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Optimisation of Multireservoir Operation Policy using Teaching-Learning Based Optimisation Algorithm

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ABSTRACT

The multi reservoir water resource system has various purposes and therefore, operation planning is becoming complex and involves a number of decision variables. This paper presents an efficient and reliable teaching-learning based approach, namely teaching-learning based optimisation (TLBO) algorithm for optimisation of multireservoir operation policy. It is based on the teaching-learning process of the education system. TLBO algorithm does not require any algorithm-specific parameters for obtaining optimal results; instead it requires only the population size and number of iterations. The time required for obtaining the specific optimised algorithm parameter is reduced and results are also near the global-optimal solution. Furthermore, the number of function evaluations required is less. This TLBO algorithm is implemented at the five-reservoir model of the upper Godavari river project in the city of Nashik in Maharashtra, India. The efficiency of the results of the TLBO algorithm is compared with the genetic algorithm (GA). The results show that TLBO algorithm is considered to be a viable alternative to the operating policy of multireservoir system and it avoids the local optimal solution.

Keywords: Multireservoir operation, optimisation, TLBO algorithm

INTRODUCTION

Optimisation of reservoir operation is a challenging for water resource planners and managers. The proper utilisation of available resources becomes necessary to develop strategies to utilise the available resources effectively and efficiently. Due to an increase in population, industrialisation, and urbanisation, the optimum utilisation of available water and proper management is becoming an important task. For optimisation of a complex reservoir system, various traditional and non-traditional techniques are implemented. Linear programming (LP), non-linear programming (NLP), and dynamic programming (DP) are the most common and principal optimisation techniques used in

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water resources system analysis. Future direction for research and application of optimisation in reservoir system management and operations is reviewed (Labadie, 2004). Also, the challenges and issues of climate change in optimisation of reservoir is reviewed (Asmadi et al., 2014).

In the case of a problem faced by multiobjective and multireservoir system optimisation, the objective function is complex with a nonlinear relationship in constraints as well as in objective function, thus LP cannot be used. In regard to a problem faced in large optimisation, where a decision is to be taken at each stage and performance of the next step is dependent on the results of the previous step, and in such a case, dynamic programming can be used. However, the use of DP in problems that have more decision variables and complex objective functions and constraints, the problem becomes high dimensional. The problems that involve a non-linear relationship in their objective function and constraints can be handled by NLP, however, it faces the problem of a slow rate of convergence and also takes up a large amount of time for computation as well as a large amount of computational storage (Jyothiprakash & Shanthi, 2006). These methods solve the problem point by point and the solution obtained is also a single optimal solution. Moreover, the solution may lie on the non-convex region of the function space (Laifa & Boudour, 2009). These are some limitations of traditional techniques for solving multiobjective optimisation problems.

To obtain the Pareto optimal solution, first, all the possible Pareto fronts are derived and then the algorithm is solved step by step. Therefore, the solution for the next iteration is improved from the previous iteration. The meta-heuristic techniques like evolutionary algorithm's (EA's) and swarm intelligence techniques are used in solving single or multiobjective, or single or multireservoir system problems. These techniques give a solution using a population in every iteration in a single run. These techniques can solve the problem of local minima by searching the solution in the entire search space using randomised initialisation and stochastic search in their operation process. Many problems cannot reach to the global optimal solution in the parameter optimisation process because difficulties arise in determining the optimal controlling parameters of algorithm for optimisation. The EA's and swarm intelligent-based algorithms are probabilistic algorithms and require common controlling parameters, such as population size, number of iterations, along with common controlling parameters. These algorithms require their own algorithm-specific parameters. The problem with multi decision variables can be solved by using nested stochastic dynamic programming (nSDP) and nested reinforcement learning (nRL) algorithms to overcome the high dimensional problem (Delipetrev et al., 2017). The performance and efficiency of the newly developed metaheuristic bat algorithm is evaluated by solving the reservoir operation optimisation problem (Hadded et al., 2014).

To overcome these difficulties of determining the optimal controlling parameters of algorithms, teaching-learning based optimisation (TLBO) algorithm is introduced (Rao et al., 2011). The TLBO has the capability of determining the best solution with a logical number of population size and corresponding number of iterations. It is a population-based optimisation technique in which the population size is considered to be learners in the teaching-learning process. The most intelligent learner among all learners is considered to be the teacher. The different subjects offered to the students are considered to be decision variables of the optimisation problem. The result from the learners is analogous to the fitness value of the optimisation problem. The TLBO algorithm does not require any algorithm specific parameters to solve the complex reservoir problems. Due to non-availability of algorithm specific parameters, less efforts are required in obtaining the optimal solution, therefore, algorithm becomes robust and powerful. Currently, TLBO algorithm has gained a wide application in the field of engineering applications for optimisation. Non-domination-based sorting multiobjective power flow problems are solved using the TLBO algorithm for minimisation (Nayak et al., 2012). Togan (2012) used the TLBO algorithm for the design of planning steel frame structures. Furthermore, multiobjective heat exchanger problems are solved using a modified version of the TLBO algorithm (Rao & Patel, 2013). TLBO algorithm is proposed (Zou et al., 2013) for multiobjective optimisation in which a non-dominating concept and computed crowding distance is adopted. For modern machining processes of manufacturing, TLBO is implemented to achieve high quality products (Rao & Kalyankar, 2013). To check the efficiency of TLBO algorithm (Rao et al., 2011), solving the constrained and unconstrained real parameter optimisation problem and performance is compared with other optimisation algorithms. Moreover, to solve large-scale non-linear optimisation problems, TLBO is proposed (Rao et al., 2012) for obtaining the global solution. The performance of the TLBO algorithm is shown in Figure 4.

METHODS

Teaching-Learning Based Optimisation (TLBO) Algorithm

The TLBO algorithm is a comparatively new algorithm (Rao et al., 2011). The performance of the algorithm is based on the teaching-learning phenomenon as seen in a classroom setting. Here, a teacher and learner are considered to be the main components in which from the teacher and from the learner's interaction, they improve the average grade of the class. It works in two phases, teacher phase and student phase. In the teacher phase, the teacher takes efforts to share his or her knowledge to improve the grade of the students. In the student phase, students use the knowledge taught by teacher and they also interact amongst themselves and improve overall knowledge. Student achievement in obtaining the best results is defined in terms of grade by learning well from the teacher (Rao et al., 2011).

TLBO is population-based method and in this optimisation method the number of the population is considered initially. This population number is considered to be the number of students in a class. The population giving the best output includes the teacher from the available students. In a class, a different subject assigned is considered to be a decision variable in the optimisation of the problem. The fitness value of an objective function is analogous to the result of the class. Working of the teacher and student phases is explained (Rao & Kalyankar, 2012).

Teacher Phase

In this phase, students learn from the teacher and the teacher tries to increase the average result of the class from value M_1 to his or her level (i.e. T_A). Practically, the teacher can move the mean result of class room M_1 to another value M_2, which shows improvement in M_1, depending upon the teaching skill of the teacher. Consider M_j as the mean value and T_i is teacher at iteration *i*.

Thus, T_i teacher tries to improve the mean value M_j towards it and the new mean is denoted as M_{new} and the difference between M_{new} and M_j is given by the equation as:

$$(\text{Difference of mean})_i = r_i (M_{new} - T_F M_j) \quad [1]$$

where, r_i is a random number that varies from [0,1], T_F is the teaching factor that decides the value of the mean difference. The value of T_F is either 1 or 2. Considering equal probability, the T_F value is decided randomly. When T_F is 1, this means there is no increase in the level of knowledge and 2 corresponds to complete transfer of knowledge.

$$T_F = \text{round}\,[1+\text{rand}\,(0,1)\{2-1\}] \quad [2]$$

The capability of students decides the transfer level of knowledge. By using the difference of the mean value's existing solution is updated using the following expression as,

$$X_{new,i} = X_{old,j} + (\text{Difference of mean})_i \quad [3]$$

Student Phase

In the second phase of the algorithm, students interact between them and increase their knowledge level. After learning from the teacher, students interact randomly with other students and learn new things if the other student has more knowledge. Mathematically, the learning phenomenon of students in this phase is expressed as, two different learners X_i and X_j at any iteration i is given by:

$$X_{new,i} = X_{old,i} + r_i (X_i - X_j) \qquad \text{if } f(X_i) < f(X_j) \quad [4]$$

$$X_{new,i} = X_{old,i} + r_i (X_j - X_i) \qquad \text{if } f(X_i) > f(X_j) \quad [5]$$

In the process of the TLBO algorithm, the solution is updated two times, i.e. in the teacher phase as well as in the learner phase. If any duplicate solution is observed while obtaining the solution, it is updated randomly. Therefore, the total number of function evolution required for TLBO algorithm is [(2 X number of population X number of iteration) + (function evolution require for elimination of duplicate solution].

Application of TLBO Algorithm

In this section, TLBO is implemented to five reservoir systems. The optimal operating policy of the multireservoir system of the Upper Godavari project is considered. In this multireservoir system, Karanjwan, Waghad, Punegaon, Ozarkhed, and Palkhed peak up weir is considered. The main purpose of these reservoirs is to allocate the water for irrigation purposes. At the downstream of the Karanjwan reservoir, an industrial area is developing, thus it is becoming necessary to provide water for industrial purposes. The schematic representation of the reservoir system is shown in Figure 1. The geological position of the reservoir system is at latitude 20°12'15" N Longitude 73°49'37.93" E in Nasik district, Maharashtra, India. The water is released for irrigation purposes from each reservoir and at the end released from each reservoir to meet the Palkhed peak up weir, which is located at a distance of 24 km downstream from the Karanjwan reservoir. Data of monthly inflow and other required data is collected from the Palkhed Irrigation department, Nashik during the period of 1985-2013. The monthly irrigation demand is calculated using FAO Penman- Monteith method.

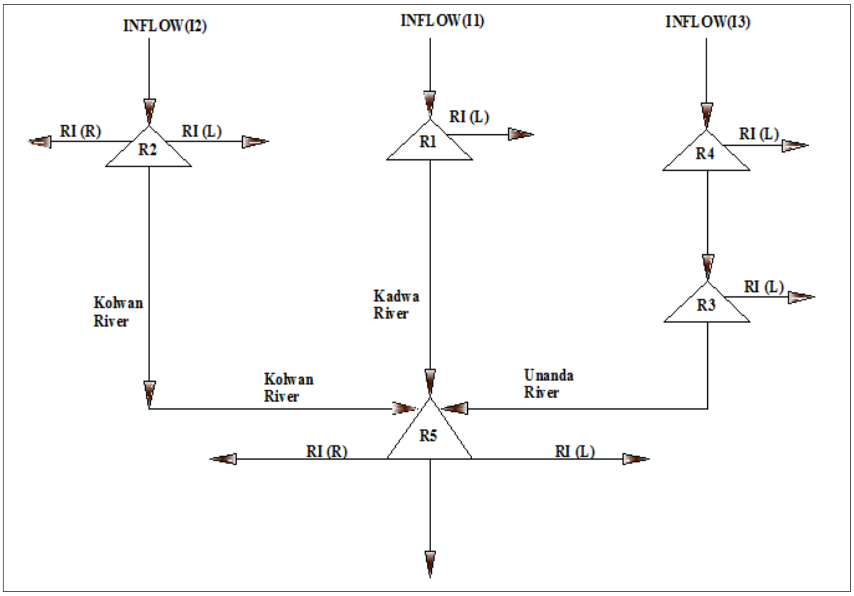

Figure 1. Schematic representation of physical system

A maximum of 90% rainfall occurs during the monsoon season (i.e. June to November). The Karanjwan Dam is constructed on Kadwa River and releases the water for irrigation from the river and from the left bank canal. The Waghad Dam is constructed along the Kolwan River, which has the left and right bank canal for irrigation purposes. Similarly, Punegaon and Ozarkhed reservoirs are in a series on the Unanda River, which is also constructed for irrigation purposes. At the end, releases from all the reservoirs meet the Palkhed peak up weir, which is also has the left and right bank canals that are constructed for irrigation purposes.

Objective Function

In formulating the problem, the main objective of a multireservoir system is to maximise the releases for irrigation. In India, the water year is considered to be from June to the end of May and in this study, the monthly allocation policy is derived.

Objective =

$$\sum_{t=1}^{t=12} RI_{1,t} + \sum_{t=1}^{t=12} RI_{2,t} + \sum_{t=1}^{t=12} RI_{3,t} + \sum_{t=1}^{t=12} RI_{4,t} + \sum_{t=1}^{t=12} RI_{5,t} \quad [6]$$

where, objective is the maximisation of releases for irrigation. $RI_{1,t}$, $RI_{2,t}$, $RI_{3,t}$, $RI_{4,t}$ and $RI_{5,t}$ are the releases from Karanjwan, Waghad, Punegaon, Ozarkhed, and Palkhed reservoirs respectively in the period of t month in Mm^3.

Irrigation Release Constraint

Releases into the canal and river are lifted from the reservoir for irrigation (RI_t) in all time periods should be less than or equal to the maximum irrigation demand (ID_{max})t to produce the targeted yield. Moreover, the releases should be greater than or equal to minimum irrigation demand (ID_{min})t to sustain the crops for all the time periods. In the present study, minimum irrigation demand is considered to be 30% of the maximum irrigation demand for all the periods.

$$8.0006 \leq RI_{1,t} \leq 16.0089 \qquad \forall t = 1,2,3,\ldots,12 \quad [7]$$

$$31.0764 \leq RI_{2,t} \leq 52.3232 \qquad \forall t = 1,2,3,\ldots,12 \quad [8]$$

$$10.8320 \leq RI_{3,t} \leq 18.0533 \qquad \forall t = 1,2,3,\ldots,12 \quad [9]$$

$$9.6442 \leq RI_{4,t} \leq 64.2949 \qquad \forall t = 1,2,3,\ldots,12 \quad [10]$$

$$54.5793 \leq RI_{5,t} \leq 181.9310 \qquad \forall t = 1,2,3,\ldots,12 \quad [11]$$

Storage Capacity Constraint

Reservoir storage should be less than or equal to the maximum storage, i.e. gross storage of the reservoir. Reservoir storage in time period 't' should be greater than or equal to the minimum storage, i.e. dead storage of the reservoir to be maintained in the reservoir for all time periods.

$$8.78 \leq S1 \leq 175 \quad [12]$$

$$6.48 \leq S_2 \leq 75.1 \quad [13]$$

$$2.11 \leq S_3 \leq 17.57 \quad [14]$$

$$7.63 \leq S_4 \leq 67.95 \quad [15]$$

$$17.7 \leq S_5 \leq 230.1 \quad [16]$$

where, S_1, S_2, S_3, S_4 and S_5 are Karanjwan, Waghad, Punegaon, Ozarkhed, and Palkhed reservoirs respectively in the water year in Mm^3.

Water Balance Equation

This constraint relates to the reservoir storage S(t), inflow I(t), release for irrigation RI(t), and losses due to leakages and evaporation L(t), as well as downstream water requirement DWR(t) for all the time periods.

$$S_1 (t+1)=S_1 (t)+I_1 (t)-RI_1 (t)-L_1 (t)-DWR_1 (t) \qquad \text{V}t=1,2,3,\ldots,12 \qquad [17]$$

$$S_2 (t+1)=S_2 (t)+I_2 (t)-RI_2 (t)-L_2 (\text{t})-DWR_2 (\text{t}) \qquad \text{V}t=1,2,3,\ldots,12 \qquad [18]$$

$$S_3 (t+1)=S_3 (t)+I_3 (t)-RI_3 (t)-L_3 (t)-DWR_3 (t) \qquad \text{V}t=1,2,3,\ldots,12 \qquad [19]$$

$$S_4 (t+1)=S_4 (t)+R\text{I}_3 (t)-RI_4 (t)-L_4 (t)-DWR_4 (t) \qquad \text{V}t=1,2,3,\ldots,12 \qquad [20]$$

$$S_5 (t+1)=S_5 (t)+RI_4 (t)+RI_1 (t)+RI_2 (t)-RI_5 (t)-L_5 (t)-DWR_5 (\text{t}) \qquad \text{V}t=1,2,3,\ldots,12 \qquad [21]$$

The above formulated model is solved using the TLBO algorithm to obtain the best fitness value of the objective function.

RESULTS AND DISCUSSION

The TLBO technique is applied to the model described in the previous section to obtain the operation policy of the multireservoir system. In this study, the decision variables are the releases for irrigation purposes from the reservoirs. These decision variables are evaluated two times to obtain the results. If any constraint is in violation in satisfying the constraints, then a penalty is assigned by a proper penalty coefficient. In this problem, the total number of decision variables are 120 (number of time periods = 12 and number of decisions for each reservoir in each period is 5). The termination criterion is either to reach the maximum number of generations, or if there is no significant improvement in the solution.

The model is evaluated for a combination of the number of population size and number of generations. After satisfying all the constraints and receiving the optimal value of the objective function, the number of function evolutions required is decided. The storage constraint satisfies the condition, storages of all the reservoirs for each time period is obtained and its values are varying between dead storage to the gross storage of the reservoir. The storages obtained from GA and TLBO are shown in Figure 2(a), Figure 2(b), Figure 2(c), Figure 2(d) and Figure 2(e). In Figure 2(a) to Figure 2(e) the comparative performance of the storages for each time period is shown. The storage results of the GA are just satisfying the constraints of the storage of the five reservoirs. As per requirement, GA is not releasing the water at the downstream, therefore, less changes in the reservoir storages. The maximum storages is available in the reservoir. The storages obtained from TLBO algorithm are also satisfying the constraints of the reservoir storages. The storages at the starting of the water year i.e. in monsoon are less. In Rabi season, crops are grown on the stored water, so the storages of the reservoir are reduced.

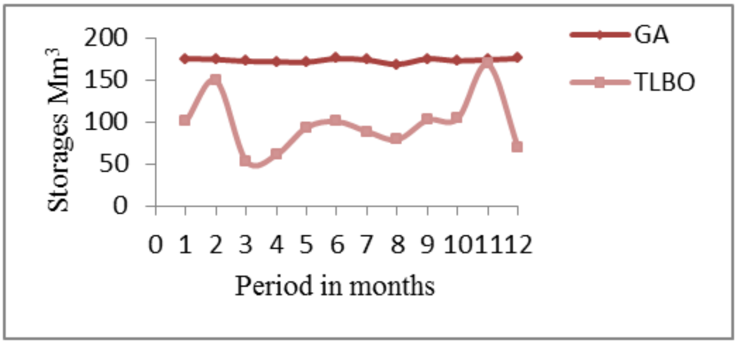

Figure 2(a). Karanjwan Reservoir storage from GA and TLBO in time period

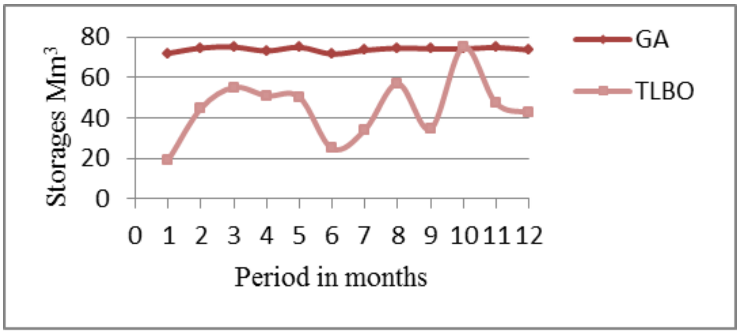

Figure 2(b). Waghad Reservoir storage from GA and TLBO in time period

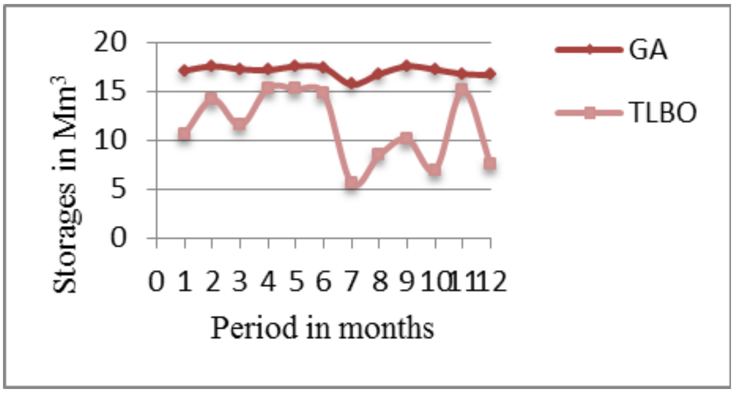

Figure 2(c). Punegaon Reservoir storage from GA and TLBO in time period

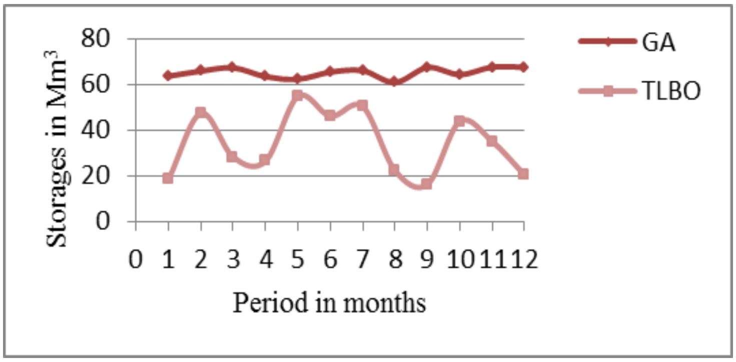

Figure 2(d). Punegaon Reservoir storage from GA and TLBO in time period

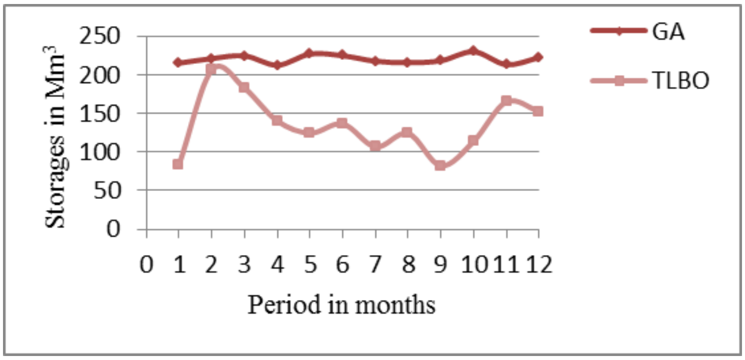

Figure 2(e). Palkhed Reservoir storage from GA and TLBO in time period

The storages for the five reservoirs for the time period are obtained using GA and TLBO. The TLBO requires a population size of 25 and the number of generations is 40. The results get evaluated twice; therefore, the numbers of evolution functions obtained are 2000. The results of GA are obtained by using the tool box of genetic algorithm in Matlab. In obtaining the solution, the population decided is 5000, creation function is used as the feasible population, and selection function is used as tournament selection. In reproduction, crossover probability is decided as 0.4, mutation is carried out with mutation function as an adaptive feasible, and crossover function is considered to be single point. Furthermore, optimisation is carried out with 50,000 numbers of function evaluations. In both the results of GA and TLBO, storages in all the time periods satisfy the defined constraints.

The releases from all the reservoirs are also determined considering the constraints of releases and irrigation demand. In obtaining the releases from all the reservoirs, they must satisfy the mass balance equations of all the reservoirs. The releases obtained from GA and from TLBO are shown in Figure 3(a), Figure 3(b), Figure 3(c), Figure 3(d) and Figure 3(e).

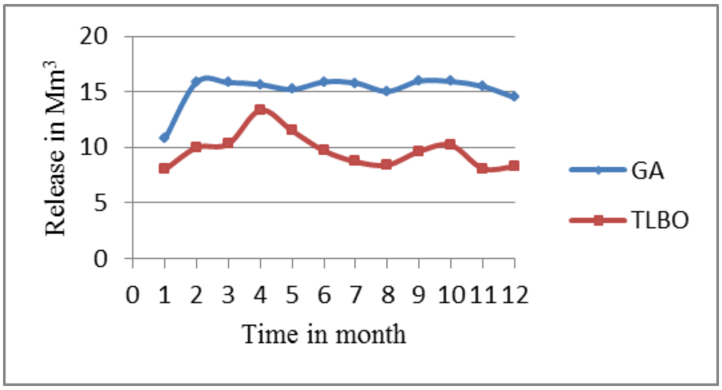

Figure 3(a). Karanjwan Reservoir releases from GA and TLBO in time period

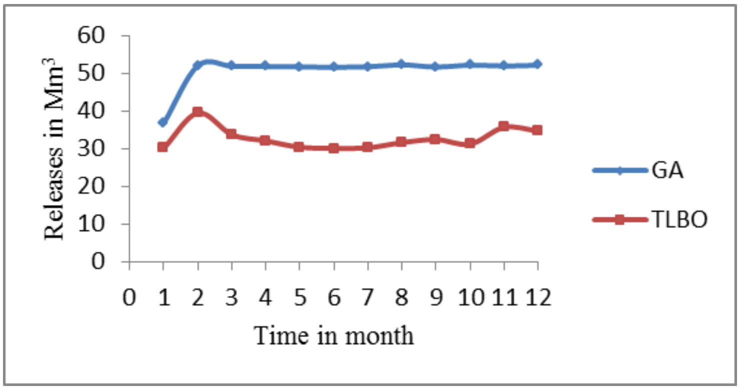

Figure 3(b). Waghad Reservoir releases from GA and TLBO in time period

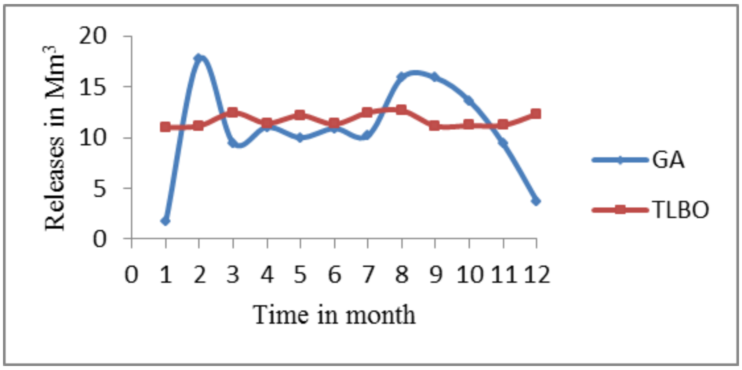

Figure 3(c) Punegaon Reservoir releases from GA and TLBO in time period

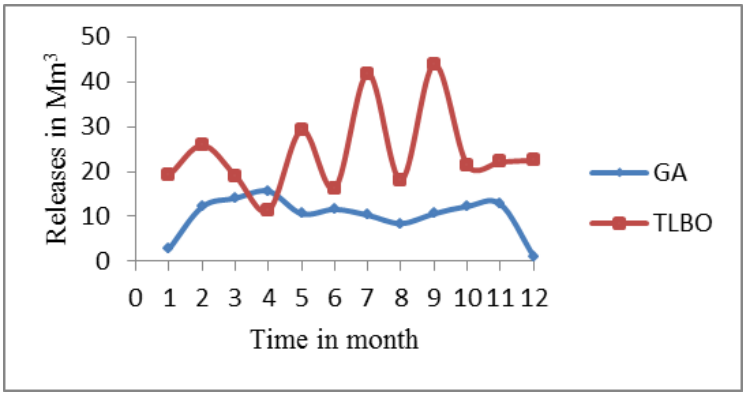

Figure 3(d). Ozarkhed Reservoir releases from GA and TLBO in time period

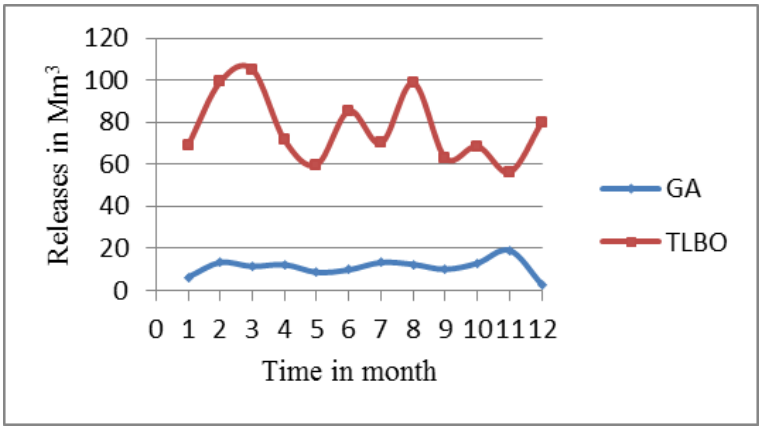

Figure 3(e). Palkhed Reservoir releases from GA and TLBO in time period

Operation policy obtained from GA and TLBO is shown in Table I which, for the Karanjwan reservoir releases obtained from GA and TLBO, they showed significantly less difference because they are satisfying the constraints of the irrigation demand and releases. For Waghad reservoir GA showing approximately the same releases in all the months of the water year except the first two months, but TLBO shows the operation policy as per requirement of irrigation and downstream demand. For the Punegaon reservoir, GA shows fluctuation in the releases for the first and last two months, whereas TLBO satisfies the constraints and as per requirement, the release policy is decided. In the Ozarkhed reservoir, releases obtained from GA at the end of the water year and at the starting of the monsoon are less. The Punegaon reservoir releases obtained from GA are much less and it could not satisfy the demand of irrigation and downstream. However, for the same reservoirs, TLBO satisfies the constraints of irrigation demand as well as water balance equation of the reservoir. From the results, it is observed that compared with GA, TLBO gives better results, which satisfies the demand as well as it distributes the water as per the requirements in all the months of the water year.

Table 1
Comparison of the releases for five reservoirs obtained by GA and TLBO

		t1	t2	t3	t4	t5	t6	t7	t8	t9	t10	t11	t12
R1	GA	10.78	15.87	15.84	15.66	15.21	15.89	15.8	15.04	15.97	15.93	15.49	14.49
	TLBO	8.00	9.98	10.30	13.35	11.51	9.70	8.72	8.41	9.64	10.19	8.10	8.27
R2	GA	36.76	52.01	51.88	51.78	51.70	51.55	51.71	52.21	51.64	52.12	51.90	52.12
	TLBO	30.15	39.47	33.71	32.05	30.38	30.07	30.21	31.60	32.43	31.20	35.66	34.69
R3	GA	1.70	17.74	9.47	11.03	10.00	10.90	10.21	15.90	15.88	13.62	9.41	3.75
	TLBO	10.98	11.16	12.44	11.42	12.17	11.32	12.46	12.67	11.13	11.17	11.21	12.32
R4	GA	2.82	12.16	14.03	15.60	10.60	11.58	10.29	8.44	10.60	12.24	12.75	1.18
	TLBO	19.16	25.84	19.03	11.30	29.23	16.24	41.82	18.07	43.89	21.43	22.13	22.49
R5	GA	6.34	13.26	11.42	12.27	8.64	9.78	13.29	12.37	10.06	12.97	19.03	2.82
	TLBO	68.99	99.31	105.13	71.48	59.76	85.44	70.03	98.84	62.99	68.58	56.28	79.93

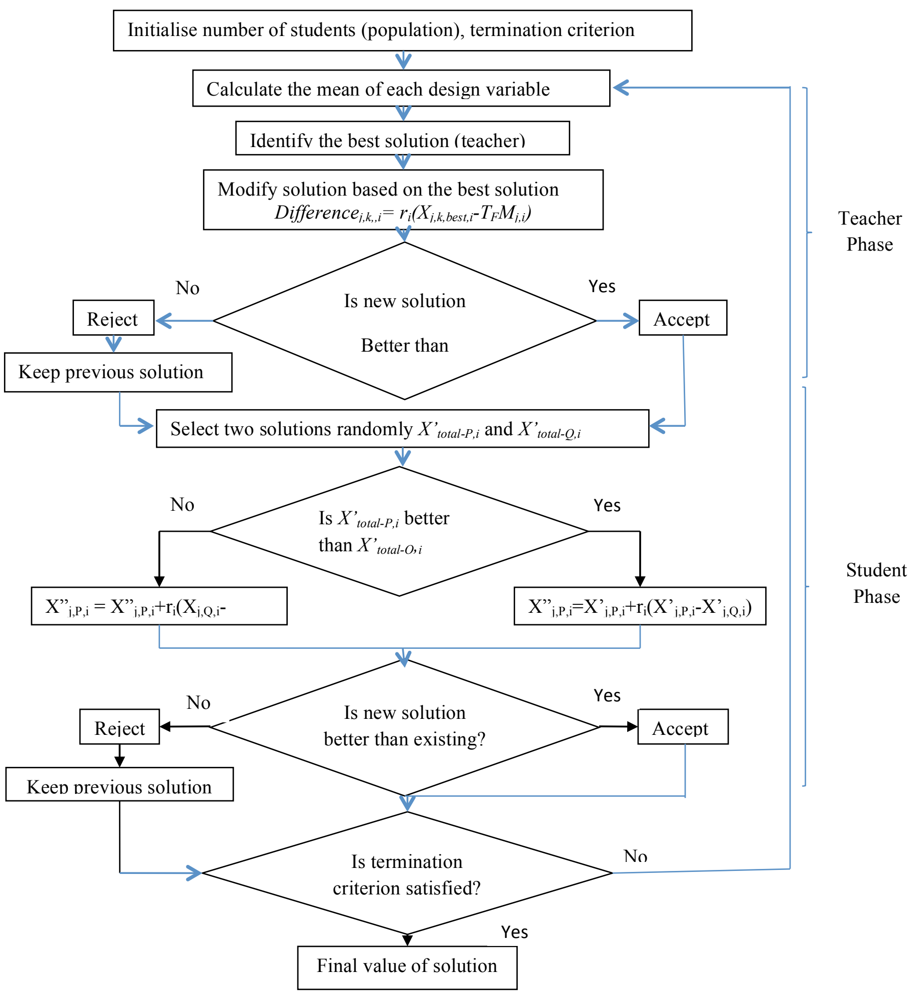

Figure 4. Performance of TLBO algorithm

CONCLUSION

A newly developed teaching-learning based optimisation algorithm is implemented for optimisation of a multireservoir operating policy. The TLBO has the capability to solve problems that contain a large number of decision variables and which are complex in nature. It is used to solve the multireservoir system of the Upper Godavari project. While obtaining the results, TLBO tries for different combinations of population size and number of generations. Because it does not require any algorithm-specific parameters, the time required for the results is also less as compared to GA. TLBO requires less numbers of function evaluations as compared to GA. Therefore, the time is also less. TLBO gives releases as per irrigation and downstream requirements of all reservoirs in each month of water year, whereas for Punegaon, Ozarkhed, and Palkhed, GA shows much less releases and thus does not even satisfy the demand. The GA requires making decisions on selecting the algorithm specific parameters. Therefore, it is concluded the operating policy of TLBO shows practical utility in the field because the results are comparatively reasonable and acceptable.

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