the hydel power plant can be modeled in terms of reservoir volume and the rate of water discharge, ignoring the net hydraulic head only in the case when the reservoir volume is relatively large [9]. The mathematical formulation of the power generation [27] is as follows:

$$P_{hj}^t = c_{1j}\left(V_{hj}^t\right)^2 + c_{2j}\left(Q_{hj}^t\right)^2 + c_{3j}\left(V_{hj}^t \cdot Q_{hj}^t\right) + c_{4j}\left(V_{hj}^t\right) + c_{5j}\left(Q_{hj}^t\right) - c_{6j} \quad (4)$$

where P_{hj}^t is the power generated by the jth hydropower plant at the time instant t; c_{1j}, c_{2j}, c_{3j}, c_{4j}, c_{5j}, and c_{6j} are the coefficients adopted in [9]; V_{hj}^t and Q_{hj}^t are the reservoir volume and the water discharge rate of the jth hydel plant at t time instant, respectively.

The short-term hydrothermal problem is modeled with various constraints, the details of which are explained below.

2.3. Power Balance Constraint

The power balance constraint is an equilibrium constraint that describes that the total power generated by the hydro and thermal power plants must satisfy the total load demand and the power losses at the time instant t:

$$\sum_{i=1}^{N_s} P_{si}^t + \sum_{j=1}^{N_h} P_{hj}^t = P_D^t \quad (5)$$

where P_D^t is the power demand of the total load connected.

2.4. Thermal Generation Limits Constraint

The power generated by the equivalent thermal power plant should be in between the lower and upper bounds, resulting in an inequality constraint [27]:

$$P_{si,min} \ \leq \ P_{si} \ \leq P_{si,max} \quad (6)$$

where $P_{si,max}$ is the maximum limit of electrical power generated by an equivalent thermal power generator. The above equation shows that the thermal power generated must be within bounds at any time instant.

2.5. Hydel Generation Limits Constraint

The power generated by each hydel power plant must be in between the lower and upper bounds [27]:

$$P_{hi,min} \leq P_{hi} \leq P_{hi,max} \tag{7}$$

where $P_{hi,min}$ and $P_{hi,max}$ are the minimum and maximum limits of the power generated by a hydel power plant. The values for the test system in hand are given in the Appendix A Section.

2.6. Reservoir Capacity Constraint

The volume of the water reservoir is a constraint to be between the lower and upper limits [27]:

$$V_{hi,min} \leq V_{hi} \leq V_{hi,max} \tag{8}$$

where $V_{hi,min}$ and $V_{hi,max}$ are the minimum and maximum limits of the water reservoir volume of the hydel power plants.

2.7. Initial and Final Storage Constraint

The reservoir volumes are constrained to be initialized and ended with a static volume value, i.e., there is a fixed initial volume for all water reservoirs. At the end of the scheduling period, the reservoirs must contain a specific volume of water. The constraint is described mathematically as follows [27]:

$$V_{hj}^{0} = V_{hj}^{initial} \tag{9}$$

$$V_{hj}^{T} = V_{hj}^{final} \tag{10}$$

The consideration of initial and final volumes of the reservoirs makes the test system realistic in 24 h short-term scheduling. The values are given in the Appendix A. As the initial and final volumes are the same at the end of each day, the reservoir is set to its initial state and the cycle begins.

2.8. Discharge Rate Limits Constraint

The discharge rates are constrained to be in upper and lower bounds. For prohibited discharge zones PDZ the limits are taken to be exclusive.

$$Q_{hj}^{min} \leq Q_{hj}^{t} \leq Q_{hj}^{max} \tag{11}$$

$$Q_{hj}^{PDZ\_min} < Q_{hj}^{t} < Q_{hj}^{PDZ\_max} \tag{12}$$

2.9. Hydraulic Continuity Constraint

The hydropower plants are considered to be cascaded, as shown in Figure 2. The details of the test system data are present in the Appendix A Section. The time delay in the flow of water from the upstream hydel reservoir to a downstream reservoir is considered in the continuity constraint. The mathematical formulation of the continuity equation for the hydel reservoir network is given by [9]:

$$V_{hj}^{t} = V_{hj}^{t-1} + I_{hj}^{t} - Q_{hj}^{t} - S_{hj}^{t} + \sum_{k=1}^{R_k} \left[Q_{hk}^{t-\tau} + S_{hk}^{t-\tau} \right] \tag{13}$$

where R_k is the set of upstream hydel power plants and S_{hj}^{t} is the spillage of the jth hydel reservoir at time interval t.

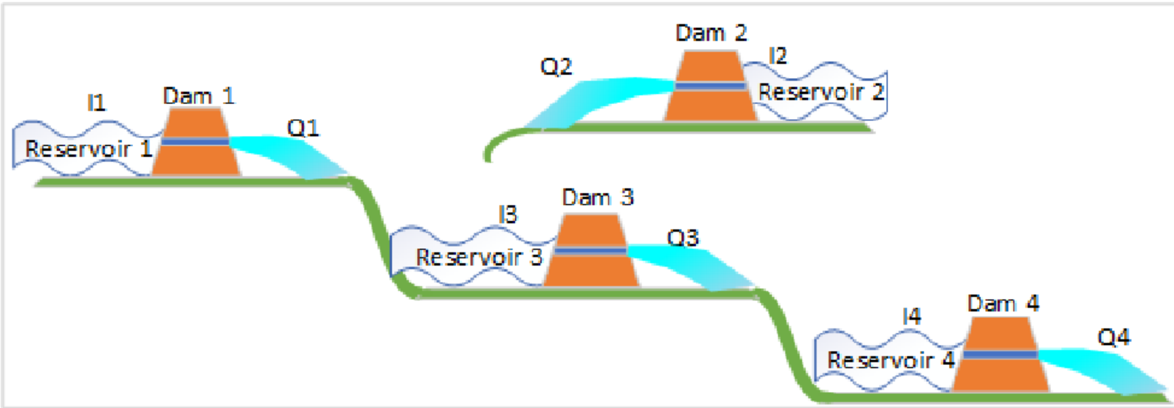


Figure 2. Modeling of continuity constraint.

In Figure 2, I1, I2, I3, and I4 are the inflows, and Q1, Q2, Q3, and Q4 are the discharge rates. It is clear from the figure that reservoir 3 has water input from the discharge of dam 1 and dam 2.

3. Methodology

The research work under consideration is the extension of work conducted in [29–34]. Here, the main focus is on the application of prohibited discharge zones using a novel constraint handling technique that yields better results in short-term hydrothermal scheduling with prohibited discharge zones. A high-level view of the methodology is depicted in Figure 3.

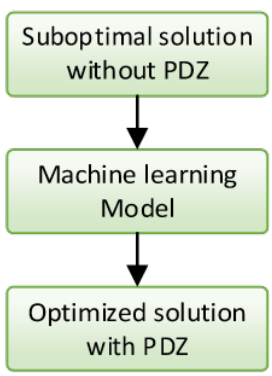


Figure 3. Research contribution and high-level methodology.

The detailed methodology of training the model consists of the following steps: data collection, data preparation, model selection, training of the model, evaluation of the model, parameter tuning, and making predictions. In this paper, the details are given for the training of the machine learning model and its operation. The description of applying the accelerated particle swarm optimization (APSO) algorithm to the STHTS problem is given in [33].

3.1. Data Collection

The accelerated particle swarm optimization (APSO) algorithm is set to solve the STHTS without prohibited discharge zones. The details of applying APSO and the constraint handling are given in [34]. It gives suboptimal results with no violations. To have a large data set, the APSO is tuned to produce the best results. Exponential decay of controlling parameters, namely alpha (α) and beta (β), is considered and their ranges are

0.853–0.633 and 0.896–0.686, respectively. The swarm size was set to 4000 and the total number of iterations was also 4000.

To have an ample amount of data, the APSO algorithm was run 100 times with the same tuning parameters as described above. Owing to the randomness in the algorithm, 100 different data sets were obtained.

3.2. Data Preparation

In this step, the common relationship is identified with each other. This will help in the training of the model. In the selected problem, a common trend is observed in each water discharge rate over the scheduling period. It is further described in the training step of the model.

3.3. Model Selection

The problem is a complex optimization that yields the minimum cost of the objective function under various constraints. Therefore, a supervised machine model is used in which the inputs and the reference data set, output, both are available. In that very case, a slight change in any discharge rate can be quickly identified by its impact on overall cost and, at the same time, compared with the previous cost to be better or worse than that.

3.4. Training of the Model

In supervised learning methodology, a model is built by examining many examples and minimizing the loss; this process is known as empirical loss minimization. Loss is a numerical value that identifies how bad the model prediction was on an example data set. In the case of short-term hydrothermal scheduling, the loss is defined as the difference in overall fuel cost to the fuel cost for the solution of the STHTS problem without prohibited discharge zones. The fuel cost has an indirect link with the discharge rates Q (explained in incoming lines). Thus, a change in discharge rate can result in negative or positive loss. The procedure used in training the model for the STHTS problem with prohibited discharge zones PDZ is explained in the following steps:

3.4.1. Step I

First of all, it is needed to identify the discharge rate of which hour is to be changed to fulfill the PDZ constraint, i.e., the hours in which Q is violated.

3.4.2. Step II

(a) Start from discharge rate related to first reservoir Q_1 because the other reservoirs are present under them.
(b) Apply the PDZ constraint on discharge rates.
(c) Calculate and sum up all the violation values identified in step I.

3.4.3. Step III

Now it is needed to compensate the violation value such that the change in overall power generation cost is minimized or, in other words, the loss is minimum. To achieve the objectives of step III the following analysis was conducted.

Consider the following equation in which the total power generated by all hydel power plants (P^t_{hT}) is calculated in the time interval 't'.

$$P^t_{hT} = P^t_{h1} + P^t_{h2} + P^t_{h3} + P^t_{h4} \tag{14}$$

The power required by the thermal power plant to be generated to meet the load demand is given by

$$P^t_S = P^t_L - P^t_{hT} \tag{15}$$

also

$$Cost \propto f\left(P^t_S\right) \tag{16}$$

Thus, the following relation can be made:

Lower Cost ⇒ Lower ${P_s}^t$ ⇒ Higher ${P_{hT}}^t$ ⇒ highest possible ${P_{h1}}^t$, ${P_{h2}}^t$, ${P_{h3}}^t$, and ${P_{h4}}^t$ satisfying the constraints.

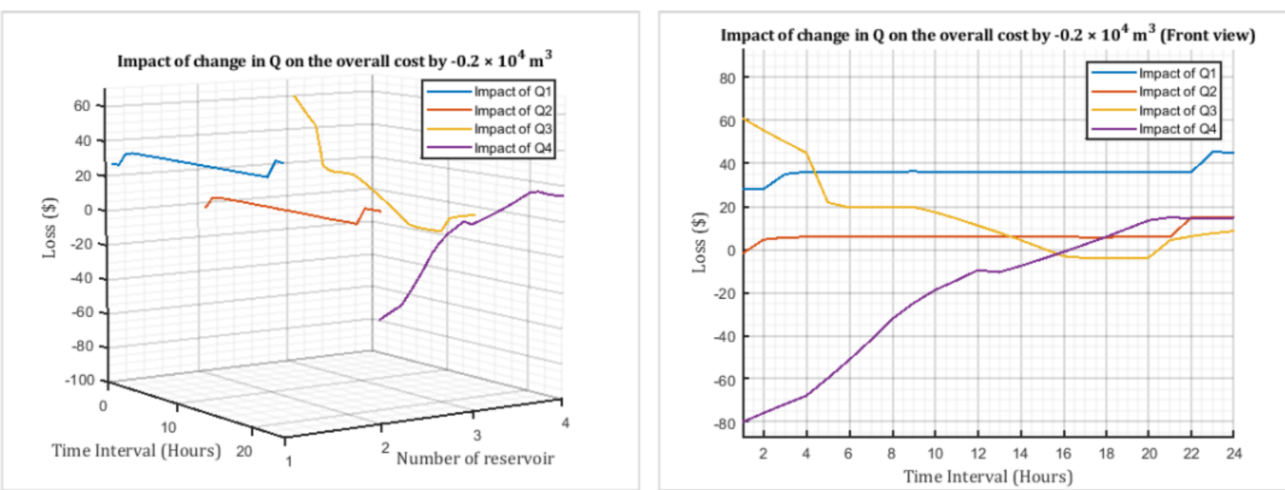
Now consider the equation for the calculation of ${P_{hj}}^t$ (Equation (4)).

In this equation, the hydel power of any hydropower plant depends on the reservoir volume and the discharge rate by some weights (the coefficients). In addition, discharge rates and volume are interconnected by Equation (13). In Equation (4), c_{1j} is negative, c_{2j} is negative, the third term is stabilized by both volume and discharge rate, and the last term is the constant, comparing c_{4j} and c_{5j}; c_{5j} is higher, so the impact of change in Q_{hj} is higher on P_{hj}.

The dependency of volume on the discharge rate (Q_{hj}) is a challenge in changing Q_{hj}. In addition, due to the time delays in the flow of water from higher reservoirs to lower reservoirs, the change in the discharge rate of the upstream reservoir not only changes the volume of its reservoir in the same time interval but also changes the volumes of the downstream reservoirs in the subsequent time intervals. To increase ${P_h}^t$, one increases discharge rate Q which will also affect volume V and the constraint may violate. Thus, it is needed to identify the "search space" in which Q is varied such that the overall cost is minimized, and no constraint is violated.

Further, the complexity comes when changing the Q_1 in its search space affects V_3 and V_4. This is similar to the case with Q_2 and Q_3, but a change in Q_4 has only its impact on V_4 simply because it is the lowest reservoir.

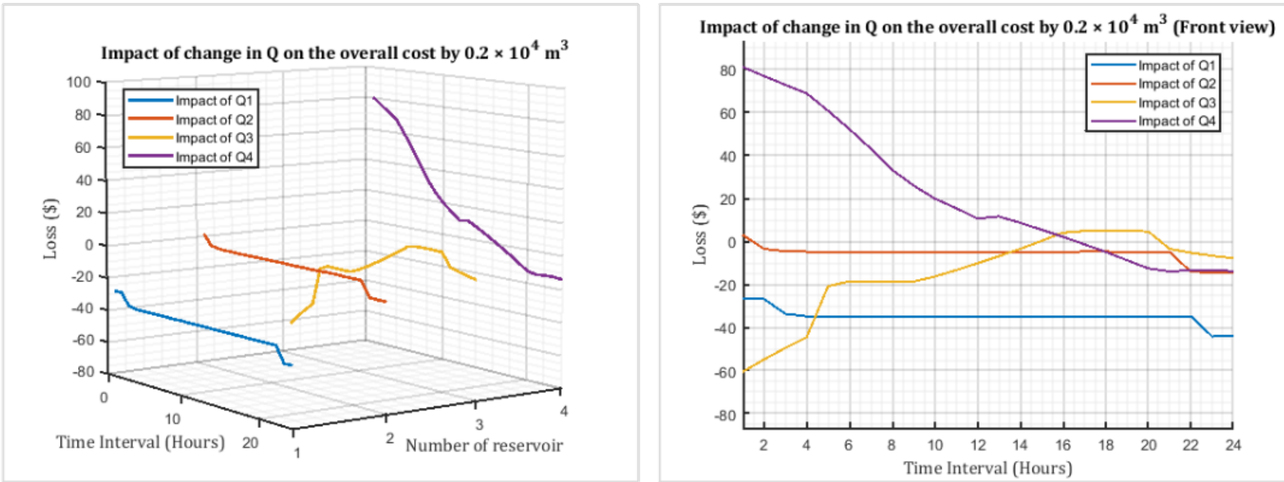
This complexity is studied by adding and subtracting some delta in every Q, that is, if it is needed to compensate for some value of V, first analyze which Q (Q_1, Q_2, Q_3, or Q_4) will give the minimum loss to compensate for that change and no equality and inequality constraint is violated. To explain it further, an example is taken to analyze the impact on loss by changing the discharge rate by, say, 0.2×10^4 m^3. Figure 4 explains the impact of decreasing the discharge rate by 0.2×10^4 m^3 on the overall cost.



(**a**) (**b**)

Figure 4. Impact of change in Q on the overall cost by "-0.2×10^4 m^3": (**a**) 3D view and (**b**) front view.

It is clear that if compensating for a value of 0.2×10^4 m^3 is needed in the volume of the 3rd reservoir, one can achieve it in either Q_3 or Q_2 or Q_1 in their respective hours including the time delays. A similar case has been studied when a value of, say, 0.2×10^4 m^3 is needed to be added in Q (Figure 5).



(**a**) (**b**)

Figure 5. Impact of change in Q on the overall cost by "0.2×10^4 m^3": (**a**) 3D view and (**b**) front view.

In some cases, compensation is required to be performed in its reservoir. In that case, the impact of change in discharge rate itself in different hours is studied. Figure 5 shows the difference in loss values versus hours. Here, the difference in loss values is determined by Equation (17). Figure 6 describes how much more costly it is to decrease the Q than increase it in a given hour.

$$Loss^t_{Difference} = \left|Loss^t_{Subtract}\right| - \left|Loss^t_{Add}\right| \tag{17}$$

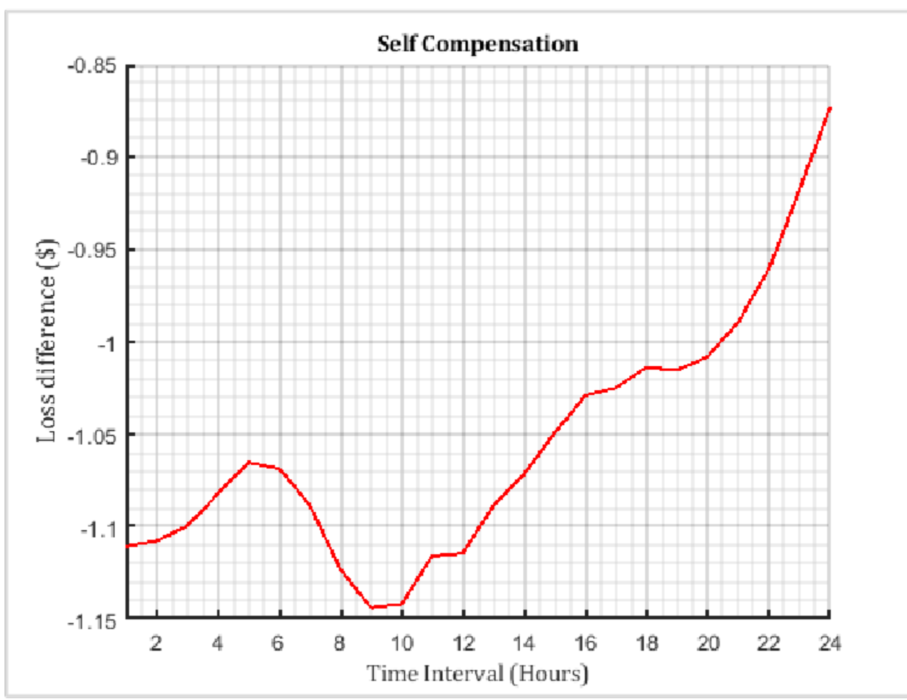


Figure 6. Loss difference determination for self-compensation.

3.4.4. Step IV

From the analysis performed in step III, the machine learning algorithm compensates for PDZ in the Q that gives the lowest loss. This process is continued until all violations have been addressed. A logical representation of how the ML model is working in its final form is given in Figure 7.

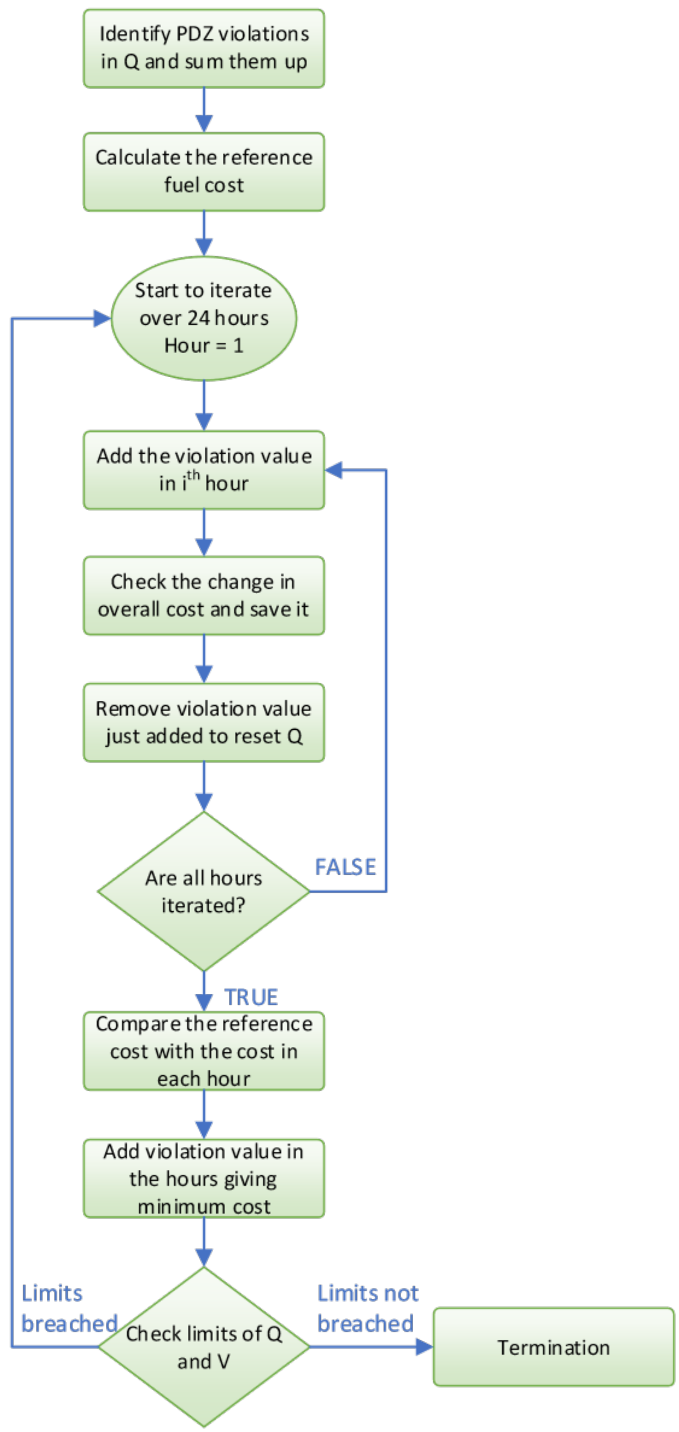


Figure 7. Logical representation of a PDZ compensator of a trained model.

3.5. Evaluating the Model

The model thus made was tested on the 100 runs collected in the data collection step based on the APSO algorithm. The model is not random: rather, its output is dependent on the values in the input, i.e., the best result for the solution of STHTS without PDZ (the input to the model) gives the best result for the STHTS with PDZ.

3.6. Parameter Tuning

In some cases, volume violations are observed in the 3rd reservoir. It was corrected by compensating it in the 1st reservoir.

3.7. Making Predictions

As the last step, extra care is taken to make the model somewhat more versatile to accept different inputs. This is achieved by considering those cases as inputs that already have end volume violations. The model shall consider those end volume violations as a value to be compensated, as described in the training model section.

4. Results and Discussion

It appears quite pertinent and even desirable to point out at the outset that the limits of prohibited discharge zones are considered to be exclusive. In some publications, such as [15], it is considered to be inclusive. The solution to STHTS with PDZ is by applying the machine learning (ML) model to the APSO algorithm using exponential decays of α and β. The minimum cost comes out to be 922,376.57 (USD). This cost is found as the minimum among the past results on prohibited discharge zones. Table 1 shows the hourly plant discharge, power generated by each power plant, and the fuel cost in each interval of time. Figure 8 explains the volumes of reservoirs in different time intervals. A comparison of the results with the previous ones is given in Table 2. Figure 9 graphically explains the comparison of the results with PDZ. The table shows that the proposed technique can be applied to the other metaheuristic algorithms and the cost of thermal generation can be significantly minimized for prohibited discharge zones. The second to last and last column show the amount of money that one can save if the proposed machine learning technique is applied for PDZ instead of only using metaheuristic algorithms. Without any suppression of fact, the metaheuristic algorithms are used first to solve STHTS without PDZ. The solution is then passed through the model to give a low-cost solution for the PDZ case.

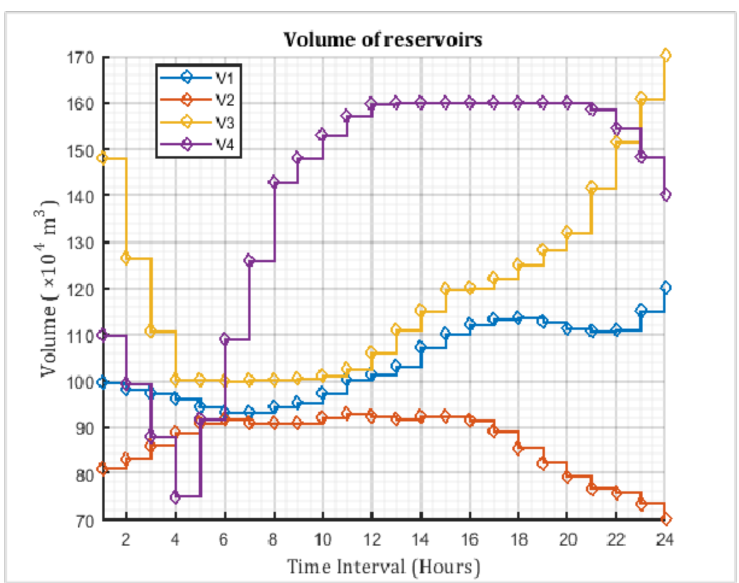


Figure 8. Volumes of reservoirs by APSO for PDZ.

Table 1. Hourly plant discharge and generation schedule using APSO for PDZ.

Time	Q_1	Q_2	Q_3	Q_4	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{hT}	P_S	Cost
Hour	**m³**	**m³**	**m³**	**m³**	**MW**	**MW**	**MW**	**MW**	**MW**	**MW**	**(USD)**
1	103,617.6	69,999.0	299,999.9	130,000.0	87.47	56.40	0.00	200.09	343.97	1026.03	26,805.29
2	103,819.5	61,509.6	299,999.9	130,000.1	87.04	51.72	0.00	187.76	326.51	1063.49	27,681.02
3	90,473.3	60,003.8	299,999.5	130,000.1	80.28	52.32	0.00	173.73	306.33	1053.67	27,450.93
4	79,999.0	60,028.1	300,000.0	130,000.0	73.92	53.93	0.00	156.79	284.64	1005.36	26,324.41
5	79,999.0	60,129.4	181,983.4	130,000.0	73.24	55.02	25.24	178.74	332.24	957.76	25,223.71
6	79,999.0	62,152.0	180,439.1	130,000.6	72.89	56.87	25.83	198.96	354.54	1055.46	27,492.78
7	79,999.0	66,302.4	168,898.3	130,000.1	72.89	59.46	30.01	217.44	379.80	1270.20	32,614.63
8	79,999.0	69,999.0	158,492.2	130,000.0	73.24	61.96	33.13	234.19	402.52	1597.48	40,775.51
9	90,001.0	80,001.0	150,788.3	130,000.1	79.30	68.33	35.01	238.96	421.61	1818.39	46,526.12
10	90,001.0	80,604.3	150,930.0	130,000.0	80.03	69.19	35.22	243.44	427.88	1892.12	48,488.90
11	90,001.0	81,608.9	153,807.6	130,001.6	81.05	70.24	35.29	246.79	433.37	1796.63	45,951.08
12	90,001.0	84,440.1	156,704.4	132,084.9	81.37	71.68	36.05	251.14	440.24	1869.76	47,891.44
13	90,001.0	84,681.9	159,999.0	146,513.1	82.00	71.57	37.38	265.47	456.41	1773.59	45,344.06
14	79,999.0	86,624.1	159,999.0	150,930.0	77.06	72.86	39.10	269.49	458.51	1741.49	44,502.15
15	79,999.0	88,027.0	159,996.8	153,807.6	77.74	73.76	40.87	272.04	464.41	1665.59	42,527.61
16	79,999.0	89,770.6	180,003.2	156,704.4	78.16	74.20	35.01	274.56	461.93	1608.07	41,046.81
17	79,584.0	93,709.8	167,406.6	159,999.0	78.08	74.99	39.86	277.36	470.29	1659.71	42,375.78
18	77,994.4	97,012.9	158,497.1	159,999.0	77.04	74.50	43.26	277.36	472.16	1667.84	42,585.87
19	76,996.1	102,581.6	147,353.6	159,999.0	76.22	75.14	46.53	277.36	475.25	1764.75	45,111.80
20	76,409.2	109,280.0	142,327.5	180,001.0	75.51	76.14	48.55	292.92	493.11	1786.89	45,694.18
21	75,359.5	117,218.3	100,000.1	183,493.7	74.67	77.34	50.59	293.81	496.40	1743.60	44,557.27
22	74,691.1	97,130.6	100,000.0	197,821.4	74.30	68.39	52.78	298.98	494.46	1625.54	41,495.21
23	51,058.3	104,421.1	100,000.0	209,003.8	55.68	70.02	54.58	298.44	478.73	1371.27	35,089.18
24	50,000.0	112,764.5	100,000.0	225,265.9	55.02	71.02	56.06	296.01	478.11	1111.89	28,820.81

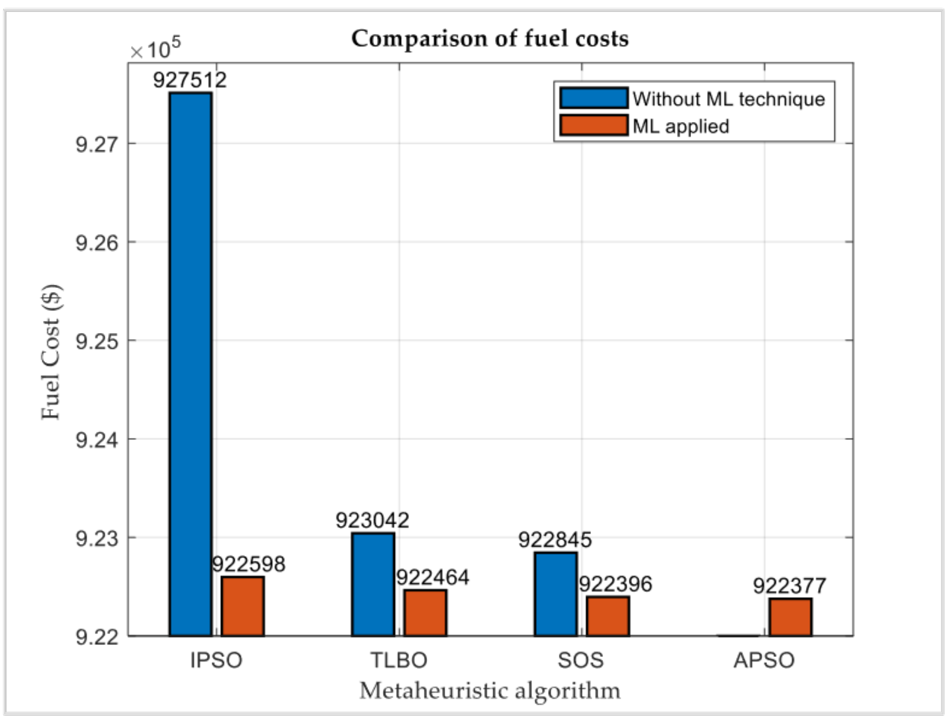


Figure 9. Comparison of applying PDZ with only metaheuristic algorithm and with the proposed technique.

Table 2. Comparison of optimal cost obtained from different algorithms for PDZ.

Technique	Constraint Violations with PDZ (If Any)	Results (without PDZ) (USD)	Reported Results (with PDZ) (USD)	Results after Applying the Proposed ML Technique with PDZ (USD)	Cost Difference (Savings per Day) (USD)	Annual Saving Using the Proposed ML Technique (USD)
IPSO [26]	V4(24): 121.2645	922,553.49	927,511.89	922,597.60	4914.29	1,793,715.71
TLBO [15]		922,373.39	923,041.91	922,463.79	578.12	211,012.43
SOS [13]		922,332.17	922,844.78	922,395.75	449.03	163,897.43
APSO		922,321.79		**922,376.57**		

The cases of prohibited discharge zones (PDZ) and valve point loading (VPL) effect are also discussed by many researchers. The aforementioned machine learning technique was used to solve STHTS with PDZ and VPL, and the results were compared with other metaheuristic algorithms used in the past. Equation (3) was used to find the cost of thermal power generation. The comparison results are shown in Table 3. The minimum cost comes out to be USD 931,901.73 using the APSO variant algorithm. The discharge rates and hourly power generated by each hydel power plant are given in Table 4. Figure 10 shows the volumes of reservoirs in each interval of time. Figure 11 shows the graphical comparison of results for PDZ and VPL.

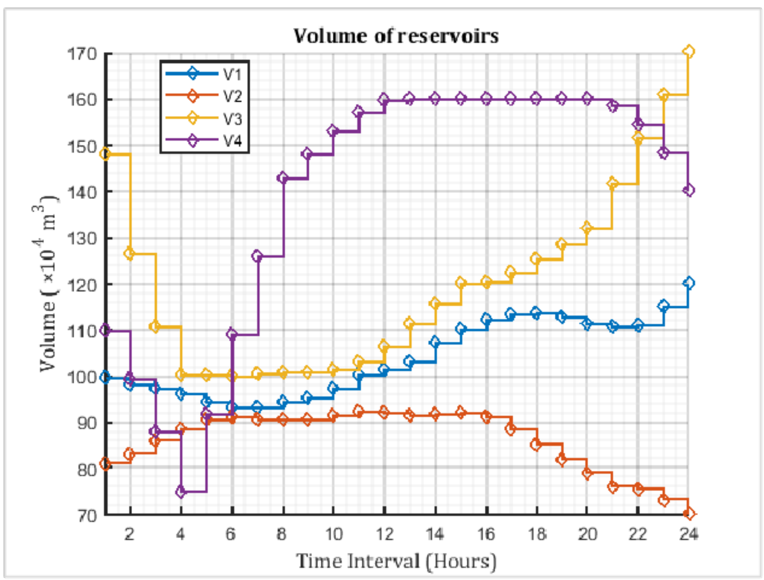


Figure 10. Volumes of reservoirs by APSO for PDZ and VPL.

Table 3. Comparison of optimal cost obtained from different algorithms for PDZ and VPL.

Technique	Reported Results (with PDZ and VPL) (USD)	Results after Applying the Proposed ML Technique with PDZ and VPL (USD)	Cost Difference (Saving per Day) (USD)	Annual Saving Using the Proposed ML Technique (USD)
MDE [26]	942,694.62	933,345.17	9349.45	3,412,549.25
ACDE [27]	–	931,909.00	–	–
MHDE [28]	941,844.77	937,786.54	4058.23	1,481,253.95
IPSO [25]	942,690.77	932,220.65	10,469.86	3,821,498.90
TLBO [15]	938,829.64	932,180.04	6649.61	2,427,107.65
SOS [13]	–	932,076.37	–	–
APSO variant	–	**931,901.73**	–	–

Table 4. Hourly plant discharge and generation schedule using APSO for PDZ and VPL.

Time	Q_1	Q_2	Q_3	Q_4	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{hT}	P_S	Cost
Hour	**m^3**	**m^3**	**m^3**	**m^3**	**MW**	**MW**	**MW**	**MW**	**MW**	**MW**	**(USD)**
1	103,618.0	69,999.0	300,000.0	130,000.0	87.47	56.40	0.00	200.09	343.97	1026.03	27,283.42
2	103,820.0	61,510.0	300,000.0	130,000.0	87.04	51.72	0.00	187.76	326.51	1063.49	28,137.09
3	90,473.0	60,004.0	300,000.0	130,000.0	80.28	52.32	0.00	173.73	306.33	1053.67	28,150.69
4	79,999.0	64,072.0	300,000.0	130,000.0	73.92	56.59	0.00	156.79	287.30	1002.70	26,539.29
5	79,999.0	60,129.0	181,983.0	130,000.0	73.24	54.81	25.24	178.74	332.03	957.97	25,404.33
6	79,999.0	62,152.0	180,439.0	130,001.0	72.89	56.66	25.83	198.96	354.34	1055.66	28,184.16
7	79,999.0	66,302.0	168,898.0	130,000.0	72.89	59.25	30.20	217.44	379.78	1270.22	33,255.29
8	79,999.0	69,999.0	158,492.0	130,000.0	73.24	61.75	33.31	234.19	402.49	1597.51	41,227.00
9	90,001.0	80,001.0	150,788.0	130,000.0	79.30	68.11	35.19	238.96	421.57	1818.43	46,938.50
10	90,001.0	80,604.0	150,930.0	130,000.0	80.03	68.98	35.40	243.44	427.85	1892.15	48,891.99
11	90,001.0	81,609.0	153,808.0	130,002.0	81.05	70.02	35.47	246.79	433.33	1796.67	46,609.71
12	90,001.0	84,440.0	156,704.0	132,085.0	81.37	71.46	36.23	251.14	440.20	1869.80	48,564.72
13	90,001.0	84,682.0	159,999.0	146,513.0	82.00	71.35	37.55	265.47	456.37	1773.63	45,371.66
14	79,999.0	86,624.0	159,999.0	150,930.0	77.06	72.65	39.26	269.49	458.46	1741.54	44,760.65
15	79,999.0	88,027.0	159,997.0	153,808.0	77.74	73.54	41.03	272.04	464.36	1665.64	42,673.72
16	79,999.0	89,771.0	180,003.0	156,704.0	78.16	73.98	35.18	274.56	461.87	1608.13	41,747.79
17	79,584.0	93,710.0	167,407.0	159,999.0	78.08	74.76	40.02	277.36	470.22	1659.78	42,577.79
18	77,994.0	97,013.0	158,497.0	159,999.0	77.04	74.26	43.41	277.36	472.07	1667.93	42,862.62
19	76,996.0	102,582.0	147,354.0	159,999.0	76.22	74.88	46.67	277.36	475.13	1764.87	45,608.65
20	76,409.0	109,280.0	146,372.0	180,001.0	75.51	75.87	48.02	292.92	492.31	1787.69	46,356.33
21	75,360.0	117,218.0	100,000.0	183,494.0	74.67	77.06	50.59	293.81	496.12	1743.88	44,945.41
22	74,691.0	95,783.0	100,000.0	197,821.0	74.30	67.55	52.78	298.98	493.62	1626.38	41,525.26
23	50,801.0	103,073.0	100,000.0	209,004.0	55.45	69.34	54.58	298.44	477.81	1372.19	35,382.68
24	50,257.0	111,416.0	100,000.0	229,310.0	55.26	70.50	56.06	297.51	479.33	1110.67	28,902.97

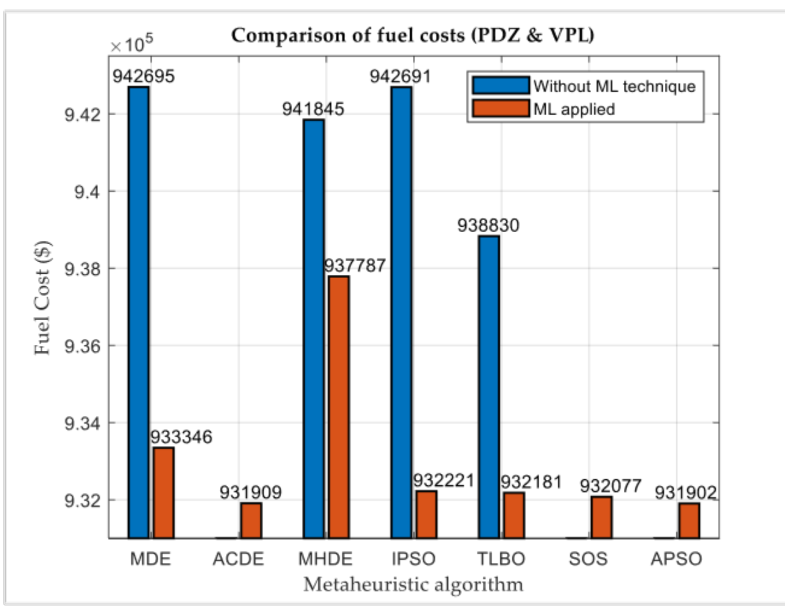


Figure 11. Comparison of applying PDZ and VPL with only metaheuristic algorithm and with the proposed technique.

The results reported in [15] for PDZ and VPL cases using TLBO are not consistent with the data provided. It seems that the reported cost (USD 924550.78) came from Equation (2), which does not include the valve point loading effect. The corrected one is given in Table 3, which was obtained from Equation (3).

5. Conclusions and Future Directions

The short-term hydrothermal scheduling problem with prohibited discharge zones has been very important in power systems and it has been solved by many metaheuristic techniques in the past. This research introduced a novel methodology to solve STHTS with PDZ and proves that its results are better than that of merely using metaheuristic techniques (Tables 2 and 3). A machine learning model was created that can be run over the results obtained from any metaheuristic technique. The output of the ML model, i.e., the solution to STHTS with PDZ, was better than those obtained by only applying the metaheuristic technique.

The extraordinary performance obtained by the proposed technique urges researchers to solve the problem at hand from scratch. In other words, starting from constant discharge rates or randomly initialized discharge rates, a model should be created that gives the best results for STHTS without PDZ. Furthermore, the existing model can be extended and can be tested over other larger and more complex hydrothermal systems.

It should be noted here that the proposed machine learning model is to be trained and reconstructed when trying to apply it to some other test system. This is the limitation of the technique proposed.

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Appendix A

The details of the test system are taken from [9]. The test system values used in solving the STHTS problem are given in the following.

The thermal power generation coefficients of the thermal power plant are given in Table A1.

Table A1. Thermal power generation coefficients.

Coefficient	Value
a_{si}	5000
b_{si}	19.20
c_{si}	0.002
d_{si}	700
e_{si}	0.085

The hydro power generation coefficients of the hydel plant are given in Table A2.

Table A2. Hydropower generation coefficients.

Plant	c_{1j}	c_{2j}	c_{3j}	c_{4j}	c_{5j}	c_{6j}
1	−0.0042	−0.42	0.03	0.9	10	−50
2	−0.004	−0.3	0.015	1.14	9.5	−70
3	−0.0016	−0.3	0.014	0.55	5.5	−40
4	−0.003	−0.31	0.027	1.44	14	−90

The hourly power demand of the power system under study are given in Table A3.

Table A3. Hourly load demand.

Hour	P_D (MW)	Hour	P_D (MW)
1	1370	13	2230
2	1390	14	2200
3	1360	15	2130
4	1290	16	2070
5	1290	17	2130
6	1410	18	2140
7	1650	19	2240
8	2000	20	2280
9	2240	21	2240
10	2320	22	2120
11	2230	23	1850
12	2310	24	1590

The generation limits of the equivalent thermal power plant is provided in Table A4.

Table A4. Thermal power generation limits.

Generation Limit	Power (MW)
$P_{si,min}$	500
$P_{si,max}$	2500

The limits of generation of the hydro power plant are given in Table A5.

Table A5. Hydropower generation limits.

Plant	$P_{hi,min}$ (MW)	$P_{hi,max}$ (MW)
1	0	500
2	0	500
3	0	500
4	0	500

The limits of the volumes of reservoirs are provided in Table A6.

Table A6. Minimum and maximum limits of volumes of reservoirs.

Plant	$V_{hi,min} \times 10^4$ (m^3)	$V_{hi,min} \times 10^4$ (m^3)
1	80	150
2	60	120
3	100	240
4	70	160

The initial and end volume limits of the water reservoirs are given in Table A7 for each reservoir.

Table A7. Initial and final limits of volumes of reservoirs.

Plant	$V_{hj,ini} \times 10^4$ (m^3)	$V_{hj,end} \times 10^4$ (m^3)
1	120	120
2	70	70
3	170	170
4	140	140

Table A8 explains the minimum and maximum limits of the discharge rates. The prohibited discharge zones for each reservoir are also given in Table A8.

Table A8. Discharge rate limits.

	Q_1 (m^3)	Q_2 (m^3)	Q_3 (m^3)	Q_4 (m^3)	
min	50,000	60,000	100,000	130,000	Inclusive
max	150,000	150,000	300,000	250,000	
Prohibited discharge zones (PDZ)					
min	80,000	70,000	220,000	160,000	Exclusive
max	90,000	80,000	270,000	180,000	

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