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Thermodynamic Optimization of Turbine Lines for Maximum Exergy Efficiency in a Binary Geothermal Power Plant

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ABSTRACT

For engineering applications related to techniques that optimize power plants or thermal systems, optimization techniques are very important. Power plants with wasted geothermal resources and inefficient organic Rankine cycle (ORC) attract the attention of researchers, engineers and decision-makers. In this study, the pressure and mass flow rates on turbine lines are optimized to maximize exergy efficiency in a binary ORC geothermal power plant (GPP). With this aim, initially data collected from a real operating GPP are used to simulate the system. Then an artificial bee colony (ABC) algorithm is developed for this model. The results showed that, the total exergy efficiency of the system was 35.25% while its value increased with the ABC optimization in the maximum possible exergy efficiency of 38.45%. Optimizing the turbine lines in the system ensured improvement rate of 4-6% for the turbines. As a result, the thermodynamic performance of the system is estimated at the same moment and with reasonable accuracy, it can be ensured that the physical process used for improvements is better understood.

Keywords:
Geothermal energy; ORC; Turbine; Exergy efficiency; Optimization

INTRODUCTION

In recent years due to the limited production and lifetime of fossil resources on earth, and their effects on the health of organisms and climate, awareness of renewable energy resources like geothermal energy has increased worldwide. Considering the issues mentioned in terms of Turkey, the importance of geothermal energy as renewable energy is obvious. Geothermal energy is a clean, safe and reliable source of renewable energy [1]. Generally high temperature resources (T>150 °C) are used for electricity production, while moderate (90 °C<T<150 °C) and low (T<90 °C) temperature resources are used in more direct use areas. In recent times, very low temperature resources (T<35 °C) have been used in heat pump applications. The situation in Turkey is that moderate and high temperature resources and, due to the large profit margin, electricity production from these resources are chosen more often compared to other uses. The results clearly show that the installed power from geothermal energy in Turkey has risen from 624 MW in 2015 to 821 MW in 2016. According to the Turkish Energy Atlas, Turkey contains 32 geothermal power plants (GPPs) with a total installed power of 921.5 MW and this is corresponding to 1.2% of the 78497.4 MW installed power in Turkey at the end of 2016 [2].

Currently with advanced level development of GPPs, the total geothermal installed power globally has reached 12640 MW [3]. This installed power comprises 5079 MW from single flash cycle, 2863 MW from dry steam, 2544 MW from double flash, 1790 MW from binary, 182 MW from triple flash and 181 MW from back-pressure cycle and hybrid cycle. However, in Turkey 198 MW of the installed power comes from binary cycle, 178 MW from double flash and 20 MW from single flash [3]. In Turkey it appears that binary organic Rankine cycle (ORC) are used more often than the other cycles. As a result, the design of a power plant is often a function of the temperature and pressure of the existing geothermal resource. Thus, to meet the increasing electricity demands globally and in Turkey, geothermal power continues to develop while engineers and policy makers desire data about feasibility and optimum design of GPPs within a spectrum of geothermal resource conditions and climates. Because of this reason, there is a need for scientifically prepared design, analysis and optimization guidelines.

After the petrol crisis occurring in the 1970s, it was understood that energy analysis alone did not determine how effectively energy is used. Thus, exergy analyses began to gain significant importance. İleri and Gürer [4] brought the energy use in addition to exergy use in Turkey up to 1995 to the agenda. The results of their study revealed how inefficient an apparently efficient system is when exergy analysis is completed.

When the literature about thermodynamic modelling and optimization of ORC is scanned, the following studies are found. To assess system performance, Wei et al. [5] presented a dynamic model to be used for design of an ORC system using waste heat recovery (WHR) with HFC-245fa as working fluid. The simulation software for this dynamic model was developed based on the platform of Modelica/Dymola. When the ambient temperature was too high, they concluded that net power and efficiency of the system deteriorated. Another study by Wei et al. [6] compared two model approaches based on moving boundaries and discretization techniques on the model developed for the same system under accuracy, complexity and simulation speed parameters. Rashidi et al. [7] conducted an optimization process for regenerative ORC with two feed water heaters for exergy efficiency and specific work by using artificial neural network (ANN) and artificial bee colony (ABC) algorithms. Sun et al. [8] proposed an ROSENB optimization algorithm to maximize the net power generation or the thermal efficiency of an ORC power plant with WHR. The effects of mass flow rates of working fluid and air-cooled condenser fans and inlet pressure of expander on thermal efficiency and net power generation of the system were investigated. Zhang et al. [9] recommended a multivariate control strategy for ORCs with WHR by combining a PI controller with a linear quadratic regulator to ensure both temporary performance and stable state energy saving. Bamgbopa and Uzgoren [10,11] developed a strategy using a finite volume approach to set evaporator flow rates to ensure stable working of a solar ORC power plant. Both stable and temporary models were developed for the system components (as pump, evaporator, expander and condenser). The model compared reasonable benchmarking numerical and experimental data in situations where the thermal inputs of the basic assumptions changed over time. The critical component of the system was determined to be the evaporator.

However, in the literature there are very few optimization studies for ORC cycles used with geothermal resources. Clarke et al. [12] compared the performance of a genetic algorithm (GA) with that of a particle swarm optimization (PSO) for constrained, nonlinear, simulation-based optimization of a double flash GPP. Another study by Clarke and McLeskey Jr. [13] used a PSO with Pareto-optimal set to determine the optimum use of a super heater and/or recuperator for a binary GPP at environmental and geothermal fluid temperatures. Saffari et al. [14] used an ABC optimization algorithm to optimize the thermal efficiency of a binary turbine based Kalina cycle with low-temperature. Additionally, the study researched the effects of separator input pressure and temperature, basic ammonia mass fraction and basic mass flow rate of working fluid on net power output and thermal efficiency of the cycle. Another study by Saffari et al. [15] compared the ABC, GA, PSO and differential evolution (DE) methods for the thermodynamic performance of the Husaviv power plant with geothermal Kalina cycle. They reported that ABC was more useful compared to the other methods. Proctor et al. [16] used the VMGSim simulation program to develop a dynamic model for a flash ORC GPP in New Zealand and confirmed it with real data from the power plant. Li et al. [17] performed an off-design performance analysis for a geothermal resource-based Kalina cycle with a thermodynamic platform (developed by Matlab and NIST Refprop). They used GA to maximize the net output power and to determine the thermodynamic parameters in the design stage. Wu et al. [18] optimized the thermodynamic performance of a GPP with trans critic ORC using CO_2-based binary zeotropic mixtures. They optimized the thermodynamic performance of the system using the pattern search algorithm (PSA) for 6 refrigerant mixtures in which CO_2 could be added. Thermodynamic and economic analyses were also completed.

As can be seen in the above literature review, the artificial bee colony (ABC) algorithm has not been used for optimization of parameters (pressure and mass flow rate) on system turbine lines to maximize exergy efficiency of a binary GPP. Additionally, the effects of the turbine line on other components of the system have not been researched. In this study, these original issues mentioned have been addressed. Firstly, the thermodynamic performance of the system and its components are assessed with exergy analysis. Then the parameters on the turbine line of the system are optimized with the ABC algorithm to maximize the thermodynamic performance of the system.

DESCRIPTION OF THE SYSTEM

As illustrated in Fig. 1, a geothermal power plant (GPP) with installed power of 24 MW operates in compliance with an air-cooled binary geothermal organic Rankine cycle (ORC). In the GPP, to ensure mixing of the artesian geothermal fluid obtained from production wells, a vertical separator in each wellhead separates two phases as geothermal fluid and steam. From the separators, first 30% NCG (non-condensable gases) and nearly 70% geothermal fluid steam is obtained. Then liquid geothermal fluid is obtained from the separators.

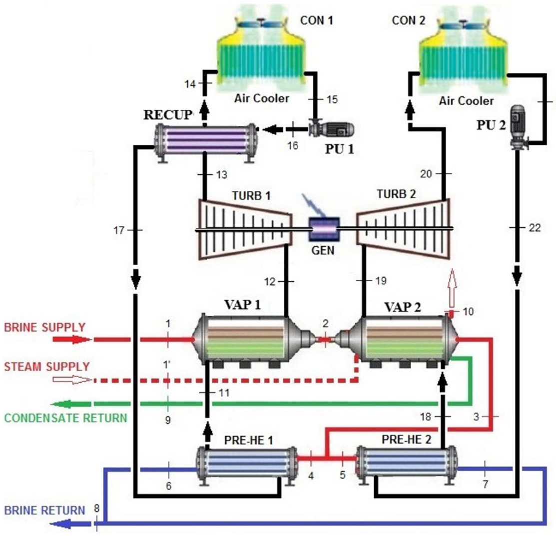

Figure 1. Schematic flow diagram of a geothermal power plant

As seen in Fig. 1, this section is outside the scope of the study, which only includes the power plant section. Binary ORC consists of two classic Rankine cycles that are side by side and different from each other. The first cycle with 160 kg/s is called level I (high pressure), while the second cycle with 196 kg/s is called level II (low pressure). The liquid geothermal fluid first passes through level I and then level II. However, due to the low temperature and pressure, the geothermal fluid steam produced from the separators is passed to level II. The geothermal fluid from both levels is pumped to re-injection wells. In both separate ORC levels, pentane as organic working fluid is used. In level I, different to level II, a recuperator is used to reduce the effect of the high temperature from the turbine output on the condenser.

Additionally, the turbines in levels I and II balance the generator in a certain cycle. Some of the electricity produced by the GPP is used to sustain the system, while the rest of generated electricity is transmitted to switchyard and to the interconnected power lines. In this study, the real operational data of temperature, pressure and mass flow rates for exergy analysis and optimization processes were collected from a GPP belonging to Maren Geothermal Inc. on 14 April 2013. The operating data belonging to the GPP on this date are listed in Table 1.

Table 1. The thermodynamics variables for line numbers on the system flow diagram illustrated in Fig. 1.

Line, i	T (i) [°C]	P (i) [kPa]	$\dot{m}$ (i) [kg/s]	$\dot{E}x$ (i) [kW]
0	25	101		
1	164	1040	445	47507
1′	165	1040	5.83	631
1′	165	1040	2.50	382
2	136	730	445	31701
3	110	690	445	19174
4	110	690	222.50	9587
5	110	690	222.50	9587
6	89	590	222.50	5681
7	81	570	222.50	4423
8	85	590	445	9910
9	107	690	0.83	34
10	107	690	5.25	214
10	107	690	2.25	259
11	105	1261	160	4080
12	137	1261	160	18508
13	82	150	160	5581
14	60	150	160	4675
15	31	150	160	89
16	37	1261	160	388
17	55	1261	160	855
18	106	687	169	4270
19	109	687	169	14859
20	69	119	169	4013
21	33	119	169	117
22	39	687	169	278
23	18	101	2000	0
24	19	106	2000	8238
25	18	101	2000	0
26	19	106	2000	8238

MASS, ENERGY AND EXERGY ANALYSES

For thermodynamic modelling of a binary GPP with ORC, the following assumptions were used in the study:

- Steady-state and steady-flow conditions are used.
- Potential and kinetic energy changes are negligible.
- Heat losses of system components are negligible.
- Pressure loss in valves and pipes is negligible.
- The thermodynamic properties of water are used in place of geothermal fluid properties.
- The air is accepted as an ideal gas.

- In condensers the air has homogeneous distribution.
- Isentropic efficiencies of turbines, pumps and fans are fixed for the thermodynamic model and optimization process. In Level I and II, the values are 0.92 and 0.81 for turbines, and 0.96 and 0.97 for pumps, respectively.
- For level I and II, the effectiveness of vaporizers is 0.82 and 0.88, respectively.
- For level I and II, the effectiveness of preheaters is 0.92 and 0.95, respectively.
- For level I and II, the effectiveness of condensers is 0.68 and 0.75, respectively.
- The effectiveness of the recuperator is 0.49 for only level I.
- The reference state temperature and pressure are taken to be 25 °C and 101.325 kPa, respectively.

For a system, in general the mass, energy and exergy balances express as follows.

$$\sum \dot{m}_{out} - \sum \dot{m}_{in} = 0 \tag{1}$$

$$\dot{Q} - \dot{W} = \sum \dot{m}_{out} h_{out} - \sum \dot{m}_{in} h_{in} \tag{2}$$

$$\dot{I} = \sum \left(1 - \frac{T_0}{T_k}\right) \dot{Q}_k - \dot{W} + \sum \dot{m}_{in} \psi_{in} - \sum \dot{m}_{out} \psi_{out} \tag{3}$$

where $\dot{m}$, $\dot{Q}$, $\dot{W}$, h and İ denote the mass flow rate, heat rate, work rate, specific enthalpy and exergy destruction, respectively. $\dot{Q}_k$ is the heat transfer rate crossing the boundary at temperature T_k at location k. The subscript 0 indicates properties at the restricted dead state of P_0 and T_0, and ψ is the specific flow exergy as expressed below:

$$\psi = (h - h_0) - T_0 (s - s_0) \tag{4}$$

where s denotes the entropy.

Using the data listed in Table 1, the above-mentioned assumptions and thermodynamic balance equations, a code is developed on the MATLAB program [19] platform. The thermodynamic properties of water, air and n-pentane in the developed code are provided by the COOLPROP program [20,21]. In the literature, there are many studies on thermodynamic modelling of binary GPP with ORC [22-25]. However, for the sake of simplicity, the thermodynamic balance equations at the component level used in the thermodynamic model of the system are not given in the text.

ARTIFICIAL BEE COLONY AS OPTIMIZATION ALGORITHM

Optimization algorithms are used in the majority of energy system applications. In this study, the artificial bee colony (ABC) developed by Karaboğa [26] to determine the optimum exergy efficiency of a thermal system is used. This optimization algorithm simulates the intelligent food search behavior of bee colonies [27]. Thus, it attempts to iteratively find the point providing the problem's minimum or maximum solution in space. As an optimization method for the majority of multi modal/dimensional and multipurpose problems, the ABC algorithm contains fewer control parameters and provides better or equal performance than other optimization methods [14,15,28,29].

The optimization process of the ABC algorithm comprises the following steps [27,30-32]:

1. It occurs by generating a random value between the upper and lower limits of each parameter using Eq. (5). In this situation the ABC algorithm randomly produces the first solutions to the problem. Random values are produced between the lower and upper limits for each parameter as in the follow.

$$x_{ij} = x_j^{\min} + rand(0,1)\left(x_j^{\max} - x_j^{\min}\right) \quad \begin{cases} i = 1,\ldots,SN \\ j = 1,\ldots,D \end{cases} \tag{5}$$

where SN and D denote the food sources number and the parameters number to be optimized, respectively.

2. After finding food sources, worker bees then begin to carry nectar to the hive. The number of worker bees assigned represents the cost function (fi=f(xi)) of each (xi) solution. A fitness value (fit) is calculated for the solution to the problem within the limits as given in:

$$fit_i = \begin{cases} \dfrac{1}{1+f_i}, & f_i \geq 0 \\ 1 + |f_i|, & f_i < 0 \end{cases} \tag{6}$$

3. Then each worker bee provides information to observer bees about the state of the food source (is the food source abundant or is a new source needed). This information is provided through dance displayed in the dance area [33]. In the basic ABC algorithm, this is fulfilled using a roulette wheel selection process linked to the fit value [34]. This is presented in the below.

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{7}$$

4. If the source is consumed, the explorer bee is directed to search for a new source. The worker bee determines a new food source near the food source it is working and assesses its quality. The new source is stored in memory if the new source is better. The simulation of determination of new sources adjacent to current sources is given by

$$v_{ij} = x_{ij} + \phi_{ij}\left(x_{ij} - x_{kj}\right) \quad \begin{cases} j = 1,2,\ldots,SN \\ k = 1,2,\ldots,SN \end{cases} \tag{8}$$

where ϕ is a random number in range of [-1,1] and j≠k. The difference between the random values of xij and xkj decreases; in this instance, solutions become more similar. Therefore, the amount of variation in the xij parameter diminishes. A greedy selection process is applied related to the nectar amounts of xi and vi as the fit value [34]. The nectar amount from the new vi solution is higher than the previous amount (xi), thus the old one is deleted from the memory of the worker bee, and the newly vi source is stored.

5. In the ABC algorithm, a repetitive optimization process continues until the required solution is obtained.

The parameters used in the ABC algorithm are listed in Table 2. In Table 2, the optimized number of parameters (D) is 1 and the single target function is the total exergy efficiency of the system. Within these parameters, there are a total of 4 decision variable parameters of the 2 turbine output pressures on the turbine line and the 2 mass flow rates for the working fluid on level I and level II. The minimum and maximum limits for these decision variables are presented in Table 2. The ABC algorithm parameters for the optimization process are set to the parameters in Table 2. In conclusion, an attempt was made to find appropriate results by repeating each optimization process at least once.

Table 2. The parameters of the ABC algorithm.

Parameters	*Symbol*	*Unit*	*Value or Constraint range*
Number of colony size	*NP*		*20*
Number of food sources	*Food number*		*20*
Food source which could not be improved though trials	*Limit*		*100*
Number of cycles for foraging	*Max cycle*		*100*
Number of parameters to be optimized (for single objective)	*D*		*1*
Turbine outlet pressure at level I	P_{13}	*kPa*	*159.6–161.6*
Turbine outlet pressure at level II	P_{20}	*kPa*	*167–172*
Mass flow rate of n-pentane at level I	$\dot{m}_{12}$	*kg/s*	*115–185*
Mass flow rate of n-pentane at level II	$\dot{m}_{19}$	*kg/s*	*90–150*

In thermodynamic evaluation (ExA), the exergy efficiency in system and component levels can respectively be expressed as

$$\varepsilon_{sys} = 1 - \frac{\dot{I}_{sys}}{\dot{E}x_{in,sys}} \quad \text{(single objective function)} \tag{9}$$

and

$$\varepsilon_{k} = 1 - \frac{\dot{I}_{k}}{\dot{E}x_{in,k}} \tag{10}$$

In the optimization process (ABC algorithm), the maximum possible exergy efficiency in system and component levels can respectively be given as

$$\varepsilon_{\max\ possible,sys} = 1 - \frac{\dot{I}_{sys,\min}}{\dot{E}x_{in,sys}} \tag{11}$$

and

$$\varepsilon_{\max\ possible,k} = 1 - \frac{\dot{I}_{k,\min}}{\dot{E}x_{in,k}} \tag{12}$$

RESULTS AND DISCUSSION

Primarily, exergy analysis (ExA) is considered to assess the effect of the turbines on maximum exergy efficiency in a binary GPP system. The results obtained from exergy analysis are listed in Table 3. Regarding Table 3, nearly 17101 kW of the total exergy input into the system is the exergy destruction rate due to components in the whole system. The highest exergy destruction rate in the system occurs in condenser CON 2 with 3342 kW. This is followed by condenser CON 1, vaporizer VAP 2 and turbine TURB 2 with 3251 kW, 2443 kW and 1840 kW, respectively. The exergy destruction rate for turbine TURB 1 is calculated as 871 kW. The components mentioned above are the components that require priority improvement to maximize the performance of the system. As can be seen in Table 3, the total exergy efficiency of the system is 35.25%. This value is the single objective function chosen for the optimization process.

Table 3. The exergetic variables for the system and its components.

Component, k	*İ (k) [kW]*	*ε (sys) [%]*
Level I		
PRE-HE 1	*681.90*	
VAP 1	*1378.46*	
TURB 1	*871.37*	
RECUP	*438.10*	
CON 1	*3251.48*	
PU 1	*611.68*	
Level II		
PRE-HE 2	*1171.77*	
VAP 2	*2443.01*	
TURB 2	*1840.19*	
CON 2	*3342.00*	
PU 2	*1070.67*	
Overall system, sys	*17100.63*	*17100.63*

The artificial bee colony (ABC) algorithm is used to maximize the total exergy efficiency of the system. Therefore, the real and optimum values for the selected decision variables along the two turbine lines are given in Table 4. It can be observed from Table 4 that the collected values for output pressure from the turbines are close to the optimum values, while the mass flow rates collected from the turbine lines are distant from the optimum values. For example, the collected value for $\dot{m}_{19}$ was 119 kg/s, while the optimized value was nearly 149 kg/s. As a result, if the decision variables can reach the optimum values, the exergy efficiency of the whole system will reach maximum.

Table 4. The collected and optimized values of the decision variables for the turbine lines.

Decision variables	Collected value	Optimum value
P_{13} - Turbine outlet pressure at level I	160	159.96
P_{20} - Turbine outlet pressure at level II	169	167.73
$\dot{m}_{12}$ - Mass flow rate of n-pentane at level I	150	161.20
$\dot{m}_{19}$ - Mass flow rate of n-pentane at level II	119	148.54

The convergence behavior of the ABC algorithm during the maximizing process (optimization) of the exergy efficiency of the system is shown in Fig. 2. Regarding Fig. 2, the total exergy efficiency of the system is maximized in the third cycle. As seen on Fig. 3, the total exergy efficiency of the system is 35.25%. The results of optimization process with the ABC algorithm can increase this value to 38.45%. This value is called as the maximum possible exergy efficiency (ε_{max} possible).

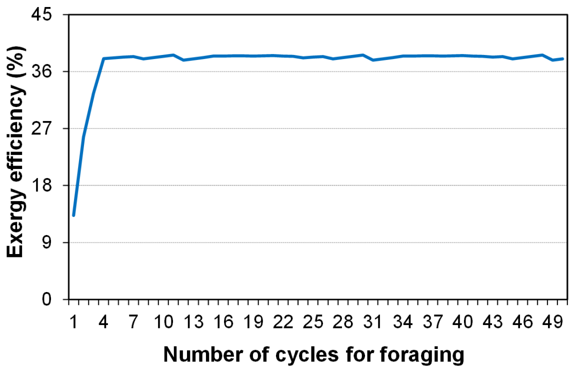

Figure 2. Convergence behavior of the ABC algorithm for optimization process

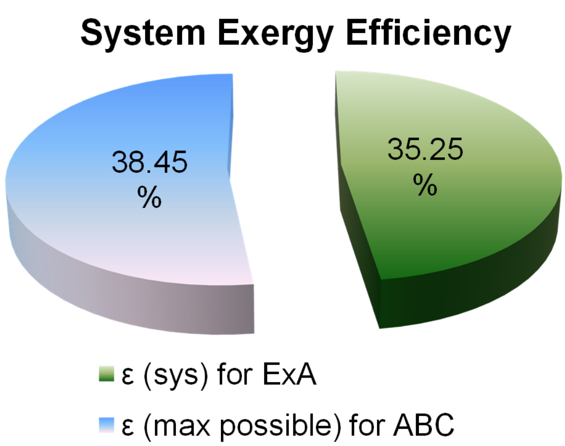

Figure 3. Total system exergy efficiency for the ExA and ABC methods

For the exergy analysis and the ABC algorithm, the changes of exergy destruction rates of system components in the GPP are presented in Fig. 4. From Fig. 4, on the route to maximize the total exergy efficiency, the exergy destruction results for system components with ABC optimization completed for decision variables chosen on the turbine line is observed to lower the exergy analysis results even further. As seen on Fig. 4, condensers CON 1 and CON 2 have highest exergy destruction rates. These values are 3342 kW and 3251 kW, respectively, while after the optimization process these values may be lowered to 2535 kW and 1675 kW. Additionally, these are the components with greatest reductions among system components of 24% and 48%, respectively. However, the result of the optimization process causes a 21% increase in the exergy destruction rate due to the recuperator RECUP. The effects of the optimization process on other system components may be observed.

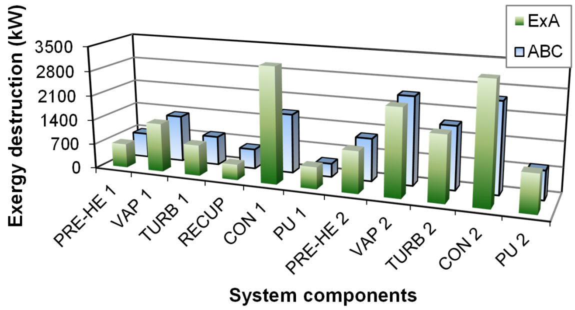

Figure 4. Changes in exergy destruction rate of the system components

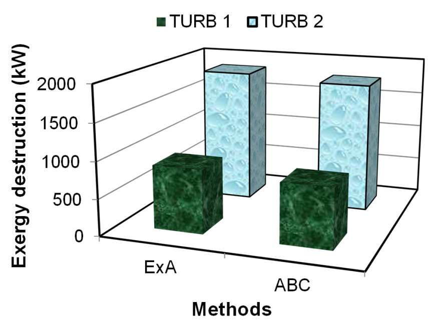

Figure 5. Changes in exergy destruction rate of the turbines in level I and II

Referring to Fig. 5, the exergy destruction rates for turbines TURB 1 and TURB 2 are 871 kW and 1840 kW, respectively, while these values could only be optimized by 6% and 4% (816 kW and 1773 kW). With the ABC optimization process, the exergy destruction rates from turbines are reduced though by a small value, as clearly seen on Fig. 5.

Fig. 6 shows the variation in maximum possible exergy efficiency for system components obtained from the ABC optimization process. As seen on the figure, when the ABC optimization process is completed, the exergy efficiency values for all system components are high, apart from the recuperator. This means that optimization processes completed on the turbine lines in the system will only produce maximum possible exergy efficiency for system components. As observed on Fig. 6, the greatest increase in exergy efficiency occurs in the condensers with 31% for CON 2 and 30% for CON 1. However, there is a 14% reduction in exergy efficiency observed for the recuperator RECUP. In Fig. 7, the variation in exergy efficiency of the turbines on level I and II is given. While the exergy efficiency for turbines TURB 1 and TURB 2 were 93.26% and 83.03%, respectively, after optimization of the system turbine lines the maximum possible exergy efficiencies were observed to be 93.45% and 83.47%.

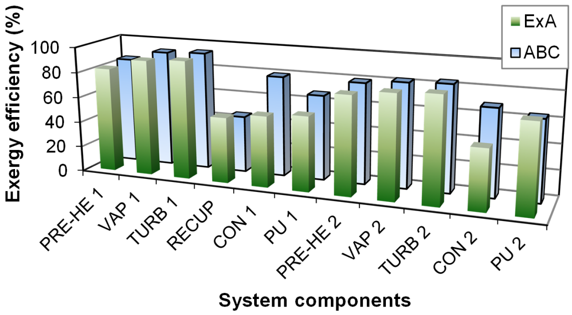

Figure 6. Changes in exergy efficiency of the system components

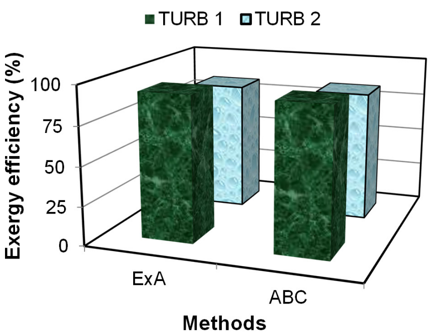

Figure 7. Changes in exergy efficiency of the turbines in level I and II

Finally, to maximize the total exergy efficiency of a binary GPP, the mass flow rates and turbine output pressures for the working fluid are optimized on level I and level II. The results of the optimization process found that the flow rates and turbine output pressures in the cycle levels should be larger than the operating system values.

CONCLUSION

In this study, the artificial bee colony (ABC) algorithm is used to maximize the total exergy efficiency of a binary GPP with ORC. For the optimization process, decision variables on the turbine lines of level I and II of the system are used. These variables are mass flow rate and the turbine output pressure of the working fluid on the turbine lines. The results of the study show that the total exergy efficiency and maximum possible exergy efficiency of the system were 35.25% and 38.45%, respectively. While the total exergy destruction rate for system components was 17101 kW, with the ABC algorithm this value could be lowered to 14227 kW. As a difference of these values, more exergy may be produced at 2874 kW. While improving system components, the system components with greatest optimization possible are the condensers CON 2 and CON 1. Optimizing the turbine lines in the system with the ABC optimization algorithm ensures improvement rates of 4-6% for the turbines. Thus, the rotational imbalances that occur in the connection of two turbines to the generator with the same shaft in binary cycles and the quality of steam content at the turbine outlet to prevent corrosion in turbine blades may be improved. Finally, the ABC optimization method can provide higher quality information than the exergy analysis.

ACKNOWLEDGEMENTS

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NOMENCLATURE

D	number of parameters to be optimized (-)
$\dot{E}x$	exergy rate (kW)
f	cost function (-)
fit	fitness value (-)
h	specific enthalpy (kJ/kg)
$\dot{I}$	exergy destruction (kW)
$\dot{m}$	mass flow rate (kg/s)
NP	number of colony size (-)
P	pressure (kPa)
$\dot{Q}$	heat transfer rate (kW)
s	specific entropy (kJ/kgK)
SN	number of food sources (-)
T	temperature (°C or K)
$\dot{W}$	work rate, power (kW)

Greek symbols

ε	exergy or second law efficiency (%)
ϕ	random number [-1,1]
ψ	flow exergy (kJ/kg)

Subscripts

in	input
min	minimum
out	output
sys	system
0	reference state

Abbreviations

ABC	artificial bee colony
ANN	artificial neural network
ExA	exergy analysis
CON	condenser
GPP	geothermal power plant
NCG	non-condensable gases
ORC	organic Rankine cycle
PRE-HE	preheater
PU	pump
RECUP	recuperator
TURB	turbine
VAP	vaporizer
WHR	waste heat recovery

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