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Applying TLBO Algorithm for Optimizing a Double Flash Geothermal Power Plant

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ABSTRACT

In this paper the teaching learning based optimization (TLBO) is applied for the nonlinear constrained simulation based optimization of a double flash (DF) geothermal power plant. The TLBO algorithm is a teaching-learning process inspired algorithm based on the effect of influence of a teacher on the output of learners in a class.

A DF system is able to achieve better energy utilization than a single flash cycle, which means that the application has a higher efficiency. The DF system modeled in this paper is a classic geothermal DF power plant. Geothermal brine exits the production well as a saturated liquid above atmospheric pressure and after completing the thermodynamic process the mechanical work of turbines is used to generate electrical power via a generator. The turbine exhaust is condensed in a condenser, while the saturated liquid exiting the separator is re injected into the geothermal reservoir via an injection well.

The objective function of optimization problem is the power plant specific output (kJ/kg) and the variables are the temperatures at which the separator operates. In the end, the performance of some algorithms was investigated and results showed TLBO algorithm has the best performance among other optimization algorithms.

1. INTRODUCTION

Nowadays, the availability of energy is a serious factor for development and economic growth of any society. Energy demand growth and the world tension on clean energy without the negative effects of fossil fuels has motivated governments and countries to apply new energy sources and technologies for producing electrical power. The use of renewable energies has become widespread throughout the world in these years. For instance geothermal energy use has increased at an approximate rate of four to five percent annually in all over the world (Paoletti et al., 2015). Different geothermal power plants have been proposed for converting earth's thermal energy to electricity and researches have been conducted on various types of geothermal power systems.

Geothermal cycles are divided into three main categories: dry, binary and flash models. the first dry-steam geothermal power plant was built back to 1904 (DiPippo, 2015) but the most of geothermal reservoirs are wet (binary and flash models) and dry steam reservoirs are rare. Therefore further researches have been done in these areas (Liu, Shen, & Duan, 2015; Zarrouk & Purnanto, 2015). fields Structure of the geothermal power generation cycle depends on the temperature of the geothermal well. Guzovic et al. (Guzović, Majcen, & Cvetković, 2012) researched about a geothermal system with binary flash that applies a medium temperature heat resource. Pambudi et al. (Pambudi, Itoi, Jalilinasrabady, & Jaelani, 2015) investigated double-flash system design and compared it with a single-flash power plant using waste brine and demonstrated the superiority of double-flash system. The temperature of this stream can be raised using absorption heat transformers and reused for other applications (Salehi, Mahmoudi, Yari, & Rosen, 2018). In this paper TLBO algorithm is proposed to maximize SPO from a DB geothermal power plant.

2. SYSTEM MODEL

Fig. 1 shows a schematic of a DB geothermal power plant. Also, temp–entropy diagram is shown in Fig. 2. As depicted in these figures saturated liquid exits from geothermal brine. Then the brine enters a separator after passing through a throttle valve, where saturated vapor is sent to a high pressure turbine. The mechanical power of both turbines is used to produce power.

In this paper specific power output (SPO) has been selected as objective function. The SPO states the amount of mechanical energy (kJ) generated by the geothermal power plant per kg of extracted geo fluid (Eq. 1)(Sarr & Mathieu-Potvin, 2015).

$$w = \frac{\dot{w}_{net}^{out}}{\dot{m}_R} = \frac{net\ power\ output\ (kJ)}{reservior\ mass\ flowrate\ (kg)} \quad (1)$$

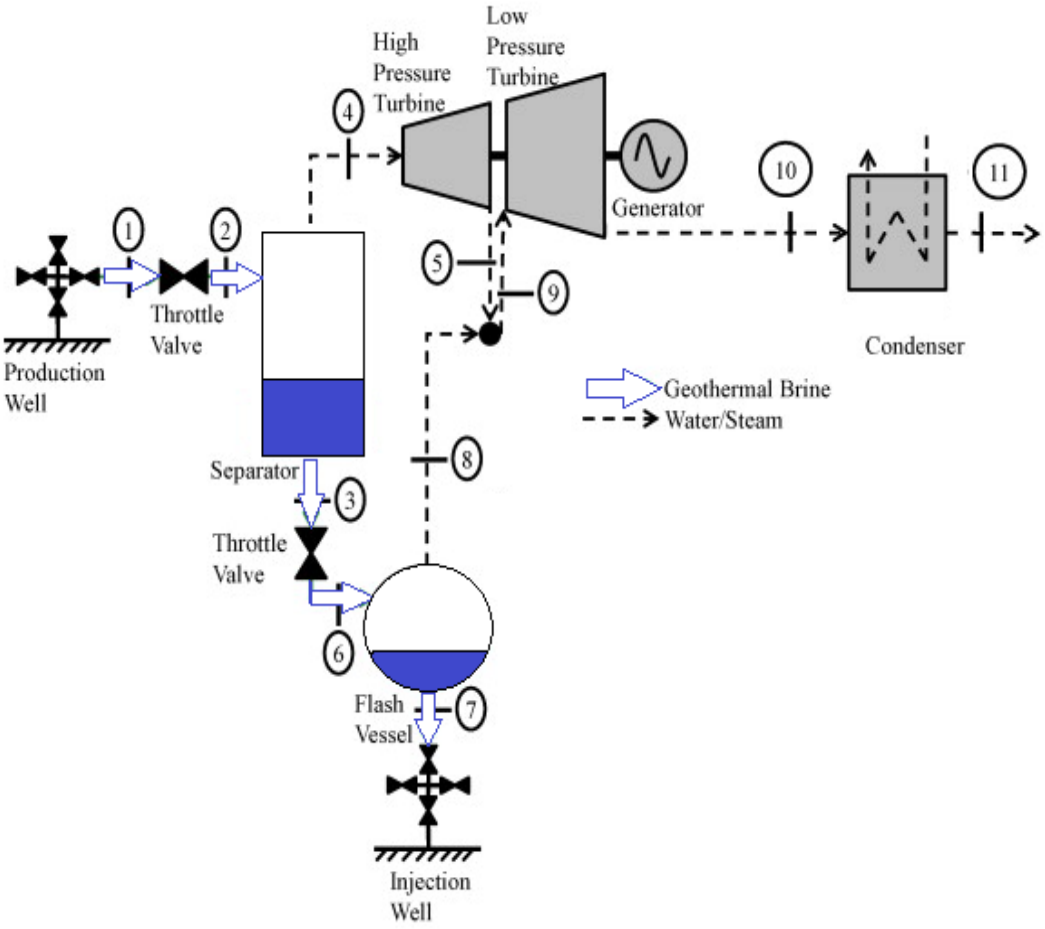


Figure 1: Double flash geothermal power plant.

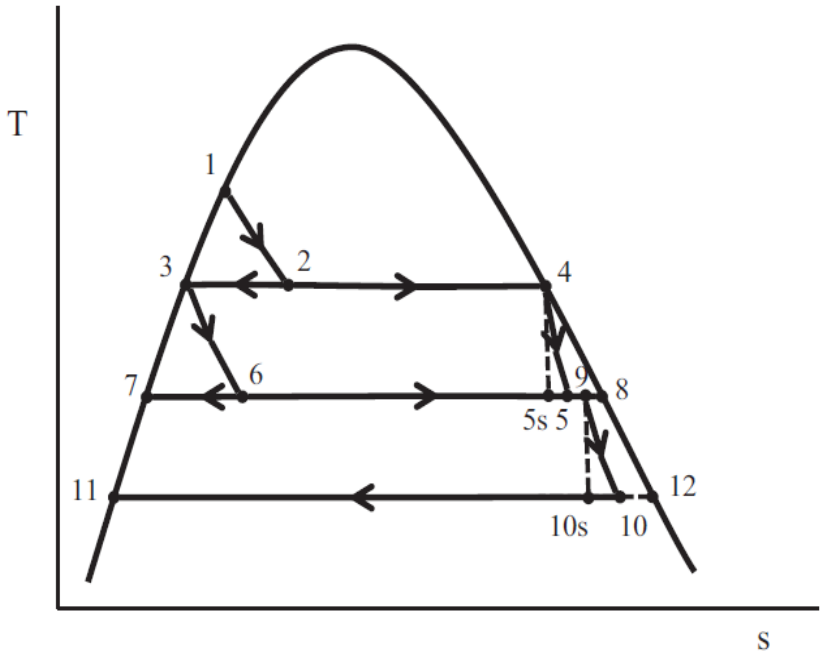


Figure 2: Temp-entropy diagram.

The selected target is validated by the fact that each additional power generated by the power plant leads to additional income. The optimization variables, TS1 and TS2 are the temperature of the separators. Problem statement, variable and constraints are stated as below:

Objective function: maximizing w

Optimization variables: *TS1* and *TS2*

Constraints: $TS2 \leq TS1 \leq TR$, $TCD \leq TS2 \leq TS1$

Fixed variables: *TR, PR, TCD, η, ε*

Which TR is reservoir temperature, TCD is condenser temperature, PR is reservoir pressure, η is turbine efficiency and ε is heat exchanger efficiency. Table 1 shows the considered value of parameters.

Table 1: Operation parameters.

TR	180 °C
PR	3500 kPa
TCD	50 °C
ε	0.80
η	0.85

3. OPTIMIZATION ALGORITHM

The Teaching-Learning-Based Optimization (TLBO) is applied to optimize the amount of SPO (kJ/kg). TLBO is a powerful algorithm influenced by learning and teaching process in a class (Rao, Savsani, & Vakharia, 2011). Such many other optimization algorithms, this algorithm uses an initial population (n pop) to reach the best solution and makes this process during two phases. In the first step the number of students determines and considers as n pop. In the second step the best particle of the population is chosen as a teacher. After that optimization process begins and in the first phase of optimization that is called teaching phase, the teacher increases the mean value of class to his level in terms of knowledge and in the second phase that is called learning phase, the mean value increases due to the interaction between students.

After teaching phase, the learning phase is performed where students can learn from each other and increase the mean value of their class by having interactions among themselves. In this phase, two students are chosen randomly (X_i, X_j). Two stories are possible here the first one is when X_j is a better solution than X_i. In this case X_i learns new things from X_j and tries to approach him. The second condition is when X_i is a better solution than X_j. X_i tries to get away from X_j and thus find a better position.

Therefor during learning, solutions are updated as below:

- For i = 1: Pn
- Random selection of two learners Xi and Xj, where $i \neq j$
- If f (Xi) < f (Xj)
- Xnew, i = Xold,i + ri(Xi − Xj)
- Else
- X new, i = Xold ,i + ri (Xj − Xi)
- End If
- End For
- Accept Xnew if it gives a better cost function.

MATLAB environment is selected to implement the algorithm. Fig.11 depicts the flowchart of TLBO. TLBO algorithm also is used for obtaining optimum parameters in different studies (Han, Liang, Ai, & Li, 2018; Joshi & Verma, 2019)

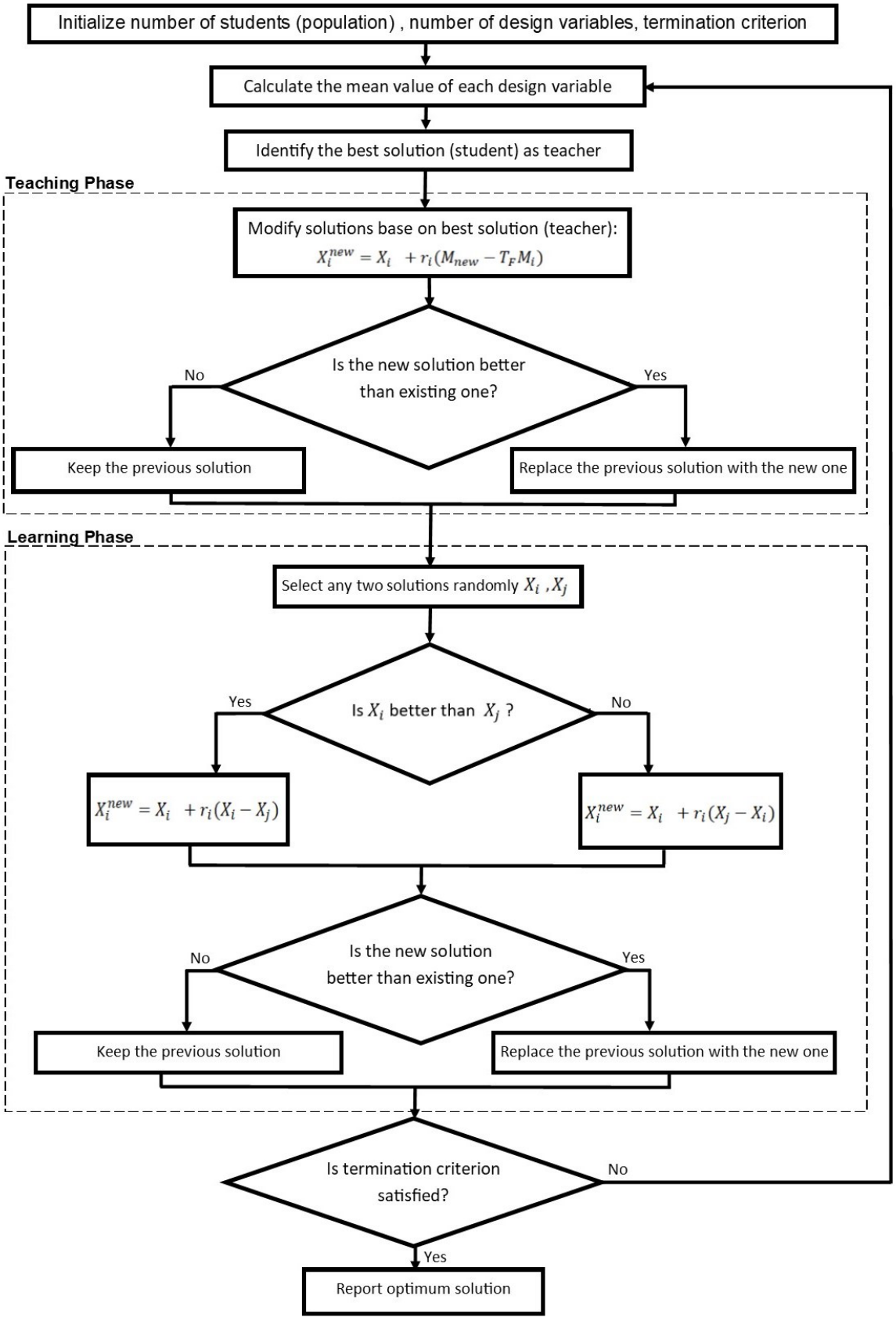
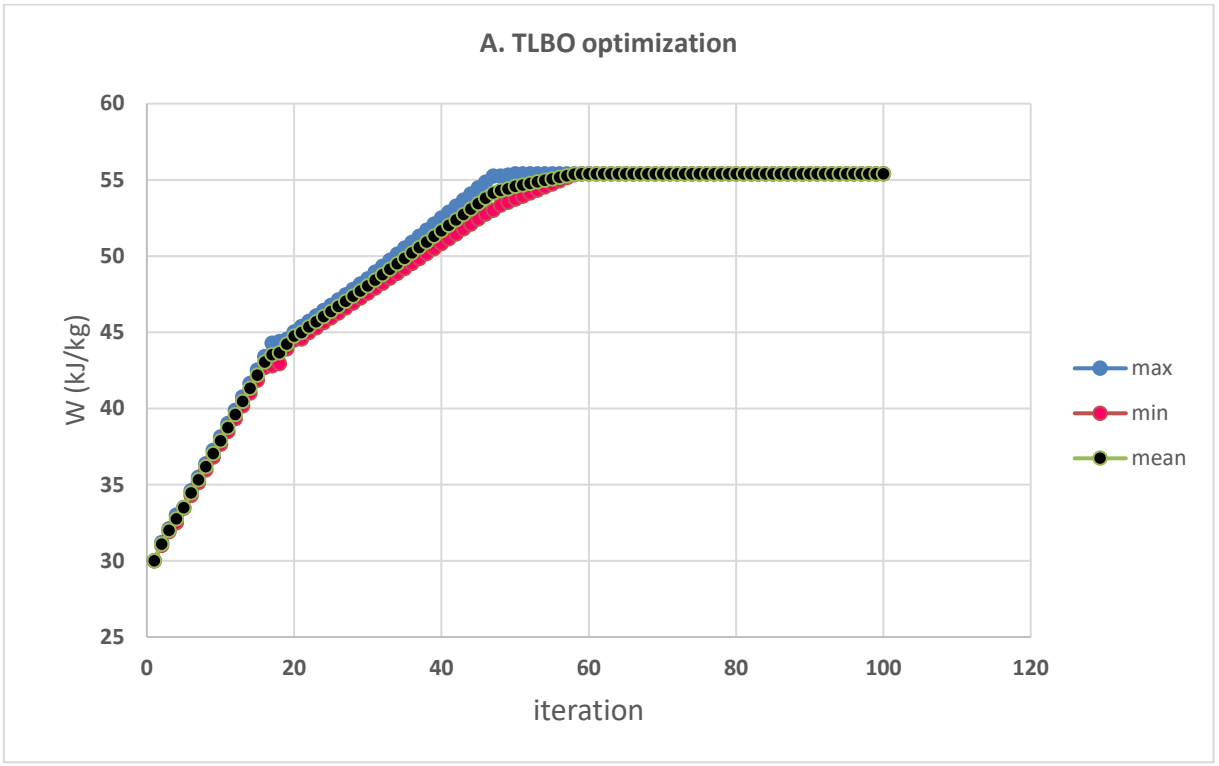
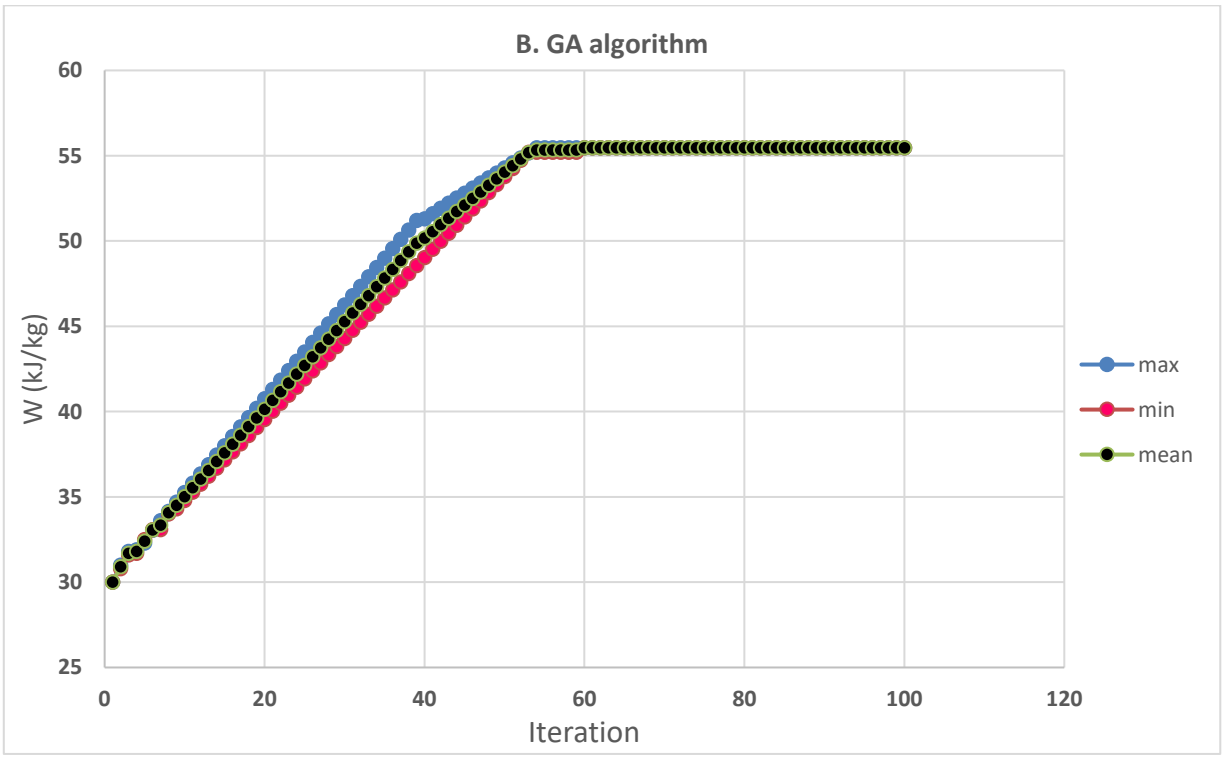


Figure 3: Flowchart of TLBO algorithm.

4. RESULT AND DISCUSSION

In the proposed algorithm, the temperatures of the separators are variables. Also maximizing the W (kJ/kg) is objective function of the TLBO algorithm. Fig. 4A shows the process of reaching final answer by TLBO. For comparing the robustness of algorithm, 10 independent runs are conducted. The maximum amount of W in best case is 55.46 (kJ/kg). The optimum amounts of variables (TS1 and TS2) are 136 °C and 89 °C respectively. Trend of minimum, mean and maximum amount of optimization is also show in this figure. Fig. 4B and C show the process of optimization by genetic algorithm (GA) and particle swarm optimization (PSO). Table 2 states the optimum results of algorithms. Although all three algorithms reach the same optimum results at the end of the optimization process, a comparison between the algorithms states that TLBO reaches to the final answer faster than PSO and GA and it shows TLBO's vigor and convergence speed.





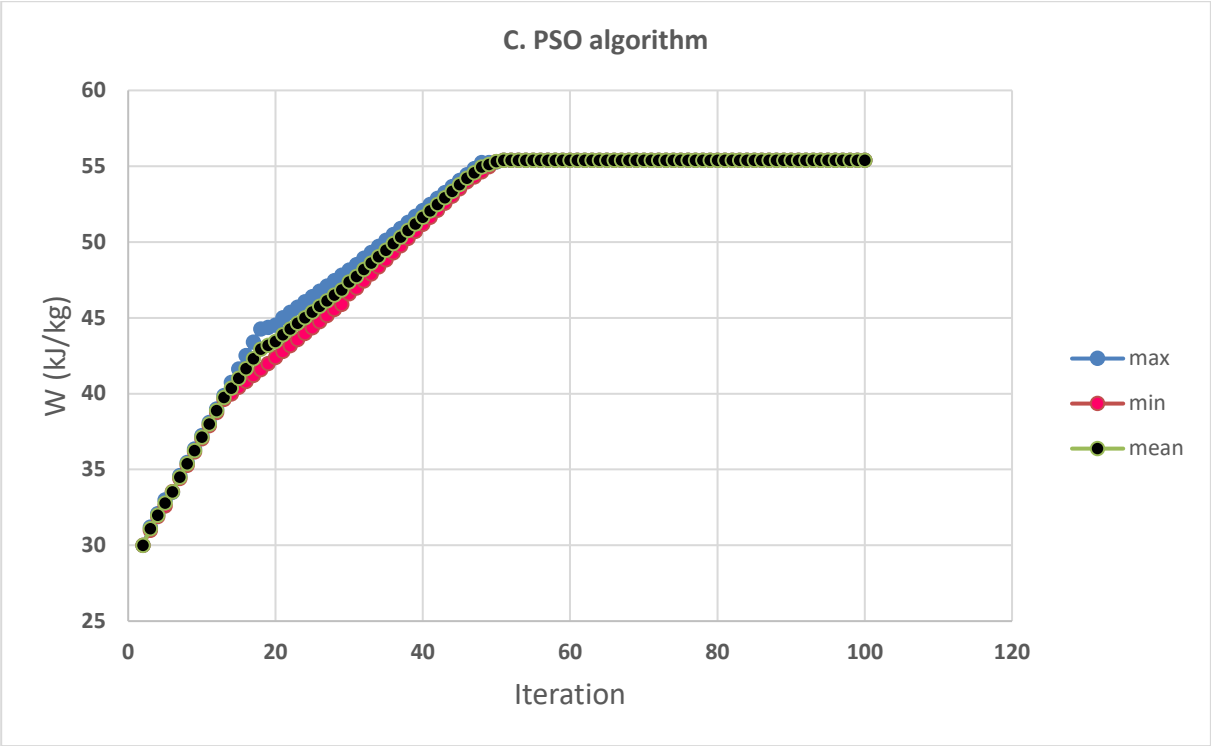
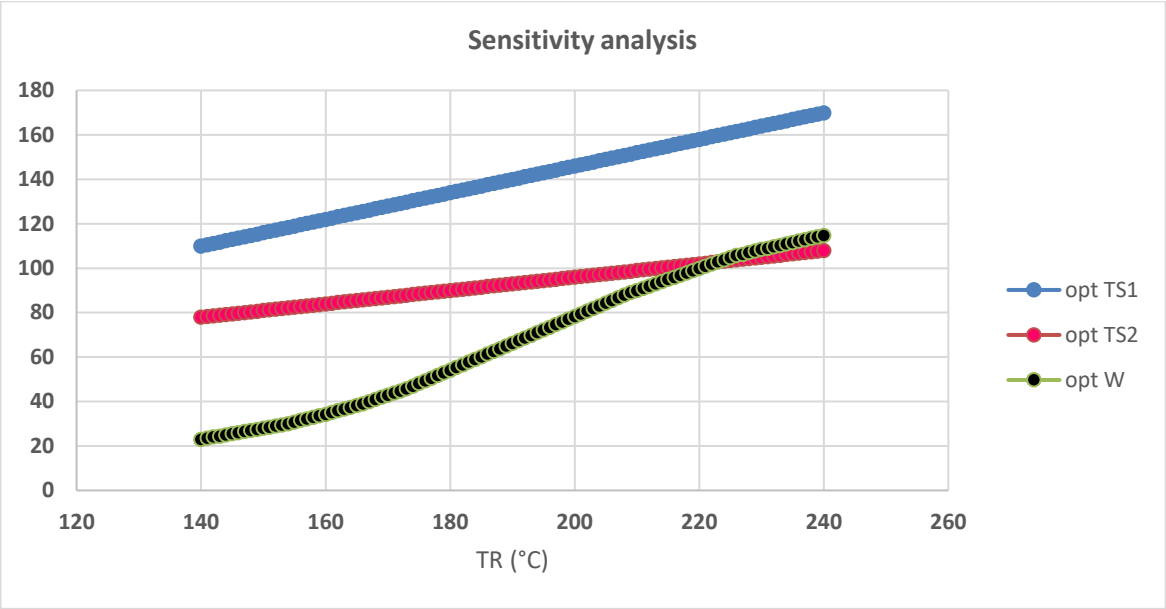


Figure 4: Obtaining optimum value of W (kJ/kg) by A) TLBO algorithm B) Genetic algorithm and C) PSO algorithm.

Table 2: Min mean and max of optimum objective function for TLBO, PSO and GA.

Algorithm	Technical parameters	W (kJ/kg)			TS1 (°C)			TS1 (°C)		
		mean	min	max	mean	min	max	mean	min	max
TLBO	Max iteration=100, n POP= 50	55.33	55.12	55.46	136	134.4	136	88.6	86.5	89
PSO	Max iteration=100, n POP= 40, (inertia weight), C1=2.05 (personal learning coefficient) , C2=2.05 (global learning coefficient)	55.24	54.79	55.46	135.5	133	136	87.8	86.5	89
GA	Max iteration=100, n POP= 50, crossover percentage=0.7, mutation percentage=0.2,	55.12	54.43	55.46	135	132.9	136	88	86	89

To illustrate the effect of changing reservoir temperature on the final results, optimization algorithm was repeated but this time for 100 different amounts of *TR* between 140 °C and 240 °C and Optimum results of W (kJ/kg), *TS1* and *TS2* (°C) obtained. As shown in Fig. 5 A to C as *TR* rises, W, *TS1* and *TS2* increase. As can be seen in 180 °C of TR the results given in the previous section will be repeated.



5. CONCLUSION

In this study, a new optimization algorithm named teaching-learning-based optimization (TLBO) was proposed to obtain maximum specific power output (SPO) from a double flash geothermal power plant. To determine the proposed algorithm performance, a comparison was done between TLBO, genetic algorithm (GA) and particle swarm optimization (GA). Results showed that TLBO has more convergence speed than GA and PSO while final results of all three algorithms were similar. In the end a sensitivity analysis on different reservoir temperatures (TR) showed that the increase in the TR is proportional to the increase in SPO and separator temperatures.

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