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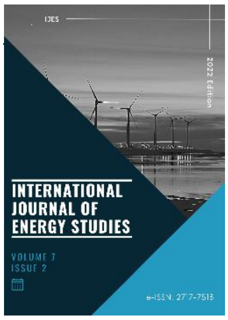

Research Article

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Metaheuristic optimization of double flash based combined heat and power system by using process simulator as black-box function generator

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Highlights

- Modelling and evaluating a geothermal power plant as a black-box model
- Coupling process simulator software with an external optimization library
- Metaheuristic optimization of a complex thermodynamic process
- Sensitivity analysis of process parameters that affect thermal efficiency
- Determination of optimum process parameters for the maximum net power

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ABSTRACT

The energy crisis in Europe has increased the importance of energy alternatives to hydrocarbons. For example, geothermal resources have long been proven to be very efficient heat sources for conventional power cycles. To get the maximum benefit from such a system, it is essential to carefully optimize the system parameters. On the other hand, the topology and nonlinear nature of the system prevent it from being expressed as an analytical function and being differentiable. Thus, derivative-based deterministic optimization methods are difficult to apply. In this study, it is proposed to model a geothermal-based dual-flash combined heat and power system in a process simulator and use it as a black-box function generator to calculate the values of the objective and constraint functions. The system parameters that will provide the maximum combined heat and power efficiency are determined by the Genetic Algorithm. Accordingly, with the optimum system design, the total net turbine power is 132.78 kW. The amount of heat utilized is 15020.10 kW.

Keywords: Process simulation, black-box modelling, metaheuristic optimization, Rankine cycle

1. INTRODUCTION

The Russian-Ukrainian war that broke out in 2021 and subsequently Russia's reduction in natural gas supply to Europe caused an energy crisis in Europe. Many European countries announced that there would be heating and electricity deficits for the winter of 2022 and had to take saving measures [1]. A similar situation emerged with the Oil Crisis in 1973, after the Arab – Israeli war, and the concepts of heat-power recovery and minimization of external energy use emerged after a break in thermal sciences and engineering [2]. The current crisis has also brought to the agenda the use of alternative sources in energy supply.

As a renewable energy source, geothermal heat has a massive potential [3]. Since the temperature level of the heat source is relatively low (100 – 200^{o}C), special considerations should be taken. One of the most common approaches is using a special working fluid that fits the temperature level. Organic Rankine Cycles (ORC) systems are commonly used for recovering geothermal energy. One of the other options is using flash steam power cycles [4] in which the working fluid is geothermal water and throttled to lower pressure to produce vapour and liquid mixture. Then vapour phase is extracted in a separator and fed to a turbine. This study deals with a double flash-based combined heat and power system.

Although it is possible to identify and model a thermal system by a set of thermodynamic and mathematical relations, it is unpractical; Topology of thermal systems is quite complex and properties of process streams may depend on each other and which necessitates iterative root-finding algorithms that are hard to implement. Also, the calculation of thermodynamic properties relies on heavy polynomial root finding (depending on the selected equation of state). Computer-aided process modelling and simulation play a heavy role here. One can parametrically model and simulate any thermal process without considering mathematics in the background too much. Although there is numerous commercial software available in the literature, DWSIM, which is an open-source simulator software, is preferred in this study [5]. One of the most powerful features of this software is the ability to interop with other software via COM interface. The process is completely exposed to third-party tools and can be manipulated programmatically through this interface.

A major drawback in the simulation and modelling of a thermal system is that the process is generally not differentiable even if it can be expressed in a set of mathematical relations. As a result, it is not possible to apply deterministic optimization methods to such systems. In this case, metaheuristic methods that do not need derivative information are often used [6].

In this study, a double flash geothermal-based combined heat and power system is modelled in a process simulator. Then, a computer program that makes process simulation act as a black box function generator, is developed. This program receives a set of process design parameters and returns several outcomes and calculated properties of the process which can be used in objective and constraint functions. Finally, the black box adaptation is coupled to a metaheuristic optimization method to determine the optimum process parameters that give maximum turbine power. Since metaheuristic methods rely heavily on random number generations, optimization is run multiple times and the standard deviation is calculated.

2. METHODOLOGY

2.1. Process Description

Figure 1 shows the topology of a double flash-based combined heat and power process. There are two pressure stages in this process. Geothermal water at the saturation temperature is taken from a production well (PRODUCTIONWELL) and then flashed to the first stage pressure by a valve (VALVE1). The vapour-liquid mixture in valve outlet (a) is fed to the first separator (SEPERATOR1). The Vapour phase (b) is expanded to an intermediate pressure (c). Liquid taken from the first separator (g) is expanded further by a second valve (VALVE2). The Outlet pressure of the valve is the same as the high-pressure turbine (HPT) outlet pressure. Vapour and liquid phases are separated in the second separator (SEPERATOR2) and the vapour outlet is mixed with the outlet of HPT in a mixer (MIXER). The outlet is in the vapour phase and fed into the low-pressure turbine (LPT). Excess heat at turbine output is taken by supply water (SUPPLY2) in a condenser (CONDENSER) and the stream is finally pumped back to the well. Excess heat at the liquid output of the second separator is taken out by supply water (SUPPLY1) and the stream is pumped back to the well.

2.2. Thermodynamic Modelling

To perform the thermodynamic analysis of the system modelled in this study, it is necessary to provide the mass, energy, and entropy balances of both the process itself and each unit operation that makes up the process. The unit operations involved in this process are separator, turbine, expansion valve, mixer, and heat exchanger. The thermodynamic relations of these unit operations can be summarized as follows:

Separator:

Mass Balance: $\dot{m} = \dot{m}_f + \dot{m}_v$ (1)

Energy balance: $\dot{m}_i h_i = \dot{m}_f h_f + \dot{m}_v h_v$ (2)

Turbine:

Mass balance: $\dot{m}_i = \dot{m}_o$ (3)

Energy balance: $\dot{W}_t = \dot{m}(h_i - h_o)$ (4)

2nd law efficiency: $\eta_s = \frac{h_i - h_o}{h_i - h_{o,s}}$ (5)

Expansion valve:

Mass balance: $\dot{m}_i = \dot{m}_o$ (6)

Energy balance: $h_i = h_o$ (7)

Mixer:

Mass balance: $\dot{m}_{i,1} + \dot{m}_{i,2} = \dot{m}_o$ (8)

Energy balance: $\dot{m}_{i,1} h_{i,1} + \dot{m}_{i,2} h_{i,2} = \dot{m}_o h_o$ (9)

Heat exchanger:

Mass balance:

$\dot{m}_{i,h} = \dot{m}_{o,h}$ (10)

$\dot{m}_{i,c} = \dot{m}_{o,c}$ (11)

Energy balance: $\dot{m}_h (h_{i,h} - h_{o,h}) = \dot{m}_c (h_{o,c} - h_{i,c})$ (12)

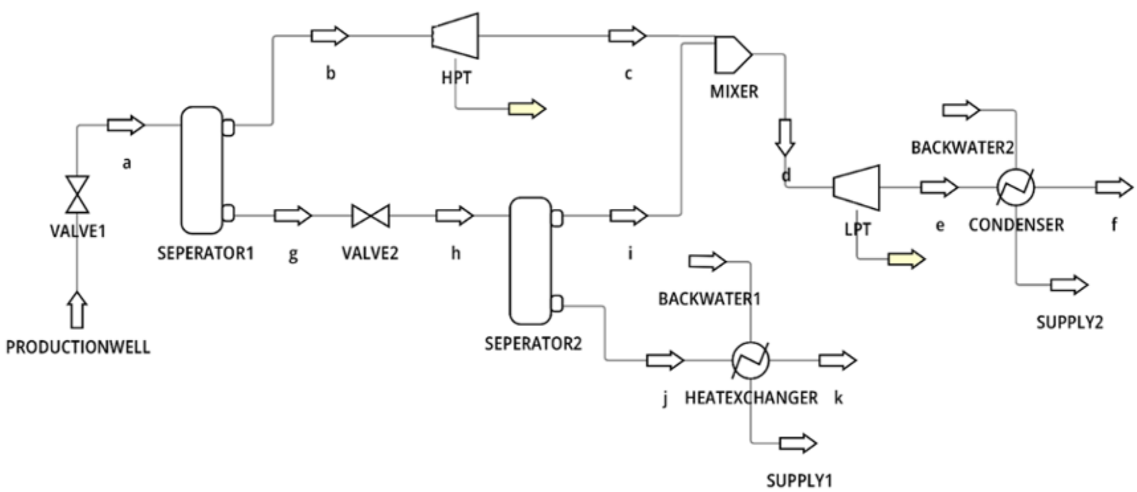

Figure 1. Topology of modelled process

The process examined in the study is modelled in DWSIM, an open-source process simulation software with a large library of unit operations. Process properties are given in Table 1. Various assumptions are made so that such a modelling is possible, and simulation can be carried out.

According to this:

- Geothermal working fluid is accepted as pure water and steam tables are used for thermodynamic properties.
- All system and unit operations operate under steady state and continuous flow.
- Kinetic and potential energy changes are neglected throughout the system.
- Pressure drops due to friction are neglected in unit operations.
- Energy losses in unit operations are neglected

Table 1. Process configuration

Parameter	**Value**
Ambient temperature	298 K
Ambient pressure	101.3 kPa
Geothermal water temperature	393 K
Geothermal water vapor fraction	0.0
Geothermal water mass flowrate	45 kg/s
ΔT_{min} in condenser and heat exchanger	5 K
Geothermal water return temperature	313 K
Supply water inlet temperature	308 K
Supply water outlet temperature	318 K
Isentropic efficiency of turbines	75%
Mechanical efficiency of turbines	95%
Electrical efficiency of generator	95%

As seen in Table 1 outlet temperatures are fixed both in the heat exchanger and the condenser. Therefore, a procedure that calculates the feedwater flow rate satisfying these temperatures using a bisection method is implemented.

2.3. Genetic Algorithm

In this study Genetic Algorithm (GA) [7] is selected as the metaheuristic optimization method. GA is an evolutionary algorithm based on Charles Darwin's survival of the fittest theorem. GA solves the optimization problems by a stochastic search of the solution space using chromosomes which represent the process parameters in our case. There are three basic operators in GA. These are selection, crossover, and mutation operators. Producing new chromosomes is handled by crossover operator. To avoid convergence to local optima, mutation operator randomly modifies chromosome values. Selection of individual genomes for later breeding is handled by selection operator. Flow diagram of GA procedure is given in Figure 2. GA calculations are carried out by means of the jMetalPy metaheuristic optimization framework [8]. Genetic Algorithm configuration is given in Table 2.

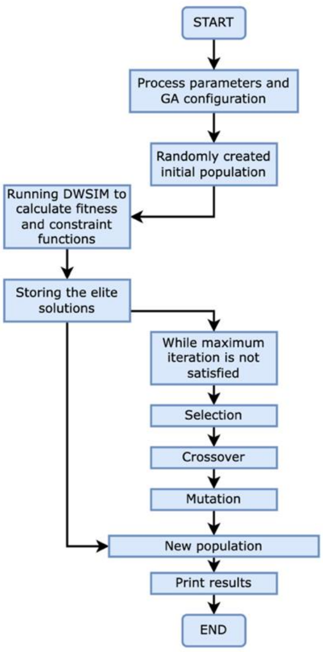

Figure 2. Flow diagram of GA procedure

Table 2. Genetic algorithm configuration

Parameter	Value
Population	20
Offspring population	20
Mutation operator	Polynomial mutation [9]
Mutation probability	$1/n_{var}$
Crossover operator	Simulated binary crossover [10]
Crossover probability	1
Selection operator	Random solution selection [11]
Max evaluation	500

3. RESULTS AND DISCUSSION

In this study, the optimization study of a geothermal-supported dual flash combined heat and power process, which gives the optimum turbine power, is carried out using the Genetic Algorithm. The working fluid in the cycle (geothermal water) is accepted as pure water and steam tables are used to calculate thermodynamic properties. The properties of the cycle and the unit operations are shown in Table 1. The output pressures of the first expansion valve (VALVE1) and the high-pressure turbine (HPT) are selected as decision variables. The lower and upper limits of the decision variables are determined by the system properties. The exit pressure of the geothermal water from the well is 197.7 kPa (saturation pressure at well inlet temperature, 393K). Therefore, the upper limit of VALVE1 outlet pressure is selected as 190.0 kPa. The condenser outlet pressure is selected as 60.0 kPa. The outlet pressure of the high-pressure turbine (HPT) must be higher than the outlet pressure of the low-pressure turbine (LPT). Then, the mathematical representation of the optimization problem is:

$$
\begin{aligned}
&\min_{P_1,P_2} \quad -\dot{\mathrm{W}}_{\mathrm{HPT}} - \dot{\mathrm{W}}_{\mathrm{LPT}} \\
&s.t. \\
&100000 \le \mathrm{P}_1 \le 190000 \\
&60000 \le P_2 \le P_1
\end{aligned}
\tag{13}
$$

Only relations between pressure levels are induced as constraints here. All other internal constraints related to the process and unit operations are handled by the process simulator.

Before carrying out the optimization problem, it is important to investigate how decision variables are affecting various system parameters. Here, the variation of turbine power and mass flow rates of supply streams with respect to pressure levels are given. Figure 3 and Figure 4 show how decision parameters affect process parameters. Since this is a combined heat and power process, the amount of produced electricity and useful heat are the most crucial parameters. Since the outlet temperatures are fixed in the condenser and the heat exchanger, mass flow rates of supply streams are direct indicators of useful heat.

In the first case, the outlet pressure of the high-pressure turbine is fixed at 80.0 kPa. When the outlet of the first valve varies from 100.0 kPa to 190.0 kPa responses of observed parameters are flat except for the power of the high-pressure turbine (Figure 3). This is a predictable result because the output pressure of the high-pressure turbine is fixed, and the only varying parameter is the pressure level between the inlet and outlet of the high-pressure turbine.

In the second case, the first valve outlet pressure is fixed at 145.0 kPa and the high-pressure turbine outlet pressure varies between 80.0 and 180.0 kPa (Figure 4). This decision variable directly affects the power outcome of both turbines. As the pressure decreases, the amount of power generated from the first turbine increases, but due to the decreasing pressure level, the power generated from the second turbine decreases.

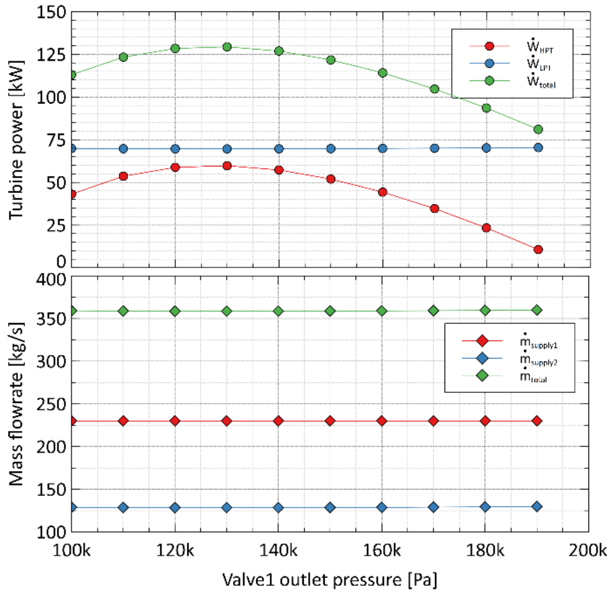

Figure 3. Variation of turbine power and supply water flowrate with respect to first valve outlet pressure

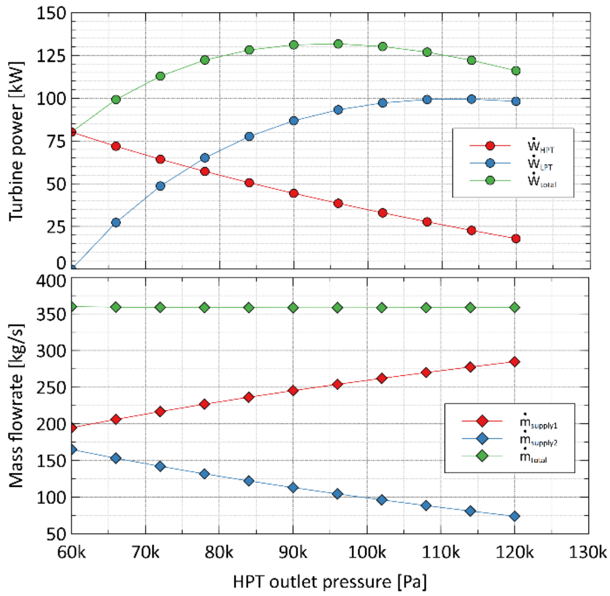

Figure 4. Variation of turbine power and supply water flowrate according to high pressure turbine outlet pressure

The second separator (SEPERATOR2) triggers the flow rates of the feed streams to be pressure sensitive; As the outlet pressure of the high-pressure turbine decreases, the outlet pressure of the second valve (VALVE2) decreases. Therefore, the vapour fraction of the stream entering the second separator (h) decreases. This reduces the amount of liquid entering the heat exchanger and increases the amount of liquid-steam mixture entering the condenser.

In evolutionary algorithms, the population is in a state of continuous evolution, and it is expected that the fitness of selected individuals to the environment will increase as time progresses. Adaptability is determined by the value of the fitness function and is defined as the total turbine power in this study. During evolution, individuals with poor fitness are ruled out, while individuals with better fitness survive to form the next generation. Accordingly, over time, individuals must congregate in the optimal region (or regions according to the situation).

Evolution of individuals' positions in solution space evolves is shown in Figure 5 – Figure 7. At the initialisation phase, individuals are scattered whole solution space since their positions are assigned from uniform random distribution (Figure 5). Maximum number of fitness function evaluation is 500 in this study. However, clustering is completed even half of generation is reached (Figure 6). When the maximum evaluation of fitness function is reached, all individuals are virtually overlapped (Figure 7). Evolution of fitness function with respect evaluation is given in detail in Figure 8.

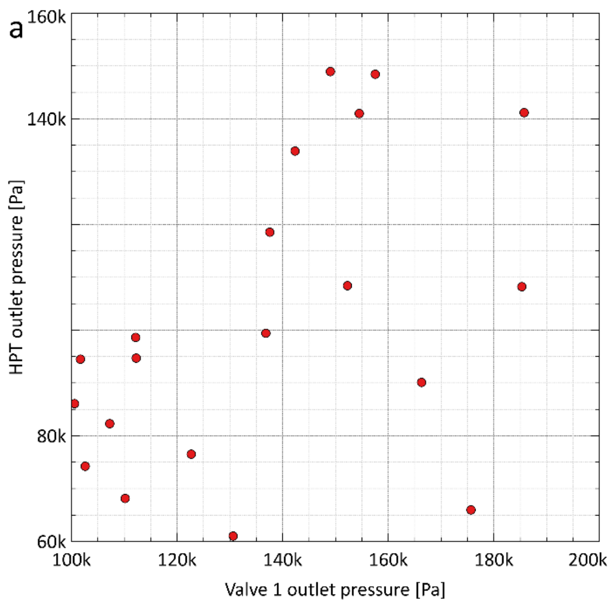

Figure 5. Distribution of individuals at the initialization

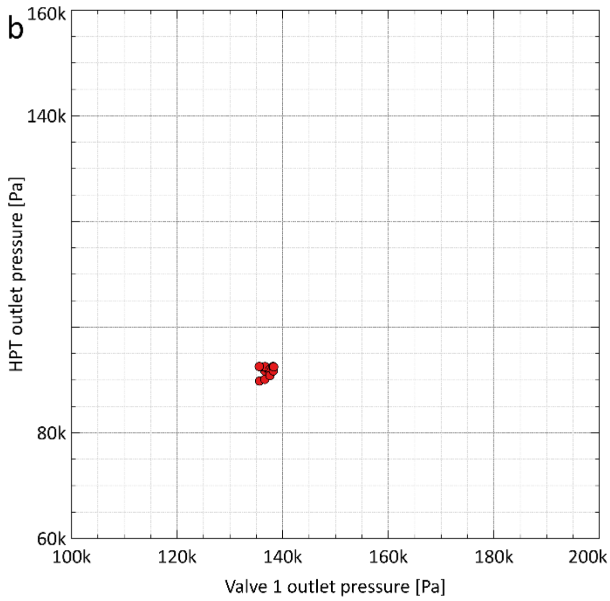

Figure 6. Distribution of individuals over the solution space at the half of generations

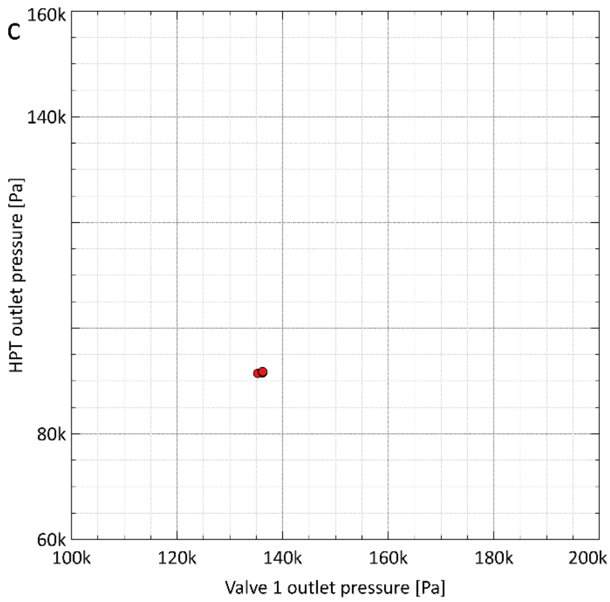

Figure 7. Distribution of individuals over the solution space at maximum number of fitness function evaluation

Although all individuals are overlapped when evolution is complete, multiple executions of the algorithm are essential to ensure that not to be stuck at the local optima. Five consecutive runs are made in this study. In each run, the fitness function is converged to the same value which is 132.7753 ± 0.0039 kW (where P_1 and P_2 are 135.5 kPa and 91.1 kPa respectively). At the optimum operation conditions, heat recovered from the heat exchanger and condenser are 10322.2 kW (with the mass flowrate of 247.0 kg/s) and 4697.9 kW (with the mass flowrate of 111.5 kg/s) respectively. The total amount of recovered heat is 15020.1 kW. All the thermodynamic properties of the process streams are tabulated in Table 3.

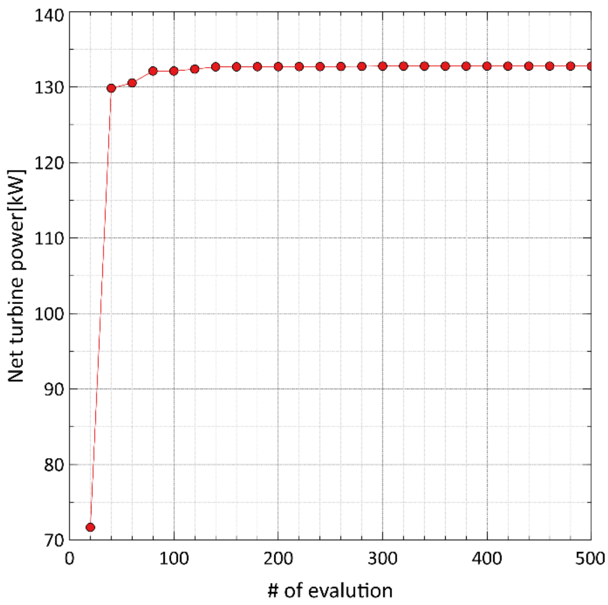

Figure 8. Evolution of fitness function with respect to number of iterations

Table 3. Stream properties at the optimum operation conditions

	PW	a	b	c	d	e	f	g
Temperature (K)	393.0	381.5	381.5	370.2	370.2	359.1	313.0	381.5
Pressure (kPa)	197.7	135.5	135.5	91.1	91.1	60.0	60.0	135.5
Mass Flow (kg/s)	45.000	45.000	0.984	0.984	1.912	1.912	1.912	44.016
Mass Fraction (-)	0	0.022	1	0.986	0.993	0.978	0	0

	h	i	j	k	BW1	SUPPLY1	BW2	SUPPLY2
Temperature (K)	370.1	370.1	370.1	313.0	308.0	318.0	308.0	318.0
Pressure (Pa)	91.1	91.1	91.1	91.1	101.3	101.3	101.3	101.3
Mass Flow (kg/s)	44.016	0.928	43.088	43.088	247.000	247.000	111.5	111.5
Mass Fraction (-)	0.022	1	0	0	0	0	0	0

4. CONCLUSION

In this study, a methodology was developed to implement the process simulator as a black box function generator into metaheuristic optimization methods. A computer program has been developed that runs the simulation by processing the inputs, calculates the values of the objective and constraint functions according to the simulation results and returns them to the optimization method. This developed methodology has been tested in the optimization of a geothermal sourced double flash combined heat and power generation system. According to the sensitivity studies, the pressure levels of the system are the most important parameters affecting the power produced. Accordingly, an optimization problem was proposed in which the decision variables are the pressure levels of the system. One of the strongest aspects of the proposed methodology is that internal constraints such as mass, energy and momentum balances are handled by the simulator. When setting up the optimization problem, it is sufficient to define the performance related constraints.

The sample process was solved using genetic algorithm and optimum process parameters were determined. Accordingly, the optimum outlet pressures of the first valve and the high-pressure turbine are 135.5 and 91.1 kPa, respectively. The maximum amount of electricity that can be obtained from the system is 132.78 kW. Achieving the same optimum values at the end of the runs with different initial values also proves the robustness of the optimization method. Therefore, it can be said that the proposed methodology is suitable for the optimization of thermal systems.

As a conclusion, geothermal heat sources have the potential to be a prolific alternative when the natural gas supply is at the stake. For a maximum exploitation from a combined heat and power generation plant using that kind of heat source, a robust methodology to determine process parameters is essential. It has been revealed that one of the most efficient ways to search such a multidimensional and complex solution space is to use process simulators, where the process can be expressed parametrically. With the developed methodology, the process simulation has been abstracted and converted into a black box function generator, so it is possible to adapt it not only to metaheuristic methods such as genetic algorithm but also to any kind of optimization method.

NOMENCLATURE

$\dot{m}$	Mass flowrate
h	Enthalpy
$\dot{W}$	Work rate
η	Efficiency
Subscripts	
f	Liquid phase
v	Vapour phase

i Inlet

o Outlet

s Isentropic

h Hot side

c Cold side

DECLARATION OF ETHICAL STANDARDS

The author of the paper submitted declares that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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