EXERGOECONOMIC OPTIMIZATION OF A THERMAL POWER PLANT USING PARTICLE SWARM OPTIMIZATION

by

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The basic concept in applying numerical optimization methods for power plants optimization problems is to combine a state-of-the-art search algorithm with a powerful, power plant simulation program to optimize the energy conversion system from both economic and thermodynamic viewpoints. Improving the energy conversion system by optimizing the design and operation and studying interactions among plant components requires the investigation of a large number of possible design and operational alternatives. State-of-the-art search algorithms can assist in the development of cost-effective power plant concepts. Although evolutionary algorithms are commonly used for multi-criteria optimization problems of power plants and provide mostly sufficient results, other alternatives of optimization techniques shall be taken into consideration as well in order to increase the variety of available tools. The aim of this paper is to present how nature-inspired swarm intelligence (especially particle swarm optimization) can be applied in the field of power plant optimization and how to find solutions for the problems arising and also to apply exergoeconomic optimization technics for thermal power plants.

Key words*: thermal power plant, particle swarm optimization, exergoeconomic optimization, exergy, thermodynamic modelling software*

Introduction

Despite the fact that Sigmund Schuckert had already built the first steam engine driven electric generators in 1878 [1] there would be no concern for an optimal power plant design until the late 50 years [2]. This delay may be attributed to several reasons such as the abundance of fuel resources at low prices, the complexity of power plants, the lack of mathematical methods of optimization appropriate for complex systems and the lack of computers capable of handling the huge number of variables involved. Only the sudden surge in oil prices was powerful enough to force a more systematic attempt towards a better design of power plants.

Although the very idea of linking thermodynamics and costing considerations and analysing a system not just from an energetic but also an economic point of view was first explored by Lotka [3] and Keenan [4] not until Tribus [5] introduced thermoeconomics for analysing desalination systems were thermodynamic analysis and economic optimization combined. Though, in the early years of thermoeconomics there were several attempts to use energy costing instead of exergy costing Gaggioli [6] demonstrated on a co-generating power plant that the use of energy as the measure for the power flow leads to error. In line with Gaggioli, tsatsaronis [7] suggested the name *Exergoeconomics* to point out that thermoeconomic analysis is based on the second law.

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Following El-Sayed and Gaggioli [8, 9] Abusoglu and Kanoglu *et al*. [10] thermoeconomic methods fall into two categories: algebraic methods and calculus methods. The algebraic methods use algebraic cost-balance equations derived from conventional economic analysis and auxiliary cost equations for each subcomponent of any system presented [11]. Calculus methods on the other hand are built on differential equations. Cost flows in a system are developed in a link between optimization procedures that are based on Lagrange multipliers. The weakness of the calculus method is that if the component fails to achieve thermoeconomic isolation the Lagrange multipliers vary from iteration to iteration making the applicability of this method difficult. Therefore exergoeconomic analysis (EEA), which is a subcategory of algebraic method has been chosen to estimate the cost-optimal structure and the cost-optimal values of the thermodynamic inefficiencies in the case study in a later section.

Due to plant performance simulation software in the field of energy engineering the complexity of search spaces is increasing and the number of variables is growing. Therefore, instead of classical optimization techniques which have limited scope in practical applications heuristic search methods become more and more frequently used tools. Evolutionary algorithms and especially genetic algorithms (GA) are commonly used for multi-criteria optimization problems of power plants.

Valdes *at al*. [12] used GA to achieve thermoeconomic optimum in a combined cycle gas turbine (CCGT). After a single pressure CCGT was tuned the algorithm was successfully applied for a two and a three pressure level heat recovery steam generator to find suitable thermodynamic parameters for optimal configuration. Manesh and Amidpour [13] also used GA for EEA to optimize coupling multi stage flash (MSF) desalination with pressurized water reactor (PWR) nuclear power plant. Though Sahoo [14] used Evolutionary programming (EP) to optimize a cogeneration system the stochastic optimization strategy of EP is still very similar to GA Hamed and Mofid [15] used GA as well for a similar problem solved by Sahoo [14] with EP. Although literature shows that evolutionary algorithms, especially GA provides sufficient results in the field of exergoeconomic power plant optimization, other alternatives of optimization techniques shall be taken into consideration as well to increase the variety of available tools.

One of the most important behaviourally inspired search algorithms appropriate to test for power plants optimization problems is the particle swarm optimization (PSO) [16]. PSO has roots in GA and evolution strategies therefore it shares many similarities with evolutionary computing such as random generation of populations at system initialization or updating generations at optima search but also differs from it in not using evolution operators such as crossover and mutation or in that each particle owns memory. Because of the many similarities PSO has many of the preferable properties of GA and used successfully in many fields. Yoshida *et al*. [17] proposed expanded PSO method for reactive power and voltage control considering voltage security assessment (VSA). Li *et al*. [18] used PSO to solve a constraint economic load dispatch problem for power systems. Since the original PSO algorithms have no mechanism to handle constraints authors introduced several selection rules and handling methods. Heo and Le [19] used hybrid PSO, evolutionary PSO, and constriction factor to find optimal mapping between unit load demand and pressure set point in a fossil fuel power unit (FFPU) and to design the reference governor for the control system. Yousefi and Darus [20] applied a GA hybrid with PSO (GAHPSO) to find the optimal design of a plate-fin heat exchanger. Based on literature PSO has been found to be robust, flexible, and stable. It is insensitive to local optima or saddle and suitable to solve complex optimization problems with many parameters. PSO is fast in solving non-linear, non-differentiable multi-modal problems [21] and just like GA it does not require gradient computation.

Based on its properties, PSO seems an appropriate choice for power plant optimization, however, the fact that each particle owns memory raises more questions. For a power plant it is very likely that a parameter set contains incalculable solutions. It has no affect on GA since its unsuccessful individuals do not participate in the production of the next generation. However, the particles of the PSO remain part of the swarm even if they represent incalculable solutions.

Therefore, the aim of this paper is to prove that with only minor changes even a conventional PSO is suitable for optima search in the field of exergoeconomic power plant optimization. Namely, if the slight modification on the structure of the PSO does not interfere with the velocity updating algorithm in the future it will provide PSO alternatives without any constrains, increasing the possibility to create more precise adaptations for different power plant problems.

The PSO concept

In the frame of multivariable optimization problems, the swarm is assumed to be of specified size with each particle located initially at random locations with zero velocity in the multidimensional design space. Particles of the swarm represent possible solutions in the search space, having the two before mentioned parameters as changeable properties [22]. Each particle keeps track of its positions in the search space and its behaviour will depend on the best position (highest fitness value) that it has discovered and on the best overall position that any member of the swarm has achieved so far. Unlike GA only the best particle shares information (position) with the others. Since its introduction many researchers have worked on improving the performance of PSO by modifying the velocity updating strategy of the original algorithm. Canonical PSO (CPSO), which has been used here only differs from the original algorithm in the use of inertia weight at velocity updating. The computational application of the applied PSO is presented in the next section.

Considering the thermoeconomic optimization as an unconstrained D-dimensional minimization problem as follows:

$$\min.\ \mathrm{f}(X), \quad X = [x^1, \ldots x^j, \ldots x^D] \tag{1}$$

where X, as a member (particle) of the swarm is a solution to be optimized in a form of a D-dimensional vector. Assumed that x_i^j is the position and v_i^j is the velocity of the i^{th} particle on the j^{th} dimension their values can be updated by iteration [15, 22, 23] as:

$$v_i^j = w v_i^j + c_1 \mathrm{rand1}_i^j (\mathrm{pbest}_i^j - x_i^j) + c_2 \mathrm{rand2}_i^j (\mathrm{gbest}^j - x_i^j) \tag{2}$$

$$x_i^j = x_i^j + v_i^j \Delta t \tag{3}$$

where $X_i = (x_i^1 \ldots x_i^j \ldots x_i^D)$ and $V_i = (v_i^1 \ldots v_i^j \ldots v_i^D)$ represents the position and velocity, respectively of the i^{th} particle in the D-dimensional search space while $\mathrm{pbest}_i = (\mathrm{pbest}_i^1 \ldots \mathrm{pbest}_i^j \ldots \mathrm{pbest}_i^D)$ and $\mathrm{gbest}_i = (\mathrm{gbest}_i^1 \ldots \mathrm{gbest}_i^j \ldots \mathrm{gbest}_i^D)$ represents the best position of the i^{th} particle and the overall best position of the swarm discovered so fare, and Δt refers to the time steps between two iterations and can be considered as 1. The acceleration constants c_1 and c_2 are the cognitive and social learning rates, respectively, denoting the relative importance of pbest and gbest positions. $\mathrm{rand1}_i^j$ and $\mathrm{rand2}_i^j$ are randomly generated numbers in the range [0,1]. The inertia weight w is used to balance the global and local search abilities. A large inertia weight is more appropriate for global exploration of new areas, meanwhile small inertia weight facilitates local search. Since its introduction, several variants of inertia weight have been proposed. One of the linearly descending inertia weights applied here is:

$$w_i = w_{\max.} - \left(\frac{w_{\max.} - w_{\min.}}{i_{\max.}} \right) i \tag{4}$$

where $w_{\max.}$ and $w_{\min.}$ are the initial and final values of the inertia weight, respectively, and $i_{\max.}$ – the maximum number of iterations. Besides $v^j_{\max.}$ maximum velocity has to be given to determine constraints [23]:

$$v^j_i = \min.[v^j_{\max.}, \max.(v^j_{\min.}, v^j_i)] \tag{5}$$

Implementation of PSO for power plants optimization problems

Depending on the purpose it serves, power plant optimizations basically fall into two categories. They are either designed to help decision makers or to achieve a more sufficient and more effective operation.

Improving the energy conversion system by optimizing the design and studying interactions among plant components requires the investigation of a large number of possible design alternatives. State-of-the-art search algorithms can assist process designers in the development of a cost-effective power plant concept. To optimize process structure in a power plant simulation environment, a superstructure can be developed which includes a limited number of the most likely design alternatives with estimated values of the process variables. Considering the superstructure as a search space, with the application of a state of the art search algorithm an optimal set of process structure can be determined. In general, the cost of electricity is more sensitive to changes in the configuration of the process structure than the modification of the values of process variables [24]. As the impact of the process variables is not as significant as the impact of the modification of process structure superstructures do not require accurate process variables.

Improving the effectiveness of operation however requires a more specified and detailed modelling of the equipment of the operating power plant. The accuracy of the provided solution of the search algorithm heavily depends on the thermodynamic model (search space) created in the power plant simulation software. To establish an accurate thermodynamic model a design case shall be created first. Design cases establish the operating characteristics and physical specifications of relevant power plant equipment. Based on the design case an off-design case can be created. Off-design cases predict the performance of a fixed plant design as conditions vary. Changes in conditions may include changes in load, ambient conditions, or process steam requirements therefore under off-design operating conditions the optimal set of process variables can be determined for various conditions. Fine-tuning of the process variables is one of the simplest ways to reduce expenses without investing on design restructuring.

After objective function (reducing fuel costs at constant load) and constraints (environmental considerations) of the problem are determined and search space (off-design case of the thermodynamic model) is created, a PSO variant shall be chosen. The algorithm chosen shall fulfil the criteria of robustness and it shall keep balance between diversity and convergence speed. To decide the number of dimensions of the power plants optimization problem the number of degrees of freedom shall be determined. The number of degrees of freedom refers to the independent process variables of the off-design model, having impact on operating conditions. The operating range of the equipment of the actual power plant determines the lower and upper limiting values of the process variables.

Drawbacks of PSO in the field of power plant optimization

In 2011, in his review paper Pezzini *et al*. [25] summarized the state-of-the-art optimization techniques applied in the field of energy engineering. A great number of issues are shown where PSO was applied however, power plant optimization problems were solved mainly with GA. PSO are mainly neglected because of the sensitivity to incalculable solutions of the parameter sets during optima search.

As it is previously mentioned the basic concept in applying numerical optimization methods for power plants optimization problems is to combine a heuristic search algorithm with a thermodynamic simulation software.

As a basic principle for thermodynamic simulation software energy conversion cycles are created by the components of a system. Each piece of equipment represents an energy and a mass balance. These equations with other relations for thermodynamic properties form an independent set of equations. This system of non-linear equations, where the number of equations and the number of unknown parameters depend on the quality and quantity of the components and process variables, is solved in an iterative way. Therefore stability and convergence for both search algorithms and numerical models depend heavily on parameter set and constrains. Although reasonable parameter set provides stability for a search algorithm it will still not guarantee the same for the solver of the thermodynamic simulator. Namely, the search space representing all theoretically possible parameter set is greater than the set of physically possible solutions. As fig. 1 illustrates a search space usually has many incalculable clouds where, with the provided parameter set physical equipment cannot operate. The result of a PSO in each time step depends on the current position of the particles and the velocity updating algorithm. Aside from hybrid PSO where velocity update algorithm is complemented with evolutionary operators velocity either depends on the particles own pbest and swarms gbest (*e. g.* CPSO) or depends on the pbest and gbest of multiple elite examples (*e. g.* CLPSO [23], ELPSO [26]). If velocity is calculated without the pbest of elite examples the chance of a solution becomes proportional with the ratio of calculable and incalculable search spaces. If a particle at initial step becomes part of an incalculable cloud neither fitness value nor pbest can be calculated as the power plant cannot operate among these conditions. Velocity update algorithm will fail to move particles outside the clouds and get stuck [27].

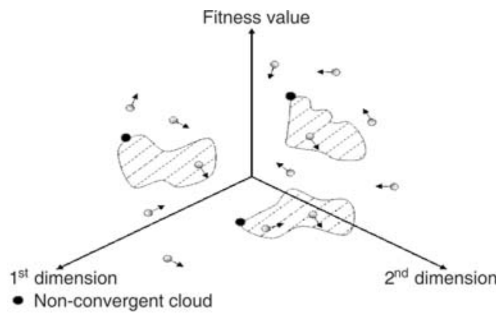

Figure 1. 2-D search space with incalculable areas

Compared to evolutionary algorithms where new generations are created from stable and convergent individuals PSO keeps all its initial particles for the entire search. Therefore the more particles stuck in incalculable clouds at the beginning, the fewer particles can search for optimum. It is only possible to use PSO with own pbest dependent velocity update algorithms, in search spaces with numerous incalculable clouds if particles do not get into these clouds at initial state. If the number of convergent particles reaches the number of elite examples, PSO with elite example dependent velocity update algorithms will not have problems with incalculable solutions either.

Case study

A case study is performed to illustrate that PSO even with own pbest dependent velocity update algorithms are capable of optimizing power plant design if a swarm has only conver-

Table 1. Simulation setup for CPSO algorithm

Parameter	Value
Population size	30
Number of generations	70
Maximum of innertia weight ($w_{max.}$)	0.9
Minimum of innertia weight ($w_{min.}$)	0.4
Cognitive learning rate (c_1)	1
Social learning rate (c_2)	1

gent members at initial state. CPSO is chosen for the demonstration with a preselected and initially convergent group of particles. The parameter setting of CPSO is shortlisted in tab. 1.

System description

To demonstrate the applicability of CPSO, a 10 MW thermal power plant is considered. When choosing a design it is an important criterion to create a model typical for this small power range. This design where a turbine has three extraction points, two at low pressure to provide deaeration and extraction steam for a deaerator and for a low pressure feedwater heater respectively, and one at high pressure to drive a high pressure feedwater heater is relatively common for small scale power plants. Figure 2 shows the structure of a thermal power plant considered in this study.

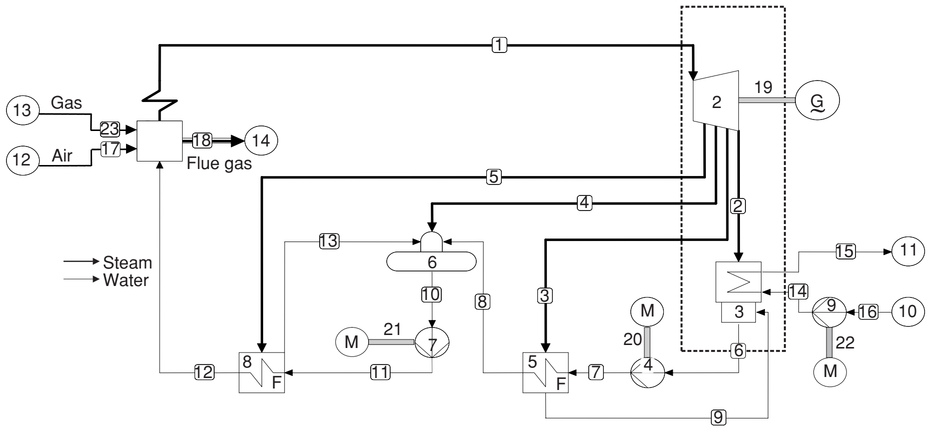

Figure 2. Schematic diagram of the thermal power plant
G – generator, M – motor which drives the pump, F – feedwater heater

CPSO can modify both physical properties of the plant and values of the process variables whenever a particle in the swarm occupies new position in the search space. In this model, the pressure and the temperature of the steam produced, the pressure of the extraction steam driving the high pressure feedwater heater, the operating pressure of the deaerator, and the pressure of the extraction steam driving the low pressure feedwater heater are considered as process variables. Process variables are real numbers restricted by the accuracy of the thermodynamic solver and their physical range only. The quality and quantity of the before mentioned design variables are suitable to provide a search space sufficient to test the applicability of PSO for exergoeconomic power plant optimization therefore no other parameter is changed during optima search. The admissible range of the decision variables considered for the thermal power plant are: 30 bar < p_1 < 120 bar, 400 °C < T_1 < 540 °C, 0.1 bar < p_3 < 120 bar, 0.1 bar < p_4 < 120 bar, and 0.1 bar < p_5 < 120 bar. The surface area of the high pressure feedwater heater, and that of the low pressure feedwater heater are considered as structural variables taking discrete values between 5-35 m^2 and 5-50 m^2, respectively. Since working range of process variables are chosen to be as wide as physically possible and the power of the thermal power plant is fixed, at

85% isentropic expansion efficiency in 10 MW the search space contains several parameter sets forming incalculable clouds.

For the purpose of analysis following assumptions are made:
- the system operates at steady-state,
- ideal-gas mixture principles apply for the air, gas and fluegas, and
- the reference environment is considered to be 298.15 K and 1.013 bar.

Exergoeconomic analysis

Thermoeconomics is the branch of engineering that combines exergy analysis identifying the location, the magnitude and the sources of thermodynamic inefficiencies in a thermal system and economic principles which help to calculate all the costs associated with a power plant investment or operation to provide the system designer or operator with information not available through conventional energy analysis and economic evaluations but crucial to the design and operation of a cost-effective system.

The thermodynamic evaluation of exergoeconomic is based on second-law analysis which is a useful tool to calculate irreversibilities. The values of the rates of exergy destruction (y_D) and exergetic efficiency (ε) provide sufficient thermodynamic measures of the system inefficiencies as it shown in eqs. (6) and (7):

$$y_{D,k} = \frac{\dot{E}_{D,k}}{\dot{E}_{D,tot}} \tag{6}$$

$$\varepsilon_k = \frac{\dot{E}_{P,k}}{\dot{E}_{F,tot}} \tag{7}$$

A comprehensive introduction to the exergoeconomic concept and its applications is provided by Bejan *et al*. [11], and Lazzaretto and Tsatsaronis [28].

Exergy costing involves cost balances formulated for each system component separately. A cost balance applied to the k^{th} component, eq. (8), shows that the sum of cost rates associated with all exiting exergy streams equals the sum of cost rates of all entering exergy streams supplemented with a component dependent cost rate ($\dot{Z}_k$) associated with investment ($\dot{Z}_k^{CI}$) and with operating and maintenance expenses ($\dot{Z}_k^{OM}$) as it is shown in eq. (9):

$$\sum_e (c_e \dot{E}_e)_k + c_{w,k} \dot{W}_k = c_{q,k} \dot{E}_{q,k} + \sum_i (c_i \dot{E}_i)_k + \dot{Z}_k \tag{8}$$

$$\dot{Z}_k = \frac{CCs + O\&M}{(PEC_{tot}\tau)} PEC_k \tag{9}$$

where *CCs*, *O&M*, *PEC,* and τ, are the annual carrying charges, the annual operating and maintenance costs, the purchased equipment costs, and the operating hours of the power plant per year, respectively. In general, carrying charges decrease while fuel and *O&M* costs increase with increasing years of operation. Therefore, levelized annual values for all cost components should be used when considering design modifications. The constant-escalation levelization factor (CELF) is shown in eq. (10):

$$CELF = \frac{k(1-k^n)}{1-k} CRF \tag{10}$$

where *CRF* is the abbreviation of capital recovery factor, given by eq. (11):

$$CRF = \frac{i_{eff}(1-i_{eff})^n}{(1-i_{eff})^n - 1} \tag{11}$$

and k is a constant, given by eq. (12):

$$k = \frac{1 + r_\mathrm{n}}{1 + i_\mathrm{eff}} \tag{12}$$

The determination of reliable purchased equipment costs are very difficult since vendors are interested primarily in selling their products for the highest price possible causing large dispersion in price even for the same equipment. To avoid inconveniences arising from the effort of profit maximization thermodynamic property dependent cost functions and constants are used [29, 30].

The most common simple relationship between the purchased cost and an attribute of the equipment related to units of capacity applied here is given by eq. (13):

$$\frac{C_1}{C_2} = \left(\frac{A_1}{A_2}\right)^n \tag{13}$$

where A_1 and A_2 refers to the required and base attribute, respectively, C_1 and C_2 refers to the purchased costs of the equipment with the required attribute and base attribute, and n refers to the cost exponent [31]. With use of eq. (14) the effect of time on purchased equipment cost were taken into consideration:

$$C_2 = \left(\frac{I_2}{I_1}\right) C_1 \tag{14}$$

where C_1 and C_2 refers to the purchased costs of the equipment at base time when cost is known and time when cost is desired, and I refers to the cost index to base time and desired time, respectively. Since several cost indices used by the industry to adjust for the effects of inflation based on the suggestion of Turton *et al.* [30] chemical engineering plant cost index was applied.

The solution of the system of costing equations provides the cost of the unknown streams of the thermal power plant. The state properties and exergies necessary for solving costing equations corresponding to fig. 2 are given in tab. 2.

A detailed thermoeconomic evaluation of a thermal system is based on a set of variables calculated for each component of the system. The average unit cost of fuel ($c_\mathrm{F,k}$), average unit cost of product ($c_\mathrm{P,\,k}$) cost rate of exergy destruction ($\dot{C}_\mathrm{D,\,k}$), and cost rate of exergy loss ($\dot{C}_\mathrm{L,\,k}$) provide useful tools to compare investment and operation costs for each component.

$$c_\mathrm{F,\,k} = \frac{\dot{C}_\mathrm{F,\,k}}{\dot{E}_\mathrm{F,\,k}} \tag{15}$$

$$c_\mathrm{P,\,k} = \frac{\dot{C}_\mathrm{P,\,k}}{\dot{E}_\mathrm{p,\,k}} \tag{16}$$

$$\dot{C}_\mathrm{D,\,k} = c_\mathrm{F,\,k} \dot{E}_\mathrm{D,\,k} \tag{17}$$

$$\dot{C}_\mathrm{L,\,k} = c_\mathrm{F,\,k} \dot{E}_\mathrm{L,\,k} \tag{18}$$

Based on the aforementioned exergoeconomic variables exergoeconomic factor (f) can be calculated which shows the relationship between the monetary impact of each component's exergy destruction and investment cost:

$$f_\mathrm{k} = \frac{\dot{Z}_\mathrm{k}}{\dot{Z}_\mathrm{k} + \dot{C}_\mathrm{D,\,k}} \tag{19}$$

The exergoeconomic variables calculated for each component of the thermal power plant for the base case operating conditions are summarized in tab. 3. The investment cost, oper-

Table 2. State properties (SP) and exergy of the system for the base case

SP	$\dot{m}$ [kgs^{-1}]	T [°C]	p [bar]	h [kJkg^{-1}]	s [kJkg^{-1}K^{-1}]	$\dot{E}$ [kW]
1	10.15	530.00	90.00	3462.45	6.76	14744.19
2	7.99	45.81	0.10	2340.27	7.39	1142.19
3	0.91	111.35	1.50	2682.63	7.20	494.62
4	0.70	186.76	4.00	2833.04	7.11	502.78
5	0.54	292.21	12.00	3029.43	7.00	515.22
6	8.90	45.81	0.10	191.81	0.65	25.00
7	8.90	45.86	4.50	192.41	0.65	29.05
8	8.90	99.53	4.00	417.35	1.30	301.55
9	0.91	111.35	1.50	467.08	1.43	40.38
10	10.15	143.61	4.00	604.72	1.78	807.72
11	10.15	144.90	90.50	615.75	1.78	907.51
12	10.15	172.43	90.00	734.31	2.06	1279.36
13	0.54	187.96	12.00	798.50	2.22	77.50
14	520.79	25.00	1.51	104.99	0.37	26.13
15	520.79	33.00	1.51	138.43	0.48	255.84
16	520.79	25.00	1.01	104.93	0.37	0.02
17	14.27	25.00	1.10	–213.95	6.89	105.06
18	15.07	143.02	1.10	–2748.14	7.57	1165.43
23	0.79	25.00	1.10	–3653.69	10.51	30140.42

Table 3. Exergoeconomic parameters of the system for the base case

k	$\dot{E}_{F,k}$ [MW]	$\dot{E}_{P,k}$ [MW]	$\dot{E}_{D,k} + \dot{E}_{L,k}$ [MW]	$y_{D,k}$ [%]	ε_k [%]	$\dot{C}_D + \dot{C}_L$ [$ per h]	$\dot{Z}_k$ [$ per h]	$\dot{Z}_k + \dot{C}_{D,k} + \dot{C}_{L,k}$ [$ per h]	f_k [–]
1	29.07	13.46	15.61	82.18	46.30	720.66	1358.44	2079.09	0.65
2	12.08	9.99	2.09	10.99	82.72	461.50	794.47	1255.97	0.63
3			0.93	4.88		323.66	29.37	353.04	0.08
4	0.01	0.00	0.00	0.02	57.46	1.04	4.89	5.93	0.82
5	0.43	0.26	0.18	0.94	58.87	62.41	3.59	66.00	0.05
6	0.50	0.42	0.08	0.43	83.90	56.45	1.77	58.21	0.03
7	0.13	0.10	0.03	0.17	75.79	11.13	16.59	27.72	0.60
8	0.44	0.37	0.07	0.35	84.96	22.99	3.54	26.53	0.13
9	0.04	0.03	0.01	0.05	72.23	3.51	9.47	12.98	0.73
System	30.08	10.00	18.99	100.00	33.07	1663.34	2222.13	3885.47	0.57

ation and maintenance expenses, and fuel costs are estimated in a detailed economic analysis conducted for each plant separately using Bejan *et al*. [11], Turton *et al*. [30], and Petrakopouloua *et al*. [32] for data. Table 4 shows the main estimations for the economic analysis.

Table 4. Input data for the economic analysis

Plant economic life [year]	20
Levelization period [year]	10
Average general inflation rate [%]	3
Average nominal escalation rate for natural gas [%]	4
Average real cost of money [%]	10
Data of commercial operation	2012
Average capacity factor [%]	85
Unit cost of natural gas [$ $GJ^{-1}LHV^{-1}$)	10

Objective function

Non-exergy-related costs depending on investment costs and operating and maintenance expenses and exergy-related costs depending on component efficiency (exergy destruction) show opposite effect on power plant behaviour. At higher total capital investment lower operating and maintenance cost can be expected meanwhile lower total capital investment usually causes higher operating and maintenance cost. Therefore, the objective function expresses the optimization criterion as a function of the dependent and independent variables is defined as to minimize the total cost function (eq. 20).

$$\dot{C}_{\rm sys} = \sum \dot{Z}_{\rm k} + \sum c_{\rm F,k}\dot{E}_{\rm D,k} + \sum c_{\rm F,k}\dot{E}_{\rm L,k} \tag{20}$$

Computer tools

The optimization process consists of two parts: thermodynamic analysis and economic calculations. Both parts are crucial for the exergoeconomic evaluation and they are performed in every iteration step. The thermal model is developed in GateCycle (GC) plant performance monitoring software and all mass flow rates, temperatures, pressures, and chemical compositions for every stream calculated with this code by using JANAF data for the properties of ideal gases and IAPWS-IF97 for the properties of water and steam. Since GC does not calculate exergy a MATLAB code is developed to provide chemical and physical exergy. The cost estimation and the detailed economic evaluation are performed in Microsoft EXCEL environment. The PSO algorithm is developed and all optimization runs are controlled in MATLAB however the dynamic data exchange is performed via Microsoft EXCEL as GC is a closed-source software and direct control is not possible.

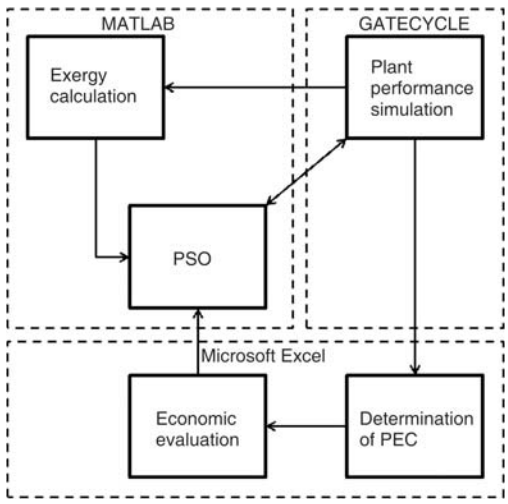

Figure 3. Structure of the PSO based optimization process

The following steps are performed at each iteration:

(1) PSO provides new design variables for GC;
(2) after simulation with new variables, GC provides thermodynamic properties for exergy calculation and PSO search algorithm, and also updated attributes to determine purchased equipment costs;
(3) after new PEC are determined, the algorithm updates the economic evaluation and calculates new cost rates;
(4) based on new thermodynamic and economic data, PSO evaluates the objective function and based on the results creates new design variables.

The structure of the optimization process is illustrated in fig. 3.

Results and discussion

The state properties and exergies for the unconstrained optimum case are given in tab. 5. If only thermodynamic aspects are considered maximum pressure (120 bar) and temperature (540 K) are expected before the steam turbine to achieve the highest average temperature possible at heat inlet and increase cycle efficiency. As high steam parameters and high cycle efficiency decreases fuel costs, in the same time it increases investment costs. Therefore, state properties of the unconstrained optimum case represent the optimum between fuel costs and capital costs.

Table 5. State properties (SP) and exergy of the system for the unconstrained optimum case

SP	$\dot{m}$ [kgs^{-1}]	T [°C]	p [bar]	h [kJkg^{-1}]	s [kJkg^{-1}K^{-1}]	$\dot{E}$ [kW]
1	12.90	400.00	37.80	3218.21	6.80	15408.84
2	10.07	45.81	0.10	2316.18	7.31	1424.15
3	1.32	107.71	1.33	2637.30	7.13	678.42
4	1.38	229.02	7.52	2906.94	6.98	1143.39
5	0.13	278.99	12.48	2998.98	6.93	121.09
6	11.39	45.81	0.10	191.81	0.65	31.99
7	11.39	45.90	8.02	192.88	0.65	41.30
8	11.39	105.54	7.52	442.95	1.37	449.25
9	1.32	107.71	1.33	451.69	1.39	53.72
10	12.90	167.88	7.52	709.93	2.02	1443.30
11	12.90	168.41	38.30	713.96	2.02	1489.92
12	12.90	173.41	37.80	735.72	2.07	1581.63
13	0.13	189.74	12.48	806.42	2.23	18.76
14	650.07	25.00	1.51	104.99	0.37	32.62
15	650.07	33.00	1.51	138.43	0.48	319.35
16	650.07	25.00	1.01	104.93	0.37	0.02
17	16.51	25.00	1.10	–213.95	6.89	121.49
18	17.42	143.02	1.10	–2748.14	7.57	1347.63
23	0.92	25.00	1.10	–3653.69	10.51	34852.48

The exergoeconomic parameters for each system components for optimum operating conditions are summarized in tab. 6. The exergoeconomic factor of the steam turbine and the low and the high pressure feedwater heaters are decreased suggesting that cost savings in the entire system might be achieved by a decrease in the investment costs at the expense of their exergetic efficiency. The exergoeconomic factor of the boiler and the deaerator are increased suggesting that total cost can be saved by increasing exergetic efficiency of these equipment via higher investment costs. The exergoeconomic factor of the overall system is decreased from 0.57 to 0.53 which is consistent with related literature.

Table 6. Exergoeconomic parameters of the system for the unconstrained optimum case

k	$\dot{E}_{F,k}$ [MW]	$\dot{E}_{P,k}$ [MW]	$\dot{E}_{D,k}+\dot{E}_{L,k}$ [MW]	$y_{D,k}$ [%]	ε_k [%]	$\dot{C}_D+\dot{C}_L$ [$ per h]	$\dot{Z}_k$ [$ per h]	$\dot{Z}_k+\dot{C}_{D,k}+\dot{C}_{L,k}$ [$ per h]	f_k [–]
1	33.63	13.83	19.80	84.50	41.12	914.06	809.60	1723.66	0.47
2	12.04	10.00	2.04	8.72	83.04	395.66	813.06	1208.72	0.67
3			1.16	4.95		365.34	34.79	400.13	0.09
4	0.02	0.01	0.01	0.03	57.46	2.17	6.83	9.00	0.76
5	0.62	0.41	0.22	0.93	65.30	68.31	7.21	75.53	0.10
6	0.99	0.83	0.17	0.72	83.08	105.96	0.88	106.84	0.01
7	0.06	0.05	0.01	0.06	76.35	4.55	11.74	16.29	0.72
8	0.10	0.09	0.01	0.05	89.62	3.35	1.75	5.10	0.34
9	0.05	0.03	0.01	0.05	72.23	3.95	10.78	14.73	0.73
System	34.80	10.00	23.43	100.00	28.74	1863.36	1696.64	3206.26	0.53

Table 7. Comparison of the decision variables for the base and optimum cases

Properties	Base case	Optimum case 1	Optimum case 2
p_1 [bar]	90.5	37.80	32.97
T_1 [°C]	530	400	406
p_3 [bar]	1.5	1.33	1.4
p_4 [bar]	4	7.52	7.58
p_5 [bar]	12	12.48	12.53
A_5 [m^2]	15	48	48
A_8 [m^2]	18	7	7

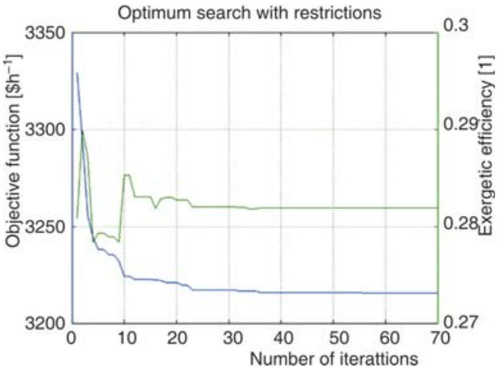

Figure 4. Variation of objective function and exergetic efficiency of the system during optimum search

Since the results of the first optimum search (Optimum case 1) presents a solution with a relatively low quality at the exit of the condensing section (88.9 %) causing erosion in the turbine a second optimum search (Optimum case 2) is run with a 90% quality restriction. Table 7 shows the state properties and exergies for the constrained optimum case. The differences between the state properties of the unconstrained and constrained optimum cases are much smaller than the difference between the base case and any other optimum cases. It is due to the fact that quality of the steam leaving the turbine is only 1.1% below the limit.

The decision variables for the base case and both optimum cases are given separately in tab. 8. as well.

Table 9 shows that quality restriction causes an increase of 2.25% in the cost of exergy destruction and only a slight decrease in the component dependent cost rates.

The costs of the streams in the base case and both optimum cases are given in tab. 10. Since the energy demands of the pumps are provided by the steam turbine self-consumption causes a very high cost for streams 14, 7, and 11. Otherwise the results meet the expectations providing in general the highest stream costs for the base case and the lowest ones for optimum case 1. Unit cost of electricity produced is reduced

Table 8. State properties (SP) and exergy of the system for the constrained optimum case

SP	$\dot{m}$ [kgs^{-1}]	T [°C]	p [bar]	h [kJkg^{-1}]	s [kJkg^{-1}K^{-1}]	$\dot{E}$ [kW]
1	13.00	405.99	32.97	3240.31	6.89	15460.65
2	10.18	45.81	0.10	2344.68	7.40	1458.77
3	1.34	109.34	1.40	2678.19	7.21	715.08
4	1.34	249.19	7.58	2950.31	7.06	1140.95
5	0.13	299.92	12.53	3044.80	7.01	122.44
6	11.53	45.81	0.10	191.81	0.65	32.38
7	11.53	45.90	8.08	192.89	0.65	41.88
8	11.53	107.02	7.58	449.23	1.39	470.32
9	1.34	109.34	1.40	458.58	1.41	56.92
10	13.00	168.21	7.58	711.36	2.02	1461.02
11	13.00	168.66	33.47	714.75	2.03	1500.57
12	13.00	173.65	32.97	736.51	2.07	1593.14
13	0.13	189.92	12.53	807.21	2.24	18.57
14	666.29	25.00	1.51	104.99	0.37	33.43
15	666.29	33.00	1.51	138.43	0.48	327.32
16	666.29	25.00	1.01	104.93	0.37	0.02
17	16.78	25.00	1.10	–213.95	6.89	123.52
18	17.71	143.02	1.10	–2748.14	7.57	1370.15
23	0.93	25.00	1.10	–3653.69	10.51	35435.05

Table 9. Exergoeconomic parameters of th system forthe constrained optimum case

k	$\dot{E}_{F,k}$ [MW]	$\dot{E}_{P,k}$ [MW]	$\dot{E}_{D,k} + \dot{E}_{L,k}$ [MW]	$y_{D,k}$ [%]	ε_k [%]	$\dot{C}_D + \dot{C}_L$ [$ per h]	$\dot{Z}_k$ [$ per h]	$\dot{Z}_k + \dot{C}_{D,k} + \dot{C}_{L,k}$ [$ per h]	f_k [–]
1	34.19	13.87	20.32	84.72	40.56	938.15	804.43	1742.58	0.46
2	12.02	9.99	2.03	8.48	83.09	396.65	813.13	1209.75	0.67
3			1.19	4.96		377.04	35.38	412.43	0.09
4	0.02	0.01	0.01	0.03	57.46	2.23	6.88	9.11	0.76
5	0.66	0.43	0.23	0.96	65.10	72.82	7.22	80.04	0.09
6	0.99	0.83	0.17	0.70	83.02	107.03	0.88	107.90	0.01
7	0.065	0.04	0.01	0.05	76.35	3.88	10.86	14.74	0.74
8	0.10	0.09	0.01	0.05	89.12	3.58	1.75	5.105.34	0.33
9	0.05	0.03	0.01	0.05	72.23	4.07	10.92	14.99	0.73
System	35.38	10.00	23.99	100.00	28.26	1905.45	1691.42	3215.75	0.53

from 34.92 cents/kWh to 31.52 cents/kWh in the first optimum case and 31.70 cents/kWh in the second one. Although these values seem a bit high, considering the technology, the temperature range of the cycle, and the fact that the unit cost of the electricity is an average value calculated for the next ten years they are acceptable.

Table 10. Cost of the streams in the system

SP	Base case		Optimum case 1		Optimum case 2	
	c [cents per kWh]	$\dot{C}$ [$/h]	c [cents per kWh]	$\dot{C}$ [$ per h]	c [cents per kWh]	$\dot{C}$ [$ per h]
1	22.10	3257.69	19.37	2984.90	19.51	3015.87
2	34.92	399.08	31.52	448.87	31.70	462.43
3	34.92	165.21	31.52	213.82	31.70	226.68
4	34.92	183.73	31.52	360.37	31.70	361.68
5	34.92	179.88	31.52	38.16	31.70	38.81
6	34.92	8.70	31.52	10.08	31.70	10.26
7	55.44	16.04	53.31	22.02	53.46	22.39
8	60.19	171.35	50.33	226.12	50.65	238.24
9	34.92	13.49	31.52	16.93	31.70	18.04
10	47.55	383.91	41.11	593.28	41.52	606.67
11	49.21	446.46	41.90	624.27	42.25	633.95
12	47.13	602.82	41.62	658.27	41.97	668.63
13	34.92	27.06	31.52	5.91	31.70	5.89
14	84.58	22.10	76.66	25.00	76.51	25.58
15	34.92	89.34	31.52	100.65	31.70	103.76
16	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00
18	8.12	94.57	6.83	91.99	6.80	93.10
19	34.92	3490.27	31.52	3151.59	31.70	3166.79
20	34.92	2.45	31.52	5.11	31.70	5.24
21	34.92	45.96	31.52	19.24	31.70	16.42
22	34.92	12.62	31.52	14.22	31.70	14.66
23	4.62	1391.01	4.62	1609.02	4.62	1635.92

The minimum value of the objective function and the corresponding exergetic efficiency of the best particle (gbest) of each iteration is shown in fig. 4. Although the exergetic efficiency has a maximum at second iteration with a value of 0.29 the result of the total cost function is relatively high (3294.2 $/h) therefore the PSO decreases the investment cost of the overall system at the expense of its exergetic efficiency. After the tenth iteration the changes in the decision variables are very small, hence the improvement after the first one-third iterations becomes small but steady.

Conclusions

The aim of an exergoeconomic optimization for power plants is to estimate the cost-optimal structure and the cost-optimal values of the thermodynamic inefficiencies in a system. A detailed thermodynamic analysis makes thermodynamic simulation software essential. As the search space of an exergoeconomic power plant analysis representing all theoretically possible parameter set is generally greater than the set of physically possible solutions it might contains incalculable solutions which cannot be excluded by constrains.

The work shows that although PSO is more sensitive to incalculable clouds at initial state than other evolutionary algorithms, since velocity updating strategies keep all their initial particles for the entire search, PSO still can be used in conjunction with exergoeconomic principles to optimize energy systems.

Via a canonical PSO with own pbest dependent velocity update algorithm, which is more sensitive to incalculable clouds than elite example dependent velocity update algorithms, it is demonstrated that if the initial particles are preselected and all particles have pbest and the swarm has a gbest then the PSO will find a solution even if the ratio of calculable and incalculable parts of the search space is small. The significance of the result is increased by the fact that pre-selection does not interfere with the velocity updating algorithm thus the solution provides PSO alternatives without any constrains, increasing the possibility to create more precise adaptations for different power plant problems.

Nomenclature

$\dot{C}$ – cost rate, [$\$h^{-1}$]
CCs – annual carrying charges, [$ per year]
c – constant, cost per exergy unit, [$ per $W^{-1}h^{-1}$]
D – number of dimension
$\dot{E}$ – exergy rate, [W]
f – exergoeconomic factor
gbest – global best
h – specific enthalpy, [Jkg^{-1}]
i – number of iterations, interest
j – dimension
k – generation counter from 1 to max. gen
$\dot{m}$ – mass flow rate, [kgs^{-1}]
max. gen – maximum generations
O&M – annual operating and maintenance costs, [$ per year]
PEC – purchased equipment costs, [$ per year]
p – pressure, [bar]
pbest – personal best
ps – population size
r – escalation rate
rand1, rand2 – random numbers ranging over 0–1
s – specific entropy, [$Jkg^{-1}K^{-1}$]
T – temperature, [°C]
v – velocity, [–]
W – work flow rate, [W]
w – inertia weight, [–]
X – *D*-dimensional vector, [–]
x – variable, [–]
y – exergy destruction ratio, [–]
$\dot{Z}$ – investment cost rate, [$ per year]

Greek symbols

ε – exergetic efficiency, [–]
τ – operating hours per year, [$ per year]

Subscripts

1, 2 ,..., 24 – state points
D – exergy destruction
e – outlet
eff – effective rate
F – fuel
i – inlet; i^{th} particle
j – j^{th} dimension
k – k^{th} component
L – exergy loss
n – nominal
P – product
q – heat transfer rate
tot – total
w – work

References

[1] Gugeli, D., Electrification of Switzerland between 1880-1914 (in German), Chronos Velag, Berlin, 1996
[2] Frangopoulos, C. A., Thermoeconomical Functional Analysis: A Method for Optimal Design or Improvement of Complex Thermal Systems, Ph. D. thesis, Georgia Institute of Technology, Atlanta, Geo., USA, 1983
[3] Lotka, A. J., Note on the Economic Conversion Factors of Energy, *A. J. Proc. Nat. Ac. Sci., 7* (1921), 7, pp. 192-197
[4] Keenan, J. H., A Steam Chart for Second-Law Analysis, A Study of Thermodynamic Availability in the Steam Power Plant, *Mechanical Engineering, 54* (1932), pp. 195-204
[5] Tribus, M., Thermodynamic and Economic Considerations in the Preparation of Fresh Water from Sea Water, Report No. 58/11 UCLA., Los Angeles., Cal., USA, 1957
[6] Gaggioli, R. A., Efficiency and Gosting – Second Law Analysis of Processes, American Chemical Society, Washington, DC, USA, 1983, ISBN13:9780841208117
[7] Tsatsaronis, G., Combination of Exergetic and Economic Analysis in Energy Conversion Processes, *Proceedings*, European Congress on Economic and Management of Energy in Industry, Albufeira-Algarve, Protugal, 1984, Vol. 1, pp. 151-157

[8] El-Sayed, Y. M., Gaggioli, R. A., A Critical Review of Second Law Costing Methods, 1, Background and Algebraic Procedures. *J. Energy Resour-ASME*, *111* (1989), 1, pp. 1-7
[9] Gaggioli, R. A., El-Sayed, Y. M., A Critical Review of Second Law Costing Methods, 2, Calculus Procedures, *J. Energy Resour-ASME*, *111* (1989), 1, pp. 8-15
[10] Abusoglu, A., Kanoglu, M., Exergoeconomic Analysis and Optimization of Combined Heat and Power Production: A review, *Renewable and Sustainable Energy Reviews*, *13* (2009), 9, pp. 2295-2308
[11] Bejan, A., *et al*., *Thermal Design and Optimization*, John Wiley and Sons Inc., New York, USA, 1996
[12] Valdes, M., *et al*., Thermoeconomic Optimization of Combined Cycle Gas Turbine Power Plants Using Genetic Algorithms, *Applied Thermal Engineering*, *23*, (2003) pp. 2169-2182
[13] Manesh, K., Amidpour, M., Multi-Objective Thermoeconomic Optimization of Coupling MSF Desalination with PWR Nuclear Power Plant through Evolutionary Algorithms, *Desalination, 249* (2009), 3, pp. 1332-1344
[14] Sahoo, P. K., Exergoeconomic Analysis and Optimization of a Cogeneration System Using Evolutionary Programming, *Applied Thermal Engineering, 28* (2008), 13, pp. 1580-1588
[15] Mofid, G. B., Hamed, G., Exergoeconomic Optimization of Gas Turbine Power Plants Operating Parameters Using Genetic Algorithms: A Case Study, *Thermal Science, 15* (2011), 1, pp. 43-54
[16] Eberhart, R., Kennedy, J., A New Optimizer Using Particle Swarm Theory, Micro Machine and Human Science, *Proceedings*, 6th International Symposium, Harisburg, Penn., USA, 1995, Vol. 1, pp. 39-43
[17] Yoshida, H., *et al*., A Particle Swarm Optimization for Reactive Power and Voltage Control Considering Voltage Security Assessment, *IEEE Transactions on Power Systems, 15* (2000), 4, pp. 1232-1239
[18] Li, X., *et al*., Power Generation Loading Optimization Using a Multi-Objective Constraint-Handling Method Via pso Algorithm, *Proceedings*, 6th IEEE International Conference on Industrial Informatics, Daejeon, Korea, 2008, Vol. 1 pp. 1632-1637
[19] Heo, J. S., Le, K. Y., Multiobjective Control of Power Plants Using Particle Swarm Optimization Techniques, *IEEE Transaction on Energy Conversion, 21* (2006), 2, pp. 552-561
[20] Yousefi, M., Darus, A. N., Optimal Design of Plate-Fin Heat Exchangers by a Hybrid Evolutionary Algorithm, *International Communications in Heat and Mass Transfer*, *39* (2012), 2, pp. 258-263
[21] Shi, Y. H., Eberhart, R. C., A Modified Particle Swarm Optimizer, IEEE International Conference on Evolutionary Computation, Anchorage, Alas., USA, 1998, Vol. 1, pp. 318-321
[22] Rao, S. S., *Engineering Optimization: Theory and Practice*, John Wiley & Sons, Inc. New York, USA, 2009
[23] Liang, J. J., *et al*., Comprehensive Learning Particle Swarm Optimizer for Global Optimization of Multimodal Functions, *IEEE Transactions on Evolutionary computation, 10* (2006), 3, pp. 281-295
[24] Koch, C., *et al*., Optimization of Combined Cycle Power Plants Using Evolutionary Algorithms, *Chemical Engineering and Processing*, *46* (2007), 11, pp. 1151-1159
[25] Pezzinia, P., *et al*., Optimization Techniques to Improve Energy Efficiency in Power Systems, *Renewable and Sustainable Energy Reviews, 15* (2011), 4, pp. 2028-2041
[26] Huang, H., *et al*., Example-Based Learning Particle Swarm Optimization for Continuous Optimization, *Information Sciences, 182* (2010), 1, pp. 125-138
[27] Groniewsky, A., Bird Flocking and Power Plants, *Proceedings*, International Conference on Heat Engines and Environmental Protection, Balatonfured, Hungary, 2011, Vol. 1, pp. 147-151
[28] Lazzaretto, A., Tsatsaronis, G., SPECO: A Systematic and General Methodology for Calculating Efficiencies and Costs in Thermal Systems, *Energy*, *31* (2006), 8-9, pp. 1257-1289
[29] Valero, A., *et al*., CGAM Problem: Definition and Conventional Solution, *Energy, 19* (1994), 3, pp. 279-286
[30] Turton, R., *et al*., *Analysis, Synthesis and Design of Chemical Processes*, Pearson Education Inc., N. J., USA, 2012
[31] Silveira, J. L., Tuna, C. E., Thermoeconomic Analysis Method for Optimization of Combined Heat and Power Systems Part I, *Prog Energy Combust Sci., 29* (2003), 6, pp. 479-485
[32] Petrakopouloua, F., *et al*., Exergoeconomic and Exergoenvironmental Evaluation of Power Plants Including CO_2 Capture, *Chemical Engineering Research and Design, 89* (2011), 9, pp. 1461-1469

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