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Exergoeconomic and Environmental Analysis of a Combined Cycle Power Plant Using the Particle Swarm Optimizer: A case study

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Abstract

In the present work, a Thermal Combined Cycle (TCC) power plant is optimized using particle swarm optimization (PSO). The design parameters of the plant considered are air compressor pressure ratio, compressor isentropic efficiency, the gas turbine outlet temperature, inlet fuel in combustion chamber and inlet fuel in HRSG, the steam temperature entering the high pressure steam turbine, the steam pressure entering the high pressure steam turbine, the steam mass flow rate entering the high pressure steam turbine and steam turbine isentropic efficiency. In addition, to optimally find the optimum design parameters, an exergoeconomic approach with multi-objective function is employed. The demanded power on the fixed design parameter is 360 MW of net power output. Since, environmental pollution and energy shortage are the two factors limiting the development of the society; nevertheless, this analysis tends to optimally find the design parameters which result in a decrease in the fuel mass flow rate. Also, this reduction (about 6.4%) in the mass flow rate and increasing exergetic efficiency can decrease the environmental impacts. The results show that exergy efficiency and cost product for plant are 8% and 3% better than base case, respectively. Finally, the analysis and comparison between the results of the current research and two other researches was done and the results are reported. Based on this comparison, the efficiency of the turbines in the current research is 0.68% less than the first research and 5.02% more than the second research.

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1. Introduction

Exergy analysis is a thermodynamic analysis technique based on the second law of thermodynamics which provides an alternative and illuminating means of assessing and comparing processes and systems rationally and meaningfully. In particular, exergy analysis yields efficiencies which provide a true measure of how nearly actual performance approaches the ideal, and identifies more clearly than energy analysis the causes and locations of thermodynamic losses. Consequently, exergy analysis can assist in improving and optimizing designs. Increasing application and recognition of the usefulness of exergy methods by those in industry, government and academia has been observed in recent years. Exergy has also become increasingly used internationally. [1]

Kallio and Siroux in a research present a review of exergy and exergy-economic approaches to evaluate hybrid renewable energy systems in buildings. In the first part of the paper, the methodology of the exergy and exergo-economic analysis is introduced as well as the main performance indicators. The influence of the reference environment is analyzed, and results show that the selection of the reference environment has a high impact on the results of the exergy analysis. In the last part of the paper, different literature studies based on exergy and exergo-economic analysis applied to the photovoltaic-thermal collectors, fuel-fired micro-cogeneration systems and hybrid renewable energy systems are reviewed. It is shown that the dynamic exergy analysis is the best way to evaluate hybrid renewable energy systems if they are operating under a dynamic environment caused by climatic conditions and/or energy demand. [2]

Exergy analysis is another useful tool that can link the energy system with its surrounding environment. The exergy analysis reveals the actual system efficiency that makes it ideal for system tuning. The careless utilisation of energy resources would have indirect side effects on economics and environment, exergy analysis is a useful method to show the impact of using energy resources on the environment, reveal the efficiency improvement, identify the magnitudes of wastes and losses, and calculate the quality of the energy resources. [3]

Exergy analysis is also one of the premier tool for the system analysis, by performing it we can actually relate the system with its overall surroundings. Exergy analysis yields ideal parameters that would be beneficial for the maintenance/tuning of the system. This analysis is also used to stop the careless utilization of energy resources by putting forward the indirect side-effects which it causes on our environment. Through monitoring the consumption of resources, the overall efficiency of system also increases while it would also be useful to calculate the total waste a system generates during the overall process. There are number of articles/studies found that conducted exergy analysis and used the results to increase the systems efficiency. [4]

The exergo-economic analysis is used to create a relation between the costs and exergy flows of the energy system. The exergo-economics are based on the exergy flows, exergetic and non-exergetic costs. [2]

In another research from Kazemi et al, 11 alternatives of natural gas combined cycle power plants based on post-combustion, pre-combustion or oxy-fuel combustion CO_2 capture with monoethanolamine (MEA) or activated methyldiethanolamine (a-MDEA) and potential ORC implementation were simulated, economically optimized and environmentally assessed to shed light on these gaps. The results show the important role of thermodynamic efficiency in the system's environmental performance. The system based on post-combustion CO_2 capture with a-MDEA and ORC showed a superior economic profile as well as a better environmental performance in terms of climate change and fossil resource depletion. [5]

Kun Yang et al propose a combined cooling, heating, and power (CCHP) system driven by biomass and solar energy integrated with an organic Rankine cycle (ORC). Its exergy, exergoeconomic, and environmental performances are investigated. First, the thermodynamic parameters of each material and energy flow for the proposed CCHP system are simulated using Aspen Plus. Second, the exergy and exergoeconomic performances of the system are investigated, and an environmental analysis of the system is performed. The results show that the unit exergy costs (UEC) of domestic hot water, electricity generated by an internal combustion engine (ICE) and the ORC, and chilled/heated water under summer/winter conditions are 2.742/2.742, 6.713/6.629, 12.930/12.930, and 27.100/12.530 MW/MW, respectively, with corresponding unit exergoeconomic costs (UEEC) of 41.11/41.11, 124.40/139.20, 181.80/181.80, and 507.10/302.60 USD/MWh, respectively. [6]

The results of another research showed that diesel reduced the plant's efficiency by 0.00022 compared to using natural gas, which was the least of the other alternatives. The environmental analysis revealed that diesel produced the least amount of CO_2 eq, but biodiesel-nanoparticle had a better CO_2 footprint due to the higher absorption of CO_2 in the cultivation phase of the raw material for biodiesel. The economic analysis for the fuels was carried out over ten years and based on the lifetime of the equipment purchased. Consequently, the total cost over the ten years for diesel was $967332.5161, which was $124475.8381 less than that for biodiesel-nanoparticle and $240935.3341 less than that for fuel oil. Finally, an overall comparison was made between the fuels using the AHP method. As the environmental criterion was the most important decision criterion, biodiesel-nanoparticle fuel was chosen with a marginal difference compared to diesel. [7]

In other work, a novel combined cooling and power (CCP) system is proposed for waste heat recovery of a natural gas-biomass dual fuel gas turbine (DFGT) based on the organic Rankine cycle (ORC) and absorption refrigeration cycle (ARC). Comprehensive thermodynamic, exergoeconomic, and environmental performance and parametric analysis of this system are performed. Results show that under the design condition, thermal efficiency, exergy efficiency, levelized cost of exergy (LCOE), and levelized environmental impact of exergy (LEIOE) of the system are 68.88%, 42.10%, and 21.16 $/GJ, and 5208.82 mPts/GJ, respectively. Among all the components, combustion chamber has the highest exergy destruction rate. The parametric analysis indicates that the thermal and exergy efficiencies rise by increasing the gas turbine inlet temperature (GTIT) and ORC turbine inlet pressure or by decreasing the preheated air temperature (PAT) and exhaust gas outlet temperature at high-temperature vapor generator. The LCOE and LEIOE present similar trends in most cases, which are most affected by the PAT and GTIT. [8]

On the other hand Mathematical Optimization is a branch of applied mathematics which is useful in many different fields. Here are a few examples:

• Manufacturing • Production • Inventory control • Transportation • Scheduling • Networks • Finance • Engineering • Mechanics • Economics • Control engineering • Marketing • Policy Modeling

In the optimization basic optimization problem consists of: [9]

• The objective function, f(x), which is the output you're trying to maximize or minimize.

• Variables, x1 x2 x3 and so on, which are the inputs – things you can control. They are abbreviated xn to refer to individuals or x to refer to them as a group.

• Constraints, which are equations that place limits on how big or small some variables can get. Equality constraints are usually noted hn (x) and inequality constraints are noted gn (x).

Genetic Algorithm (GA) is a search-based optimization technique based on the principles of Genetics and Natural Selection. It is frequently used to find optimal or near-optimal solutions to difficult problems which otherwise would take a lifetime to solve. It is frequently used to solve optimization problems, in research, and in machine learning. Genetic Algorithms (GAs) are search based algorithms based on the concepts of natural selection and genetics. GAs are a subset of a much larger branch of computation known as Evolutionary Computation. GAs were developed by John Holland and his students and colleagues at the University of Michigan, most notably David E. Goldberg and has since been tried on various optimization problems with a high degree of success. In GAs, we have a pool or a population of possible solutions to the given problem. These solutions then undergo recombination and mutation (like in natural genetics), producing new children, and the process is repeated over various generations. Each individual (or candidate solution) is assigned a fitness value (based on its objective function value) and the fitter individuals are given a higher chance to mate and yield more "fitter" individuals. This is in line with the Darwinian Theory of "Survival of the Fittest". [10]

In recent years, exergoeconomic concepts have been used with search algorithms, such as genetic algorithm and evolutionary algorithm, to find out realistic optimal solution(s) of thermal systems.

Lorencin et al used a genetic algorithm (GA) approach to design of multi-layer perceptron (MLP) for combined cycle power plant power output estimation. Dataset used in this research is a part of publicly available UCI Machine Learning Repository and it consists of 9568 data points (power plant operating regimes) that is divided on training dataset that consists of 7500data points and testing dataset containing 2068 data points. Presented research was performed with aim of increasing regression performances of MLP in comparison to ones available in the literature by utilizing heuristic algorithm. [11]

2. The PSO concept

It is necessary to explore approaches that integrate intelligence based on natural phenomena (soft computing methods), which are at the forefront of current research. One solution to this issue is to use the particle swarm optimization (PSO) technique. PSO is a soft computing optimization method inspired by the social behavior of particles, which is inspired by the cooperative movement of individuals in a swarm. In the context of optimizing photovoltaic systems. PSO optimization overcomes oscillations around local power points by efficiently locating the global power point, even in the case of partial shading. The PSO particles adjust their position by moving towards the best personal individual and towards the best global individual, thereby maximizing the energy efficiency of the photovoltaic system. As a result, the PSO represents a promising solution for improving maximum power point tracking under variable and complex weather conditions in solar the solar water pumping systems. [12]

In another article a new methodology were introduced, named PSOPARSIMONY, which uses an adapted particle swarm optimization (PSO) to search for parsimonious and accurate models by means of hyperparameter optimization (HO), feature selection (FS), and the promotion of the best solutions according to two criteria: low complexity and high accuracy. This paper also includes a comparison in performance with GA-parsimony, our previously published methodology based on GA that has been successfully applied in a variety of contexts such as steel industrial processes, hotel room-booking forecasting, mechanical design, hospital energy demand, and solar radiation forecasting [13].

Optimization algorithms, like the Particle Swarm Optimization (PSO), often suffer from premature convergence, providing poor convergence quality and slow convergence rates. In addition, striking a balance between exploration and exploitation adds complexity to its implementation. Moreover, while the algorithm's simplicity with a few parameters is advantageous for ease of use, it poses a significant challenge for improvement. This work presents a modified PSO variant, the Random Adaptive Backtracking Particle Swarm Optimization (RAB-PSO) algorithm. This algorithm combines three complementary modifications to address the limitations of PSO. Its main objective is to improve convergence quality while minimizing iteration counts required for achieving global minima. [14]

Hilali et al focuse on the optimization of solar water pumping systems (SWPS) by combining the particle swarm optimization (PSO) technique on the generator photovoltaic (GPV) side and direct torque control (DTC) on the pump motor side. The integration of a maximum power point tracking system (MPPT-PSO) represents a significant advance, enabling maximum power to be extracted from the GPV whatever the weather conditions. The main objective is to improve the energy efficiency of the SWPS system by maximizing the electrical power dedicated to the pumping system. [12]

Divasón et al present PSO-PARSIMONY, a new methodology to search for parsimonious and highly accurate models by means of particle swarm optimization. PSO-PARSIMONY uses automatic hyperparameter optimization and feature selection to search for accurate models with low complexity. To evaluate the new proposal, a comparative study with multilayer perceptron algorithm was performed with public datasets and by applying it to predict two important parameters of the force–displacement curve in T-stub steel connections: initial stiffness and maximum strength. Models optimized with PSO-PARSIMONY showed an excellent trade-off between goodness-of-fit and parsimony. [13]

Barrios and Gerardo used a hybrid algorithm. This algorithm combines three complementary modifications to address the limitations of PSO and Its main objective is to improve convergence quality while minimizing iteration counts required for achieving global minimal. [14]

In the research of Khademi and colleagues, energy, exergy and economic analyses is performed for a combined cycle power plant (CCPP) with a supplementary firing system. The purpose of this analyses is to evaluate the economic feasibility of a CCPP by applying an optimization techniques based on Evolutionary algorithms. Actually, the evolutionary algorithms of Firefly, PSO and NSGA-II are applied to minimize the cost function and to optimally adjust the operating design variables of a CCPP. The input parameters are measured in real case study (i.e., Yazd city, Iran) and they are used to model and optimize the system performance. In following of optimization procedure, a thermo-economic method is employed to compare the impact of operating parameters from an economic standpoint by COMFAR III (Computer Model for Feasibility Analysis and Reporting) software. The results showed that the optimization results are economically more feasible than the base case. In addition, among different optimization techniques, Firefly algorithm improves the economic justification of CCPP. At the end, the results of sensitivity analysis show that by decreasing the operation costs, fixed assets and sales revenue by 40%, the IRR increases by 6.7%, 42.8% and decreases by 41.4%, respectively. Furthermore, the lowest sensitivity of IRR is related to operation cost, while the highest sensitivity of IRR is corresponding to variations of fixed assets.. [15]

Searching procedures by PSO based on the above concept can be described as follows: bird flocking optimizes certain objective function. Each agent knows its best value so far (pbest) and its xy position. Moreover, each agent knows the best value so far in the group (g best) among pbests. The modified velocity of each agent can be calculated using the following information.

- The current positions (x, y)
- The current velocities (vx, vy)
- The distance between the current position and pbest
- The distance between the current position and g best

This modification can be represented by the concept of velocity. The velocity of each agent can be modified by the following equation:

$$v_i^{t+1} = wv_i^t + c_1 rand_1 \times (pbest_i - s_i^t) + c_2 rand_2 \times (gbest - s_i^t) \quad (1)$$

Where,

t+1: denotes the next iteration number

t : denotes the current iteration number

v_i^t : Velocity of agent i at iteration t

$Pbest_i$: pbest of agent i (the best previous position yielding the best fitness value for the ith particle)

gbest : gbest of the group (the best position discovered by the whole population)

w: the static inertia weight chosen in the interval (0, 1)

c_1 : the cognitive acceleration coefficient

c_2 : the social acceleration coefficient

rand : random number between 0 and 1

s_i^t : Current position of agent i at iteration t

A suitable selection of weighting function w in (2) provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. The following weighting function is usually utilized in:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad (2)$$

Where,

w_{max} : initial weight,

w_{min} : final weight,

$iter_{max}$: maximum iteration number,

iter : current iteration number.

Using the above equation, a certain velocity, which gradually gets close to pbest and gbest can be calculated. The current position (searching point in the solution space) can be modified and the position of a particle is updated every time step using the equation:

$$s_i^{t+1} = s_i^t + v_i^{t+1} \quad (3)$$

The constants $c_1$and c_2 represent the weighting of the stochastic acceleration terms that pull each particle toward the pbest and gbest positions. Lower values allow particles to far from the target regions and higher values result in the abrupt movement toward, or past, target regions. Hence, the acceleration constants $c_1$and c_2 is often set to be 2.0 according to past experiences.

The next iteration takes place after all particles have been moved. Eventually the swarm as a whole, like a flock of birds collectively foraging for food, is likely to move close to the best location. The following alternative velocity-update equation was developed:

$$v_i^{t+1} = k\,(v_i^t + c_1 rand_1 \times (pbest_i - s_i^t) + c_2 rand_2 \times (gbest - s_i^t)) \quad (4)$$

Where k is a constant called the constriction coefficient. If c_1, c_2 and k (or w), are correctly chosen, the PSO is guaranteed to be stable without the need for special constraints (e.g., Bounding of velocities and positions). [14]

The Accomplish of optimization consists of five steps : [16-17]

Step 1: Swarm Initialization

The optimization process begins by randomly initializing positions between a minimum and maximum per dimension as per Relation (5). The most common benchmarks use the same minimum and maximum per dimension. For application problems, however, these might differ depending on the characteristics being optimized; hence, the general formula is provided, which uses subscript j to indicate the dimension.

$$s_{i,j}(t=0) \in U\left(s_j^{min}, s_j^{max}\right) \tag{5}$$

Where $j \in \{1,2,\dots,n-1,n\}$ and n denotes the problem dimensionally. Velocities are similarly initialized according to Relation (6). For application problems with a different range of feasible values on one dimension than on another, different step sizes per dimension would make sense; hence, the general form is presented, which avoids unnecessarily imposing the same range of feasible values of all characteristics to be optimized.

$$v_{i,j}(t=0) \in U\left(-v_j^{max}, v_j^{max}\right) \tag{6}$$

Each particle's personal best is initialized to its starting position as shown in Equation (7).

$$\overrightarrow{pbest}_i(t=0) = \vec{s}_i(t=0) \tag{7}$$

The global best is always the best of all personal bests as shown in Equation (8).

$$\overrightarrow{gbest}(t) = \arg\min f\left(pbest_i(t)\right) \tag{8}$$
$$\forall pbest_i(t)$$

Iterative Optimization Routine

Once the swarm has been initialized, particles iteratively: (i) accelerate (i.e. adjust their velocity vectors) toward the global best and their own personal bests, (ii) update and clamp their velocities, (iii) update their positions, and (iv) update their personal bests and the global best. This routine is repeated until reaching a user-specified termination criterion. For convenience, the relevant equations are restated below as needed in order of implementation.

Setp2: Velocity updating:

$$\vec{v}_i^{t+1} = w\vec{v}_i^{t} + c_1\overrightarrow{rand}_{1,i} \times \left(\overrightarrow{pbest^t}_i - \vec{s}_i^t\right) + c_2\overrightarrow{rand}_{2,i} \times \left(\overrightarrow{gbest}^t - s_i^t\right) \tag{9}$$

$$v_{i,j}^{t+1} = sign\left(v_{i,j}^{t+1}\right)\max\left(\left|v_{i,j}^{t+1}\right|, v_j^{max}\right) \tag{10}$$

Step3: Position updating:

$$\vec{s}_i^{t+1} = \vec{s}_i^{t} + \vec{v}_i^{t+1} \tag{11}$$

Step 4: Memory updating:

A particle's personal best is only updated when the new position offers a better function value:

$$\overrightarrow{pbest}_i^{t+1}\begin{cases}\vec{x}_i^{t+1} \text{ if } f(\vec{s}_i^{t+1}) < f\left(\overrightarrow{pbest}_i^{t}\right)\\ \overrightarrow{pbest}_i^{t} \text{ Otherwise}\end{cases} \tag{12}$$

The global best is always the best of all personal bests:

$$\overrightarrow{gbest}(t+1) = \arg\min f\left(pbest_i(t1)\right) \tag{13}$$
$$\forall pbest_i(t)$$

Step 5: Termination criteria examination:

The algorithm repeats Step 2 to Step 4 until certain stopping rules are satisfied. Once terminated, the algorithm outputs the $\overrightarrow{gbest}$ and $f(\overrightarrow{gbest})$ as its solution. Rather than accelerating due to external physical forces, particles adjust toward solutions of relative quality. Each position encountered as particle swarm is evaluated and compared to existing bests. Though the behavior of each individual is simple, the collective result is an optimization algorithm capable of maximizing or minimizing problems that would be difficult to tackle with straightforward mathematical analyses, either because the problem is not well understood in advance or simply because the problem is quite complicated.

3. Exergy and the thermoeconomic mathematical Model

Exergy of stream flow

The specific exergy at control volume with negligible kinetic and potential energies are given by: [4]

$$ex = ex^{PH} + ex^{CH} \quad (14)$$

That the specific physical and chemical exergy of a stream are calculated as follows: [4]

$$ex^{PH} = (h - T_0 s)_{P,T} - (h - T_0 s)_{P_0,T_0} \quad (15)$$

$$ex^{CH} = \sum_{i=1}^{j} y_i ex_i^{CH} + RT_0 \sum_{i=1}^{j} y_i \ln y_i \quad (16)$$

Then, the exergy transfer rates at control volume inlets and outlets are denoted, respectively, as $\dot{Ex}_i = \dot{m}_i\, ex_i$ and $\dot{Ex}_e = \dot{m}_e\, ex_e$.

Work exergy

Exergy is determined as the maximum work potential, the work transfer rate in the control volume, $\dot{W}_{cv}$, equivalent to the exergy transfer rate.

Heat transfer exergy

Assuming a uniform temperature distribution at the location on the boundary of the control volume, the exergy transfer rate, $\dot{Ex}_{Q,j}$ Connected with the heat transfer rate,$\dot{Q}_j$ Can be calculated by the following formula:

$$\dot{Ex}_{Q,j} = \left(1 - \frac{T_0}{T_j}\right)\dot{Q}_j \quad (17)$$

That the *Tj* is instantaneous temperature. In this paper, heat transfer exergy is negligible because assumed each component is well isolated.

3.1 Exergoeconomic analysis

The target of this study is to minimize the sum cost of producing (produced electricity) and maximize the exergetic efficiency for the whole system. In this part, according to the economic parameters used and also the fixed cost of the equipment, the relationship between efficiency and cost in this system has been investigated. In fact, it has been investigated how the efficiency has changed with the cost reduction.The objective functions of exergoeconomic optimization are: [18-19]

Obj.Func. Minimize $\dot{C}_{P_{tot}} = \dot{C}_{F_{tot}} + \dot{Z}_{tot}^{CI} + \dot{Z}_{tot}^{O\&M}$ (18)

Obj.Func Maximum $\varepsilon_{tot} = \frac{(2\times \dot{W}_{net_{GT}}) + \dot{W}_{net_{ST}}}{2\times(\dot{m}_{fuel_{CB}} + \dot{m}_{fuel_{SF}})\times LHV}$ (19)

The above equations expresses that the cost rate associated with the product of the stream $\dot{C}_P$ it equals the total rate expenditures made to generate the product, namely the fuel cost rate $\dot{C}_F$ and the cost rates associated with capital investment and operations and maintenance $\dot{Z}^{CI} + \dot{Z}^{O\&M}$.

The capital investment and operating and maintenance term of the right-hand side of the above equation $\dot{Z}^{CI} + \dot{Z}^{O\&M}$ is calculated using the illustrated relations in Ref [19].

In order to exergoeconomic analysis of each control volume, two targets suggested by [19] were calculated exergoeconomic factor and the relative cost difference, respectively: [19]

$$f_k = \frac{\dot{Z}_k}{\dot{Z}_k + \dot{C}_{D,k}} \quad (20)$$

$$r_k = \frac{1-\varepsilon_k}{\varepsilon_k} + \frac{\dot{Z}_k^{CI} + \dot{Z}_k^{O\&M}}{c_{F,k}\dot{Ex}_{P,k}} \quad (21)$$

When the value of an exergoeconomic factor for a component is high, suggesting that a decrease in the investment costs of this component at the expensed of its exergetic efficiency. The relative cost difference for a component expresses the degree to which each subsystem contributes to increasing the final cost of the products. The exergoeconomic parameters for each of the components of the TCC power plant for the base case and optimum operating conditions are summarized in Table 2 and 5. The r and f parameters are generally used in the classical economic exergy calculation, but in this research, they were calculated and analyzed through the pso algorithm. Due to the use of pso algorithm in this research, several random points were investigated and the speed of the calculation along with the accuracy has increased. [19]

4. Simulations

4.1 Details and Assumptions

The selected case study is DAMAVAND thermal combined cycle power plant located in the near of Tehran, Iran (see Fig 1). The superheated steam enters the two-stage single reheat steam turbine at 520 °C/90bar and 230 °C/8.5bar, for high and low pressure stages, respectively. The condenser pressure is 11 kPa. The simulation process and the most important parameters are described in this section. In order to simulate the existing plant, the following assumptions were made:

1. Ambient pressure (P_0) and temperature (T_0) of the reference environment are considered as 0.9 bar and 290 K, respectively (local climatic conditions).

2. The chemical composition of the reference environment model constitutes (in mole fractions):

N_2: 0.7646,O_2:0.1375, H_2O: 0.0641,CO_2: 0.0337 and others: 0.0001.

3. Pressure drop in the pipes and steam generator is assumed equal to that in the reference power plants.

4. Fuel gas temperature is equal to ambient air temperature when entering the combustor.

5. Standard air composition is used for plant air inlet.

6. Gas fuel ultimate analysis on volumetric basis is:N_2: 0.05,CH_4: 0.88,C_2H_6: 0.04, C_3H_8:0.02,CO_2:0.01.

7. All processes are steady state and steady flow with negligible potential and kinetic energy effects.

8. Ideal-gas mixture principles apply to the air and the combustion products.

9. The combustion reaction is complete.

10. Heat loss from the combustion chamber (CC) is neglected.

11. The air side and water side pressure losses in the heat recovery steam generator (HRSG) are existed to be 3% and 5-10%, respectively, of the inlet pressure. Pressure losses due to friction in pipelines are neglected.

12. The exergies of kinetic and potential are neglected.

13. The exergetic analyses are made on the lower heating value (LHV) basis of natural gas.

The thermodynamic properties of air and steam were found using the Engineering Equation Solver (EES) software package.

Air, Gas Combustion and Steam property

The specific heat of air and exhaust gas at constant pressure are assumed to be a function of temperature, given by the polynomial adopted from [20] as follows:

In the temperature range of 273-1800 K

$$C_{P_{air}} = 0.99871 + 1.06430 \times 10^{-4}.T + 1.64860 \times 10^{-7}.T^2 - 7.01176 \times 10^{-11}.T^3 \quad (22)$$

The specific heat capacity of the combustion gases as follows:

In the temperature range of 273-1800 K

$$C_{P_{gas}} = 0.97031 + 0.67898 \times 10^{-4}.T + 1.65757 \times 10^{-7}.T^2 - 6.78633 \times 10^{-11}.T^3 \quad (23)$$

Therefore, enthalpy and entropy of working fluid are found using the above polynomials and derived by using the ideal gas tables, can be obtained from [21]:

$$\Delta h_T = h_{298.15} + \int_{298.15}^{T} \Delta c_P \, dT \quad (24)$$

$$\Delta s_T = s_{298.15} + \int_{298.15}^{T} \Delta c_P \, dT \quad (25)$$

Where $h_{298.15}$ And $s_{298.15}$ Are the enthalpy and entropy at a reference temperature, respectively. Likewise, the main data for steam system in a TCC power station give in the table 1.

4.2 Design Parameters

The 9 decision variables are to be optimized, which have been defined as follows:

– Inlet fuel in Combustion Chamber $\dot{m}_{fuel}$;

– Inlet fuel in HRSG$\dot{m}_{24}$,$\dot{m}_{25}$;

– Isentropic efficiency of the compressor $\eta_{s_{comp}}$;

– Steam temperature entering the high pressure steam turbine T_{13};

– Steam pressure entering the high pressure steam turbineP_{13};

– Steam mass flow rate entering the high pressure steam turbine $\dot{m}_{13}$;

– Exhaust gas temperature exhalant the gas turbine T_4&T_9;

– Compressor pressure ratio $r_{p_{comp.}}$;

– Isentropic efficiency of the steam turbine η_{ST};

5 Design optimization

In order to achieve feasible design parameters some physical constraints should be considered seriously. The decision variables are generated randomly within the admissible range mentioned. The list of these constraints and their reasons are briefed in Table3. In continuing a Particle swarm optimization code is developed in Matlab Software Programming .The parameter setting of PSO listed Table 4.

6. Results and discussion

After modeling and simulating the system, the effects of the main parameters on the performance of the system were studied. Table 2 summarizes the thermoeconomic variables calculated for each component of the power plant using main data. Result from multi objective optimization is shown in Table 5. The table variables include the exergy efficiency ε, rate of fuel exergy $\dot{Ex}_F$, the rate of product exergy $\dot{Ex}_P$, the rate of exergy destruction $\dot{Ex}_D$, exergy destruction ratio y_D, average costs per unit of fuel exergy c_F , average costs per unit of product exergy c_P, cost rate of exery destruction $\dot{C}_D$, investment and O&M cost rate $\dot{Z}$, relative cost difference r, exergoeconomic factor f , and data for various components of the power plant in base design and various optimizations, respectively. It shows the particle swarm solution for TCC power plant with objective functions indicated in equations (18-19) in multi objective optimization. Optimum design parameters of the TCC power plant are obtained in a situation with an ambient temperature of 16.6 °C which could provide 320 MW of electric power. Table 6 shows a comparison of the operating decision variables (design parameters) in the base design and the optimum case. The table shows that $\dot{m}_{fuel}$,$\dot{m}_{24}$,$\dot{m}_{25}$ And η_{ST} The optimal values are 6%, 9%, 9% and 6% lower in the base case , respectively.

The comparative results of the base case and the optimum case for multi-objective function are given in Table 7. It is observed that the exergetic efficiency is increased from about 35.7% to 38.62% in the PSO method. In the optimized system the total capital investment has increased from 9798.1 to 11119 $/h while the total exergy destruction has decreased from 398.27 to 334.39 MW and the product cost per unit exergy is decreased by 3%. The decrease in product cost can be attributed to higher savings in exergy destruction and exergy loss. This is achieved, however, with a 11 % increase in capital investment. It should be noted that in multi objective optimization and the Partial Swarm Optimization each point can be the optimized point. Therefore, selection of the optimum solution is depending on constraints and criteria of each decision-maker. Hence, each decision-maker may choose a different point as optimum result which better suits with his/her desires.

According to the results obtained from the research of Khademi and Colleagues, the overall efficiency of the cycle after the optimization was 42.6% and the efficiency of the pump and turbine was 83.7 and 84.8%, respectively. Also, the internal rate of return on investment of this power plant according to the used algorithms is 47.45% [15]

Another research was performed with aim of increasing regression performances of MLP in comparison to ones available in the literature by utilizing heuristic algorithm. The GA described in this paper is performed by using mutation and crossover procedures. These procedures are utilized for design of 20 different chromosomes in 50 different generations. In this study average hourly electrical power output was 420.26-495.76 MW. [11]

But in the current research, the efficiency of gas turbine and pump after the optimization is 84.23 and 44.77%, respectively, and the overall efficiency of the desired cycle is 38.62%, and this shows the relative closeness of the efficiency of similar components in the cycle of the mentioned researches. This information and their comparison can be seen in Table

9. In this table, the percentage of changes in parameters such as pump efficiency, turbine efficiency, and overall power plant efficiency in the current study and two similar studies have been calculated and analyzed.

7. Environmental impact analysis (especially NOx and CO_2)

In the recent years, new demands for more energy production at lower cost and reduced environmental impact are increased. Global climate change, including global warming, refers to the warming contribution of the earth of increased atmospheric concentration of CO2 and other greenhouse gases. CO2 emissions account for about 50% of the anthropogenic greenhouse effect. The ultimate global warming effect can cause dangerous climatic changes on Earth. [1]

Steadily increasing emissions of other atmospheric pollutants such as sulfur and nitrogen oxides are also very damaging to the environment. Therefore the reduction of all emissions from the energy sector is of the utmost importance.

The major factors affecting NOx production in the gas turbine combustor is as follows: [22]

- ✓ Firing temperature
- ✓ Oxygen availability
- ✓ Duration of the combustion

NOx is formed mainly when the temperatures are high, such as those found in the flame of a gas turbine combustor. The flame temperature depends on the excess air ratio. As excess air is a reduced, theoretical flame temperature increase. This has the effect of reducing the stack loss and increasing the thermal efficiency. Although, higher flame temperatures reduce the fuel consumption for a given process heating duty, there is one significant disadvantage. Higher flame temperatures increase the formation of oxides of nitrogen, which are environmentally harmful. Very low excess air ratios are beneficial from the point of view of NOx formation but are very detrimental to efficiency and cause the production of large amounts of CO and unburned hydrocarbons.

In the present work, the combustion reaction is assumed complete and air mass flow ($\dot{m}_{air}$) is permanent. Natural gas enters to combustor with 22 bars and 25 °C. In the initial case, for a 427.8 air/fuel, mass ratio (air/fuel ratio in moles: 29.51), the general combustion equation of this system in the base case is as follows:

$$1\times\ [88\ CH_4+\ 4C_2H_6+2C_3H_8+CO_2+5N_2] +620[O_2+3.76N_2] \rightarrow 103\ CO_2+2336\ N_2+420\ O_2+196\ H_2O \quad (26)$$

After optimization, general combustion equation changes as follows:

$$0.936\times\ [88\ CH_4+\ 4C_2H_6+2C_3H_8+CO_2+5N_2] +620[O_2+3.76N_2] \rightarrow 96.4\ CO_2+2335.9\ N_2+432.75\ O_2+183.5\ H_2O \quad (27)$$

To compare of Eq. 26 and 27, it shows that CO_2 emission has decreased about 6.8 %. Likewise, NOx formation is decreased because Excess air and theoretical flame temperature are changing according to Table 8.

Also, the results show an increase in the total exergy efficiency of about 8% and a decrease in the total cost product of about 3%. Exergy efficiency is not an alternative to energy security but rather a vital component in achieving it. The efficient use of exergy is very important to keep supply security and to decrease the environmental impact. The most important factor in exergy efficiency is energy saving. Energy saving, which is generally understood as consuming less energy; is minimizing fuel consumption, here, is about 6.4% lower from the base case. [23]

8. Conclusions

In this paper, a TCC power plant was optimally designed using a PSO optimizer technique. Exergy and exergoeconomic equations for all parts of a system were developed. The decision variables were compressor pressure ratio, compressor isentropic efficiency, gas turbine outlet temperature, inlet fuel in the combustion chamber and inlet fuel in HRSG, steam temperature entering the high pressure steam turbine, steam pressure entering the high pressure steam turbine, steam mass flow rate entering the high pressure steam turbine and steam turbine isentropic efficiency as well as nine design limitations for configuration of the system. In the present optimization problem, the total exergetic efficiency and total product cost per unit exergy were considered as two objective functions. Also, gas turbines and steam turbine network are assumed constant with 420.73 MW value. The results revealed the level of accordance between the two objectives in the case study. According to the results obtained from modeling as shown in the tables, some conclusions are as follows:

- Combustion chamber, Gas turbine, and HRSG have the highest values of the *sum* $\dot{C}_D + \dot{Z}$ and are, therefore, the most important components from the thermo economic viewpoint.
- By increasing compressor pressure ratio and decrease the isentropic efficiencies of compressor, gas turbine and steam turbine as suggested by the evaluation of the air compressor, gas turbine and steam turbine.
- By increasing the value of T_2 And T_7 as suggested by the evaluation of the combustion chamber and HRSG.
- An 8% increase in total efficiency and a 3% decrease in total product cost per unit exergy were found that are reasonable.
- The summation of exergy destroyed in all components of the optimized cycle is lower by about 14% in comparison to basic cycle.
- Decrease of NOx formation and CO_2 emission.
- Based on the final comparison, the efficiency of the turbines in the current research is 0.68% less than the first research and 5.02% more than the second research.

Hence; it is observed that PSO can be a superior tool for optimization of the TCC power plant in the above terms.

Nomenclatures

$\dot{C}$— Cost flow rate, $/h

c — Cost per unit exergy, $/GJ

r_p — Pressure ratio

$\dot{E}x$ — Exergy flow rate, MW

f — Exergoeconomic factor

$\dot{m}$ — Mass flow rate, kg/h

P — Pressure, kPa

r — Relative cost difference

T — Temperature, K

$\dot{W}$— Power, MW

$\dot{Z}$— Rate of the capital cost

y — Exergy destruction ratio

h— Enthalpy

s— Entropy

$\dot{S}$ — Entropy rate

y— Mole fraction

Greek letters

η_s — Isentropic efficiency

ε — exergetic efficiency

Subscripts

ARC — absorption refrigeration cycle

CB — combustion chamber

CCP — combined cooling and power

D — Destruction

DFGT — dual fuel gas turbine

DTC — direct torque control

e — exit stream

F — Fuel

FS — feature selection

GA — Genetic Algorithm

GPV — generator photovoltaic

GT—gas turbine

GTIT— gas turbine inlet temperature

HO — hyperparameter optimization

i — inlet stream

ICE — internal combustion engine

k — component

L — Loss

LCOE — levelized cost of exergy

LEIOE — levelized environmental impact of exergy

MEA — monoethanolamine

MLP — multi-layer perceptron

ORC — organic Rankine cycle

P — Product

PAT — preheated air temperature

PSO — particle swarm optimization

ST— steam turbine

SWPS — solar water pumping systems

UEEC — unit exergoeconomic costs

Table 1: **the main data in seam system**

State	Stream	Mass Flow Rate (kg/s)	Temperature (K)	Pressure (bar)
HP enters the steam turbine	steam	134.14	793	90.73
LP enters the steam turbine	steam	18	503	8.5
Exit Steam turbine	Saturate steam Quality=0. 879	152	319	0.101
Entering HRSG	Water	76.07	320	19.74

Table 2: **Base Design Case indexes**

Component	ε (%)	$\dot{E}x_F$	$\dot{E}x_P$	$\dot{E}x_D$	y_D^* (%)	c_F ($/GJ)	c_P ($/GJ)	$\dot{C}_D$ ($/h)	$\dot{Z}$ ($/h)	$\dot{C}_D+\dot{Z}$ ($/h)	r (%)	f (%)

Air Compressor	92.63	151.44	140.28	11.16	2.8	19.84	24.09	798	1469.63	2268	22.62	64.82
Combustion chamber	77.98	394.22	305.6	86.79	21.79	8.56	15.28	2675	82.3	2757	28.23	2.98
Gas Turbine	85.02	331.04	281.44	49.6	12.45	15.28	19.84	2728	1556.35	4284	27.68	36.32
HRSG	65.09	121.78	79.26	42.52	10.67	13.73	22.45	2102	1588.69	3691	94.18	43.04
Steam Turbine	92.66	173.45	160.73	12.72	3.19	16.69	19.84	764	374.09	1138	11.79	32.86
Condenser	83.16	29.21	24.29	4.92	1.23	0.15	17.92	2.73	7.24	10	73.98	72.63
Pump	43.84	0.95	0.42	0.53	0.13	19.84	22.82	38	22.82	61	204.81	37.45
overall plant	35.7	1178.5	420.73	398.27	100	8.56	30.46	12279	9798.1	22078	255.66	44.38

$*$ y_D For compressor, combustion chamber, gas turbine and HRSG is equal to add y_D'S two compressors, combustion chamber, gas turbine and HRSG.

Table 3: the Design Parameters and Their Range of Allowable Variation

Design Parameters	**Unit**	**From**	**To**
Inlet fuel in Combustion Chamber	kg/s	8	11
Supplementary Firing	kg/s	0	2
Isentropic Efficiency of compressor	%	75	90
Pressure Ratio of compressor	_	9	16
Change value of Exhaust temperature of gas turbine	Kelvin	817	821
Change value of Steam turbine inlet temperature of HP steams	Kelvin	793	808
Change value of Steam turbine inlet pressure of HP steams	Bar	85.5	94.5
Change value of Steam turbine inlet mass flow rate of HP steams	kg/s	134	149
Isentropic Efficiency of steam turbine	%	75	92

Table 4: simulation setup for PSO algorithm

Parameter	**Value**
Population size	400

Maximum no. of iteration	200
Initial of inertia weigh (w_{max})	0.9
Final of inertia weight (w_{min})	0.4
Cognitive learning rate (c_1)	2
Social learning rate (c_2)	2

Table 5: PSO Optimization indexes

Component	ε (%)	$\dot{E}x_F$	$\dot{E}x_P$	$\dot{E}x_D$	y_D (%)	c_F ($/GJ)	c_P ($/GJ)	$\dot{C}_D$ ($/h)	$\dot{Z}$ ($/h)	$\dot{C}_D+\dot{Z}$ ($/h)	r (%)	f (%)
Air Compressor	93.12	171.49	159.68	11.81	4.41	19.15	24.51	1017	2082.24	3099	29.09	67.18
Combustion chamber	88.98	356.82	315.67	39.34	11.76	8.56	14.71	1212	115.56	1328	12.39	8.71
Gas Turbine	84.23	355.39	299.33	56.06	16.76	14.71	19.15	2968	1458.72	4427	27.94	32.96
HRSG	64.41	125.84	81.06	44.79	13.39	13.07	21.6	2107	1705.32	3812	99.97	44.73
Steam Turbine	89.7	179.18	160.73	18.45	5.52	15.71	19.15	1044	364.32	1408	15.49	25.88
Condenser	81.44	29.82	24.29	5.53	1.66	0.15	17.68	3.07	7.20	10	77.12	70.45
Pump	44.77	0.95	0.43	0.52	0.16	19.15	20.33	36	23.04	59	202.4	39.04
overall plant	38.62	1089.3	420.73	334.39	100	8.56	29.51	10308	11119.0	21427	244.64	51.89

Table 6: Comparison exergoeconomic decisions variables of the system for optimum and base case

Decisions Variables	**Unit**	**Base case**	**PSO opts.**	**Difference**
Inlet fuel in Combustion Chamber	kg/s	9	8.45	-0.06
Supplementary Firing	kg/s	0.64	0.58	-0.09
Isentropic Efficiency of compressor	%	86	85.5	-0.01
Pressure Ratio of compressor	_	11.8	14.66	0.24
Exhaust temperature of gas turbine	Kelvin	819	819	0.00
Steam turbine inlet temperature of HP steams	Kelvin	793	802	0.01

Steam turbine inlet pressure of HP steams	Bar	90	92.15	0.02
Steam turbine inlet mass flow rate of HP steams	kg/s	134	139.59	0.04
Isentropic Efficiency of steam turbine	%	88	82.7	-0.06

Table 7 Comparison of Exergy Efficiency and Product Cost per unit exergy ($/GJ) in base case design an optimum solutionined at an optimum solution in this paper

Component	Exergy Efficiency			Product Cost per unit exergy ($/GJ)		
	Base design case	PSO Opt.	Difference	Base design case	PSO Opt.	Difference
Air Compressor	92.63	93.12	0.01	24.09	24.51	0.02
Combustion chamber	77.98	88.98	0.14	15.28	14.71	-0.04
Gas Turbine	85.02	84.23	-0.01	19.84	19.15	-0.03
HRSG	65.09	64.41	-0.01	22.45	21.6	-0.04
Steam Turbine	92.66	89.7	-0.03	19.84	19.15	-0.03
Condenser	83.16	81.44	-0.02	17.92	17.68	-0.01
Pump	43.84	44.77	0.02	22.82	20.33	-0.11
Overall plant	35.7	38.62	0.08	30.46	29.51	-0.03

Table 8: Comparison of Excess air and Flame temperature at an optimum solution in this paper

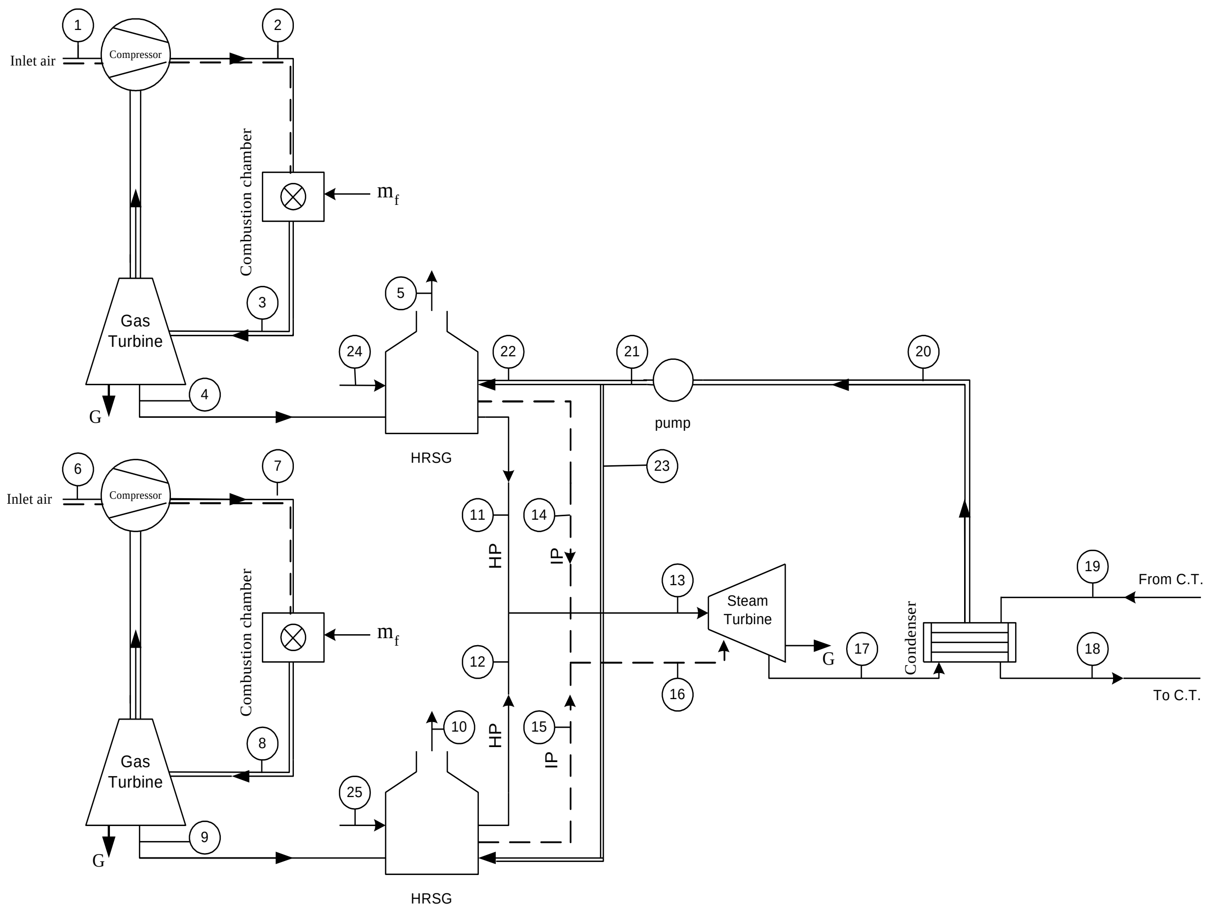
Variable	Base design case	PSO Opt.	Difference (%)
Excess air (%)	209	230	+10
Flame temperature (K)	1397	1385	-1

Table 9: Comparison of common parameters between two studies and the current study

Parameter	Khademi and colleagues (A)	Lorencin and colleagues (B)	Current study	The percentage of changes between research (A) and the current research (%)	The percentage of changes between research (B) and the current research (%)

Maximum production power (MW)	484	420.26-495.76	420.73	13.07	8.14
Efficiency of the pump (%)	83.7	80 - 85	44.77	87.25	84.56
Efficiency of the turbine (%)	84.8	80	84.23	0.68	-5.02
Overall efficiency (%)	42.6	------	38.62	10.31	------

Figure. 1: The schematic of the TCC power plant system investigated [24]



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