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Exergoeconomic optimization and improvement of a cogeneration system modeled in a process simulator using direct search and evolutionary methods

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Abstract
The optimal design and operation of energy systems are critical tasks to sustain economic growth and reduce environmental impacts. In this context, this paper presents the mathematical optimization and exergoeconomic improvement of an energy system modeled in a professional thermodynamic process simulator using the direct search method of Powell and an evolutionary stochastic method of the genetic type. In the mathematical optimization approach, as usual, the minimum system total cost is sought by simultaneous manipulation of the entire set of decision variables. At times, the global minimum is not exactly reached. On the other hand, the exergoeconomic improvement methodology determines, based on the exergetic and economic analyses of the system at each iteration, a subset of most significant decision variables which should be modified for each component, and applies an optimization algorithm to these variables only. In the improvement process an appreciable reduction, not strict minimization, of the system total cost is sought. The energy system analyzed is a 24-component cogeneration plant, denoted CP-24, which is representative of complex industrial installations. As opposed to a conventional optimization approach, the integrated optimization with a professional process simulator eliminates the necessity to implement explicitly the constraints associated with the physical and thermodynamic models of the system. Therefore, the integrated strategy can tackle large systems, and ought to be more easily applied by practicing energy engineers. The results obtained permit, first, to compare the performance of mathematical optimization algorithms belonging to different classes, and, second, to evaluate the effectiveness of the iterative exergoeconomic improvement methodology working with these algorithms.

Keywords: Cogeneration, Direct search methods, Exergoeconomic improvement, Process simulator, Thermoeconomic optimization.

1. Introduction

Throughout the world, the optimal design and operation of energy systems are critical objectives to sustain economic growth and reduce environmental impacts. Therefore, efficient optimization and improvement methodologies ought to be available and easily applicable by practicing energy engineers.

In this context, a considerable amount of recent research effort has been expended (e.g., [1-9]). The present work contributes with a pointful appraisal of the mathematical optimization and exergoeconomic improvement of energy systems modeled in a professional thermodynamic process simulator.

First, for mathematical optimization, the direct-search method of Powell [10] and a genetic algorithm [11] are selected, and their performances are evaluated. Both methods do not require the calculation of derivatives of the objective function, thus avoiding differentiability issues, and streamlining the computational implementation of the optimization problem solution when a process simulator is used. It is known that the method of Powell can be made efficient [10, 12], and, among the evolutionary stochastic methods, genetic algorithms have demonstrated robustness when applied to diverse optimization problems in engineering [12, 13]. In the mathematical optimization approach, as usual, the minimum system total cost is sought by simultaneous manipulation of the entire set of decision variables. At times, the global minimum may not be exactly reached [14].

Second, the performance of an iterative exergoeconomic improvement methodology using these same optimization algorithms is here evaluated. The methodology, originally proposed by Vieira et al. [15], aims to obtain an appreciable reduction, not strict minimization, of the system total cost, and has been recently termed the EIS method [16, 17]. The EIS method establishes, based on the exergoeconomic analysis of the system at each iteration and on several qualitative and quantitative objective criteria, a hierarchical classification of the system components, and the associated subsets of most significant decision variables. For each component deemed relevant, an optimization algorithm is then applied to the respective reduced-set decision variables only. The iterations proceed until a user-prescribed stopping criterion is met for the reduction of the objective function.

The energy system analyzed here is a 24-component cogeneration plant, denoted CP-24, which is representative of complex energy systems found in industry. The professional process simulator IPSEpro [18] has been selected to model the CP-24 system. As opposed to a conventional optimization approach, the integrated optimization with a process simulator eliminates the necessity to implement explicitly the constraints associated with the physical and thermodynamic models of the system. Therefore, the integrated strategy can effectively tackle large systems [16, 17, 19].

Several optimization and improvement exercises for the CP-24 system are carried out. The results obtained permit, first, to compare the performances of mathematical optimization algorithms belonging to different classes, and, second, to evaluate the effectiveness of the iterative exergoeconomic improvement methodology working with these algorithms. In addition, the new findings and results obtained here are compared with those presented by Vieira et al. [16, 19] for the same CP-24 system, where only the flexible polyhedron algorithm by Nelder and Mead [10] had been used.

2. The cogeneration plant CP-24

The 24-component cogeneration system, whose flow diagram is shown in Figure 1, includes two gas turbines (GT01, GT01a), one extraction steam turbine (ST01), one condensation steam turbine (ST02), two heat recovery steam generators (HRSG01, HRSG01a), two water heaters (Heater01, Heater01a), one deaerator, one condenser, one cooling tower, and various pumps (P01, P02, P02a, P03), mixers (M1, M2), splitters (S1, S2, S3, S4) and blockage valves (V1, V2, V3). The system possesses 52 mass streams, including plant inflows and outflows. The products of CP-24 are the electricity from the gas and steam turbines, the superheated process steam, and the process hot water. The fuel for the gas turbines is natural gas. The plant is considered complex, because it includes all the major components of a real energy system, and it requires $O(10^3)$ variables for its simulation. It is remarked that this cogeneration system is the same as that used by Vieira et al. [19], such that, for ease of comparison of results, the notation adopted in that reference is also employed here. The plant is modeled with the IPSEpro process simulation software.

With respect to the mass flows in the CP-24, the expansion of combustion gases in the gas turbines generates part of the produced electricity. In the sequence, heat is transferred from these gases to the water to produce superheated steam in the two HRSGs. The two steam flows are mixed, and the resulting stream follows to the extraction turbine. After partial expansion in this turbine, a fraction of the steam is extracted for use in the process. The condensate of the process steam returns to the deaerator. The remnant steam further expands in the condensation steam turbine, producing more electricity. A condenser and a cooling tower are responsible for steam condensation after expansion in the turbine. The condensate then follows to the deaerator. The combustion gases, after leaving the HRSGs, are further used to produce hot water to the process. Finally, they are discharged to the atmosphere.

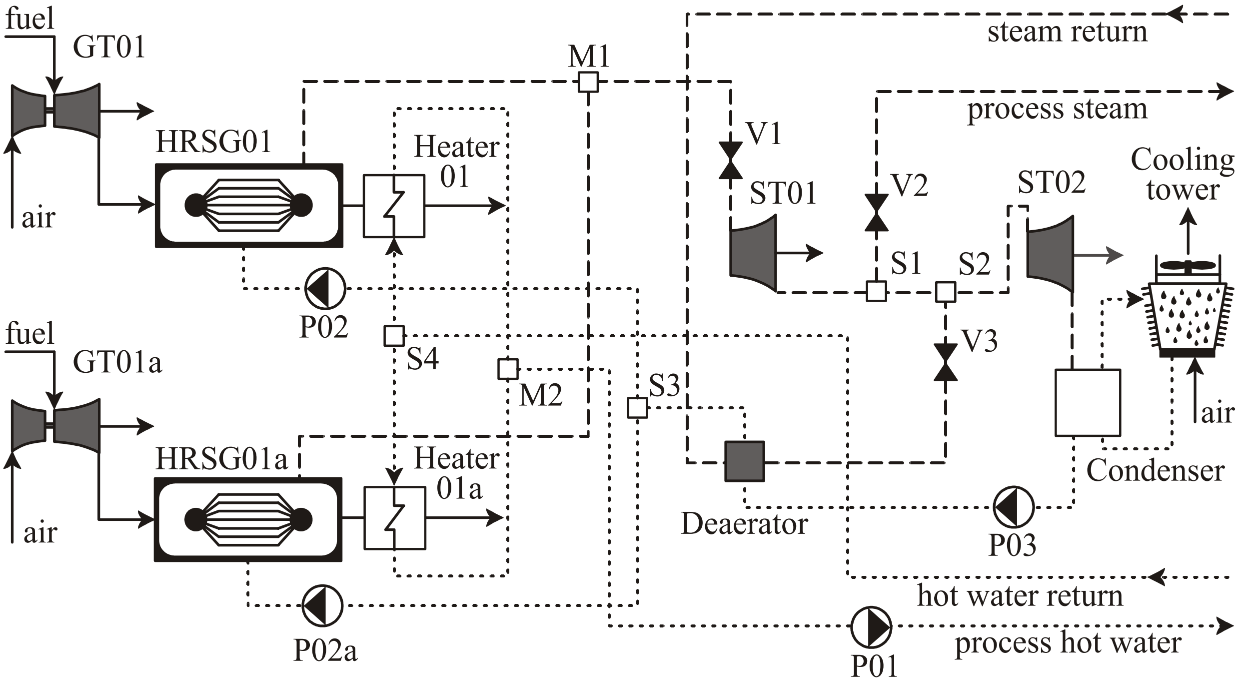

Figure 1. Schematic flow diagram of the cogeneration plant CP-24

3. Problem formulation

Three optimization problems with 8, 9, and 11 decision variables are formulated and solved in [16,19] for the CP-24 cogeneration plant, respectively denoted by OP8, OP9, and OP11. For all problems, the objective function *OF* is the same, and the process steam and process hot water demands are assumed constant. Here, the larger problem OP11 is considered for both mathematical optimization and exergoeconomic improvement. Table 1 shows the descriptions of the decision variables, the denominations used, and their minimum and maximum allowable values. In problem OP11, in addition to the evident consideration of the turbines and HRSGs, some decision variables associated with the condenser and cooling tower are weighed in the investigation.

Table 1. Decision variables for the optimization problem OP11 of system CP-24

Variable	**Symbol**	**Lower limit**	**Upper limit**
Power (ISO) of gas turbine GT01 (kW)	*GT01.kW*	40000	100000
Power (ISO) of gas turbine GT01a (kW)	*GT01a.kW*	40000	100000
Load of gas turbine GT01	*GT01.f*	0.50	1.00
Load of gas turbine GT01a	*GT01a.f*	0.50	1.00
Steam pressure at exit of mixer M1 (bar)	*S09.p*	20.0	120.0
Steam temperature at exit of HRSG01 (ºC)	*S08.t*	350.0	600.0
Steam temperature at exit of HRSG01a (ºC)	*S08a.t*	350.0	600.0
Steam pressure at extraction of ST01 (bar)	*S14.p*	2.0	10.0
Inlet condenser pressure (bar)	*S16.p*	0.05	0.50
Cooling tower range (ºC)	*Range*	2.0	10.0
Cooling tower approach (ºC)	*Approach*	2.0	10.0

The objective function to be minimized is the sum of the specific costs of the system products, which include the costs of capital investment, fuel, and operation and maintenance. The total system product is the sum of the exergies of the generated electrical power, superheated process steam, and process hot water. The objective function *OF* in US$ per unit exergy may be expressed by [16, 19]

$$OF = \sum_{i=1}^{NP} c_{Pi} = \frac{\sum_{k=1}^{NK} \dot{Z}_k + \sum_{i=1}^{NF} c_{F_i} \dot{E}_{F_i}}{\sum_{i=1}^{NP} \dot{E}_{P_i}} \tag{1}$$

where c means specific cost, $\dot{Z}$ denotes cost rate, $\dot{E}$ denotes rate of exergy transfer, subscripts F and P indicate system fuel and system product, respectively, NK is the number of system components, and NP and NF are the numbers of system products and fuels, respectively. The sum of the capital investment and the operation and maintenance cost rates for the NK components of the plant is given by [16, 19, 20]

$$\sum_{k=1}^{NK} \dot{Z}_k = \frac{\left(\sum_{k=1}^{NK} (CRF + \gamma) TCI_k \right)}{\tau} \tag{2}$$

In Eq. (2), $TCI_k = \beta\ PEC_k$ is the total capital investment for component k, $k = 1,\ldots NK$, PEC_k is the purchased-equipment cost of component k, $CRF = i(1 + i)^l/((1 + i)^l - 1)$ is the capital recovery factor, τ is the number of hours the plant operates in one year, γ is the maintenance factor, here assumed constant, and l and i are, respectively, the useful system life and interest rate. The constant factor β purports to account for all direct and indirect costs of the system [20]. The values of the economic parameters used in all calculations are [16, 19]: $\beta = 2$, $i = 12.7\%$, $l = 10$ years, $\tau = 8000$ hours, and $\gamma = 0.06$. The equations for PEC_k, $k = 1,\ldots NK$, are found in [19].

The mass and energy balances for the plant are equality constraints of the optimization problem. In addition, the fixed process steam and process hot water demands are also equality constraints [19]. The inequality constraints are represented by the allowable ranges of variation of the decision variables, presented in Table 1.

4. Problem solution integrated with a process simulator

The formulated optimization problem is solved by integrating the optimization and improvement routines with the modular process simulator IPSEpro [15, 19]. Integration requires a two-way communication interface, provided by the MS-Excel supplement PSExcel [18]. The optimization and improvement routines are written in the VBA (Visual Basic for Applications) language, run without user intervention, and perform the following tasks: (i) send plant data to the simulator; (ii) issue the command to run a simulation ('RunCalculation'); (iii) receive new plant data from the simulator; (iv) effect calculations of the optimization (sections 5 and 6) or improvement (section 7) algorithm; (v) return to task (i) while a stopping criterion is not met.

The thermodynamic calculations of the simulator impose the equality constraints associated with the mass and energy balances for the plant CP-24. As commonly employed in direct search optimization algorithms [10, 19, 21], the inequality constraints are incorporated through penalties applied to the objective function. Here, a penalty increases the objective function OF by a relatively large amount, which is proportional to the magnitude of the difference between the current (not admissible) value of the constrained decision variable and the respective limiting value. Furthermore, a penalty is applied to the objective function, whenever thermodynamic infeasibility is obtained in the process simulator along the search process. For the evolutionary algorithm, the computational implementation does not already allow tentative points (individuals) with decision variables (genes) outside the limits to be part of the population considered by the algorithm.

An optimization exercise thus consists of the application of the integrated optimization or improvement approach to the CP-24 simulation model starting at an initial design point, with ensuing execution of the algorithm until a stopping criterion is satisfied, so that a final design point is obtained. The initial point is generically denoted by $\mathbf{X}_0 = (x_{1,0}, x_{2,0},\ldots, x_{n,0})$, and possesses an associated value of the objective function, OF_0. The point obtained at the end of the procedure, $\mathbf{X}_f = (x_{1,f}, x_{2,f},\ldots, x_{n,f})$, contains the final values of the decision variables, and is associated with the final value OF_f; of course, OF_f is improved relative to OF_0. Indeed, one expects that $\mathbf{X}_f$ is close to, if not coincident with, the system global optimum point $\mathbf{X}^*$, associated with OF^*.

5. The method of Powell

The direct-search method of Powell [10] is applicable to the optimization of functions of several variables for which there are no constraints. When constraints are imposed, as noted in the previous section, one may couple the algorithm to a penalty method. Powell's method locates the minimum of a multivariable function by successive one-dimensional searches along a set of conjugate directions generated by the algorithm itself. Therefore, at each stage, it is necessary to apply a one-dimensional search method, i.e., an algorithm for extremization of a function of one variable only.

In the present work, the term Powell's method actually refers to a combination of two algorithms [10, 22]: the improved, or modified, *n*-D Powell's method, and the efficient combined DSC-Powell 1-D search algorithm. The *n*-D and 1-D algorithms are schematically described in Figures 2 and 3, respectively. Powell's method has been implemented in VBA, integrated with the IPSEpro simulator. Validation of the implementation has been carried out in Ref. [22] through application to standard functions, and also through comparison to the results of Refs. [15, 23, 24] for the benchmark CGAM system [20, 25]. As will be verified in the results section, the performance of Powell's method is significantly better than that of the flexible polyhedron method by Nelder and Mead [10, 16, 19].

BEGIN

Select initial point $\mathbf{x}_0^0$ (superscript denotes stage, subscript denotes stage's point), set stage $k = 0$, and set $\mathbf{d}_i^0 = \mathbf{e}_i$, $i = 1,2,\ldots,n$ ($\mathbf{e}_i$ is the unit vector along ith coordinate axis).

Effect n one-dimensional searches (see Fig. 3): for each $i = 1,2,\ldots,n$, calculate α_i such that $f\left(\mathbf{x}_{i-1}^k + \alpha_i \mathbf{d}_i^k\right)$ is a minimum, and define $\mathbf{x}_i^k = \mathbf{x}_{i-1}^k + \alpha_i \mathbf{d}_i^k$.

Calculate the point $\mathbf{x}_{n+1}^k = 2\mathbf{x}_n^k - \mathbf{x}_0^k$.

Calculate $\Delta^k = \max\limits_{i=1,\ldots,n}\left\{f\left(\mathbf{x}_{i-1}^k\right) - f\left(\mathbf{x}_i^k\right)\right\}$, and denote by $\mathbf{d}_m^k$ the search direction corresponding to this maximum change in $f\left(\mathbf{x}\right)$. Let $f_1 = f\left(\mathbf{x}_0^k\right)$, $f_2 = f\left(\mathbf{x}_n^k\right)$, and $f_3 = f\left(\mathbf{x}_{n+1}^k\right)$.

Test: If $f_3 \geq f_1$ or $\left(f_1 - 2f_2 + f_3\right)\left(f_1 - f_2 - \Delta^k\right)^2 \geq 0.5\,\Delta^k\left(f_1 - f_3\right)^2$, then set $\mathbf{d}_i^{k+1} = \mathbf{d}_i^k$, $i = 1,2,\ldots,n$, for the next stage k+1, and start at point $\mathbf{x}_0^{k+1} = \mathbf{x}_n^k$, or at $\mathbf{x}_{n+1}^k$ if $f_3 < f_2$.

Otherwise if Test fails: use directions $\left[\mathbf{d}_1^{k+1}\ \mathbf{d}_2^{k+1} \ldots\ \mathbf{d}_n^{k+1}\right] = \left[\mathbf{d}_1^k\ \mathbf{d}_2^k\ \ldots\ \mathbf{d}_{m-1}^k\ \mathbf{d}_{m+1}^k\ \ldots\ \mathbf{d}_n^k\ \mathbf{d}^k\right]$ in the next stage k+1, where the direction $\mathbf{d}_m^k$ of maximum change in stage k is eliminated, and the new direction $\mathbf{d}^k$ from $\mathbf{x}_0^k$ to $\mathbf{x}_n^k$ is inserted in the last column of the matrix of directions; the corresponding value of α is obtained via 1-D minimization along direction $\mathbf{d}^k$, and let $\mathbf{x}_0^{k+1} = \mathbf{x}_n^k + \alpha\mathbf{d}^k$.

For a user-prescribed tolerance ε, if $\left\|\mathbf{x}_n^k - \mathbf{x}_0^k\right\| \leq \varepsilon$, then **terminate**. Otherwise, set $k \leftarrow k + 1$ and return to the step of the n one-dimensional searches.

END

Figure 2. Algorithm for the improved *n*-D Powell's method to minimize *f*(**x**) [10, 22]

BEGIN

I. Calculate $g(x)$ at initial point x_0. Test: If $g(x_0+\Delta x)\le g(x_0)$, then go to II. Otherwise if Test fails: let $\Delta x = -\Delta x$, and go to II.

II. Calculate $x_{k+1} = x_k + \Delta x$.

III. Calculate $g(x_{k+1})$.

IV. Test: If $g(x_{k+1})\le g(x_k)$, multiply Δx by 2, and return to II. with $k = k + 1$. Otherwise if Test fails: denote x_{k+1} by x_m, x_k by x_{m-1}, and so on; multiply Δx by 0.5; and re-execute II. and III. only once.

V. Of the four equally spaced values of x in the set $\{x_{m+1}, x_m, x_{m-1}, x_{m-2}\}$, drop x_m or x_{m-2}, the one further away from point x corresponding to the smallest value of $g(x)$ in the set; denote the remaining three values of x by x_a, x_b, and x_c, where x_b is the center point, $x_a = x_b - \Delta x$, and $x_c = x_b + \Delta x$.

VI. Effect a quadratic interpolation to estimate the value of x at the minimum of $g(x)$, x_*, where

$$x_* = x_b + \frac{\Delta x\left[g(x_a)-g(x_c)\right]}{2\left[g(x_a)-2g(x_b)+g(x_c)\right]}.$$

VII. Test: If the difference between x_* and the one value of x belonging to the set $\{x_a, x_b, x_c\}$ corresponding to the smallest value of $g(x)$ is less than the prescribed tolerance for x, then **terminate** the search. Otherwise if Test fails: calculate $g(x_*)$; drop from the set $\{x_a, x_b, x_c\}$ that value corresponding to the largest value of $g(x)$, unless in so doing the bracket on the minimum of $g(x)$ is lost; in this case, drop the value of x such that the bracket is kept; then go to VIII.

VIII. Re-label the remaining three values of x by x_a, x_b, and x_c, where x_a is to the left of x_b, and x_c is to the right of x_b; then re-estimate the value of x at the minimum of $g(x)$, x_*, where now

$$x_* = \frac{\left[(x_b)^2-(x_c)^2\right]g(x_a)+\left[(x_c)^2-(x_a)^2\right]g(x_b)+\left[(x_a)^2-(x_b)^2\right]g(x_c)}{2\left[(x_b-x_c)\,g(x_a)+(x_c-x_a)\,g(x_b)+(x_a-x_b)\,g(x_c)\right]};\text{ go to VII.}$$

END

Figure 3. Algorithm for the combined DSC-Powell 1-D search to minimize $g(x)$ [10, 22]

6. The genetic algorithm

Genetic algorithms [11, 13] are stochastic evolutionary optimization techniques, based heuristically on the biological principle of natural selection, which warrants survival of the fittest individuals in a given population. Usually, the aptitude of an individual is represented quantitatively by the associated value of the objective function, such that at the end of the optimization process the fittest individual constitutes the problem optimal solution. From an initial random population, natural selection works its way thru generations, modifying the individuals by means of crossover and/or mutation, leading to new populations. Genetic algorithms are known to be robust, in that they tend to find the global optimum, albeit at the cost of intensive computational time.

The steps of the genetic algorithm are illustrated in Figure 4 [22, 23]. In the present problem, an individual contains a chromosome with 11 genes, 1 for each decision variable, plus an extra one for *OF*. Due to the nature and variation ranges of the decision variables, here the chromosomes have been coded with real numbers. Accordingly, the classical genetic operators of crossover and mutation are also implemented with real coding. Selection has been effected by tournament. To improve the performance of the algorithm, and to avoid stochastic deviations due to pseudo-random number generation, the elitism operator has also been used, which guarantees that the fittest individual in a given generation will be present in the following generation.

The performance of a genetic algorithm with respect to convergence to the global optimum point in the search space depends on the values assigned to its various control (adjustable) parameters. The size of the population (i.e., number of individuals), N_{ind}, and the probability of occurrence of a mutation, P_{m}, are two such parameters associated with the diversity of the population. The greater the diversity, the greater are the chances that some individual will be close to the global optimum of the objective function. The population diversity is maximum at the beginning of the genetic algorithm search process, and decreases along the N_{gen} generations. The probability of occurrence of a crossover, P_{c}, and the method of selection, on the other hand, determine the selection pressure of the genetic algorithm. The selection pressure is responsible for guiding the search to promising regions of the space. The larger the selection pressure, the larger is the speed of convergence to such regions. Because of the somewhat competing tendencies just described, a parametric study has been carried out [22, 23], to judiciously adjust the values of all the control parameters to be used with the genetic algorithm in the optimization and exergoeconomic improvement processes of the CP-24 system. The selected values of the control parameters are shown in Table 2. Because the improvement approach (section 7) works with reduced sets of decision variables, the number of generations N_{gen} can be much reduced relative to that for the optimization process.

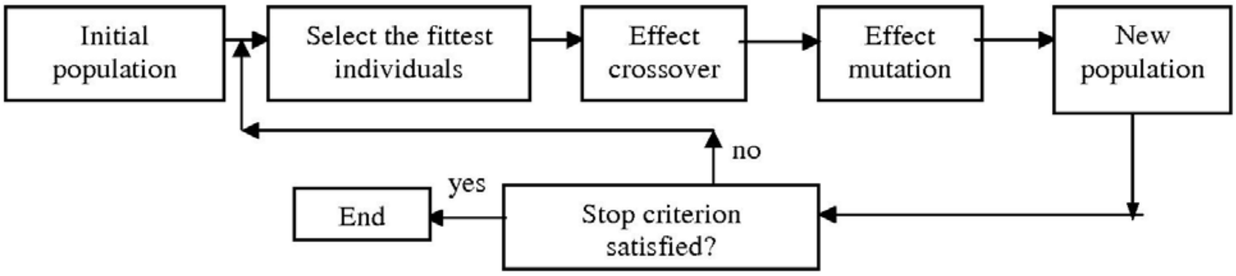

Figure 4. Steps of the genetic algorithm [22, 23]

Table 2. Values of the genetic algorithm parameters for optimization and improvement of plant CP-24

Parameter	Value for Optimization	Value for Improvement
N_{ind}	80	50
N_{gen}	50	3
P_{c} (%)	65	65
P_{m} (%)	5	5

7. The exergoeconomic methodology

The iterative exergoeconomic improvement methodology, or EIS approach, encompasses qualitative and quantitative criteria to hierarchically classify the thermal system components, and to select subgroups of decision variables to be modified for the components in the course of the procedure. The EIS approach requires no user intervention, and consists of six steps, described in detail in Refs. [15, 16]: (i) exergoeconomic analysis of the thermal system; (ii) analysis of the influence of the decision variables on the system exergetic efficiency and on the system total cost; (iii) ranking of system components into main, secondary, and remainder; (iv) identification of the predominant cost (exergy destruction or investment) for main and secondary components; (v) selection of subgroups of decision variables; (vi) mathematical optimization of main and secondary components.

A mathematical method modifies all n decision variables (x_1, x_2,…, x_n) simultaneously, to obtain the optimal values (x_1*, x_2*,…, x_n*). In contrast, in the EIS approach, an exergoeconomic analysis of the system at the beginning of each iteration is performed. The analysis provides information to hierarchically classify the components as main, secondary, and remainder, and to define main decision variables subgroups associated with the main and secondary components. The subgroups may have common decision variables, and their sizes may vary. Appropriate values for the parameters in the first step are chosen, so that the size of a subgroup of decision variables is always less than n. After the assembly of the subgroups, a mathematical optimization method is applied, first to those associated with the main components, and then to those associated with the secondary components. This sequence is repeated until no further improvement of the objective function is obtained, to within a user-prescribed tolerance.

In contrast to the conventional mathematical strategy, because EIS performs a preceding exergoeconomic analysis of the system, it will exclude some decision variables from the improvement process, when they no longer affect the value of the objective function. In fact, the EIS approach always selects the more important decision variables inside the improvement process, and these change as the system approaches the optimum. Two distinct alternatives are developed for the choice of main decision variables for each component. Alternative 1 uses modified structural bond coefficients, based on the cost of exergy destruction and the total cost (investment plus exergy destruction costs) of component k, k = 1,…,NK. Alternative 2 is based on the relative deviations between the actual and the optimal values of exergetic efficiency and relative cost difference for each main and secondary component. In principle, any mathematical optimization algorithm can be chosen to perform the optimizations along the iterations of the EIS approach.

In practice, the integrated EIS procedure is coded in the VBA language. Excel macros are used to control data exchange between the simulator and the VBA routine. The simulator is called by the VBA routine each time a decision variable is modified, to compute all mass, energy, and exergy flow rates of the system streams. To prevent execution failure due to errors caused by infeasible thermodynamic data selected in the VBA routine, a penalty is applied whenever the simulator returns an error code. Total computational time for any of the integrated approaches ends up proportional to the number of calls to the simulator, N_C, which is equal to the number of evaluations of the objective function. It is remarked that no specific efforts have been expended in this study to accelerate the EIS approach, either by optimizing user parameters values, or by employing advanced exergetic analysis [4].

8. Results and discussion

In this section the results of the exercises to optimize and improve the cogeneration plant CP-24 are presented and analyzed. In one exercise, a solution of the optimization or improvement problem is obtained starting from one specific set of initial values of the decision variables, with one chosen mathematical technique, and one chosen Alternative (1 or 2) for the EIS approach. Two initial points have been selected, $\mathbf{X}_{0,1}$ and $\mathbf{X}_{0,2}$, corresponding to Case 1 and Case 2, respectively, as shown in Table 3. Also shown in Table 3 are the initial values of the objective function for each case. One notes that Case 2 corresponds to a higher initial objective function value. By testing with different initial points, first, the likelihood of reaching the global minimum is increased [14], and, second, the robustness of the employed procedure is evaluated.

8.1 Results obtained with the method of Powell

Table 4 presents the results obtained when Powell's method is employed in the mathematical optimization strategy and in Alternatives 1 and 2 of the exergoeconomic improvement approach. From the results in Table 4 it is observed, first, that the three schemes are effective and robust, because plant costs at the final points are significantly reduced relative to those at the respective initial points (about 10% reduction in Case 1, 15% in Case 2). With regard to the influence of the initial set of values of the decision variables, one observes for each method that the results for Cases 1 and 2 are essentially equivalent in terms of the final value of the objective function. However, the number of evaluations of the objective function, N_C (equal to the number of calls to the simulator), for EIS' Alternatives 1 and 2 and for the mathematical optimization is, respectively, 29%, 82%, and 15% greater for Case 2 than for Case 1. This verification is not surprising, since for Case 2 the initial value of OF is greater (by about 7%) than that for Case 1.

On further analysis of the results in Table 4, one notes that, when Powell's method is applied to the CP-24 problems, the mathematical optimization has an overall better performance than the exergoeconomic improvement. The best value for OF and second to best value for N_C are, respectively, 43.01 US$/MWh and 475, obtained with the mathematical optimization applied to Case 1. With the EIS approach, the final values of the objective function are only about 4% higher. Alternative 2 leads to slightly higher objective function values than Alternative 1, but at significantly lower computational costs. For Case 1, the value of *OF* is only 0.1% higher for Alternative 2, however, N_C is 37% smaller.

Comparing now the final values of the decision variables for the mathematical optimization with those for the EIS method, an overall satisfactory agreement is obtained (see also section 8.3). It is possible to observe larger differences for the extraction pressure of the steam turbine (*S14.p* variable). In the EIS method, this variable is not modified (see Tables 3 and 4), because the exergoeconomic analyses in all iterations indicate that this variable has a minor effect on the reduction of the objective function.

Table 3. Initial values of the decision variables and objective function for Cases 1 and 2

Variable symbol	**Case 1** Initial point $\mathbf{X}_{0,1}$	**Case 2** Initial point $\mathbf{X}_{0,2}$
GT01.kW (kW)	52800	70000
GT01a.kW (kW)	52800	70000
GT01.f	0.90	0.90
GT01a.f	0.90	0.90
S09.p (bar)	79.9	59.9
S14.p (bar)	3.0	2.0
S08.t (°C)	500.0	400.0
S08a.t (°C)	500.0	400.0
S16.p (bar)	0.08	0.08
Range (°C)	5.5	5.5
Approach (°C)	5.0	5.0
OF (US$/MWh)	$OF_{0,1}$ 49.42	$OF_{0,2}$ 52.97

Table 4. Results obtained with the method of Powell

Decision variable	Case 1			Case 2		
	EIS Alternative 1	EIS Alternative 2	Mathematical optimization	EIS Alternative 1	EIS Alternative 2	Mathematical optimization
GT01.kW (kW)	40000	40000	40008	40000	40001	40094
GT01a.kW (kW)	40000	40200	40000	40001	40000	40094
GT01.f	0.75	0.75	0.74	0.75	0.75	0.74
GT01a.f	0.75	0.75	0.75	0.75	0.75	0.79
S09.p (bar)	117.7	117.7	119.8	116.0	119.5	119.5
S14.p (bar)	3.0	3.0	10.0	2.0	2.0	10.0
S08.t (°C)	500.0	500.0	519.0	518.8	518.8	520.8
S08a.t (°C)	500.0	500.0	519.0	518.8	514.0	518.8
S16.p (bar)	0.08	0.08	0.08	0.08	0.08	0.08
Range (°C)	9.3	9.1	9.9	9.2	9.0	10.0
Approach (°C)	3.4	3.6	3.1	3.4	3.6	2.6
OF (US$/MWh)	44.64	44.68	43.01	44.71	44.83	43.16
N_C	723	455	475	930	828	547

8.2 Results obtained with the genetic algorithm

Table 5 presents the results obtained when the genetic algorithm is employed in the mathematical optimization strategy and in Alternatives 1 and 2 of the exergoeconomic improvement approach. One observes from Table 5 that the three schemes are robust, and that the mathematical optimization, again, leads to lower values of the objective function than does the exergoeconomic improvement. However, the relative difference between the smallest value of *OF* obtained with the EIS approach (Alternative 1, Case 2) and that obtained with the mathematical optimization is only 3.2%. Furthermore, among the schemes, Alternative 2 requires a much lower number of evaluations of the objective function. In fact for Alternative 2, respectively for Cases 1 and 2, N_C is 33% and 51% smaller than the values for the mathematical optimization.

Table 5. Results obtained with the genetic algorithm

Decision variable	Case 1			Case 2		
	EIS Alternative 1	EIS Alternative 2	Mathematical optimization	EIS Alternative 1	EIS Alternative 2	Mathematical optimization
GT01.kW (kW)	40601	40601	41407	41097	45493	41026
GT01a.kW (kW)	41097	41097	42162	41097	41097	42162
GT01.f	0.75	0.75	0.53	0.74	0.76	0.53
GT01a.f	0.75	0.74	0.71	0.75	0.76	0.64
S09.p (bar)	110.5	105.9	108.2	118.8	118.8	109.3
S14.p (bar)	3.0	3.0	9.4	2.0	2.0	9.1
S08.t (^oC)	500.0	500.0	519.9	515.4	516.2	505.3
S08a.t (^oC)	500.0	500.0	522.2	502.4	516.3	522.2
S16.p (bar)	0.08	0.08	0.08	0.08	0.08	0.08
Range (^oC)	9.1	9.1	9.3	9.5	9.1	9.8
Approach (^oC)	5.0	2.7	3.9	3.1	5.0	2.6
OF (US$/MWh)	44.98	44.98	43.46	44.85	45.29	43.52
N_C	5400	2700	4000	6750	1950	4000

As regards the final values of the decision variables, one observes the same tendencies with respect to the initial values as the ones verified with Powell's method (see also section 8.3). However, larger discrepancies among the variables are obtained with the use of the genetic algorithm applied to the CP-24 problems. Again, the larger differences occur in the extraction pressure of the steam turbine, because this variable is not modified in the EIS approach. In spite of all discrepancies, the final values of the objective function are essentially equivalent for engineering purposes (less than 5% spread). This reality is further evidence of the difficulty to achieve a unique set of final values of the decision variables and objective function in the optimization or improvement of complex thermal systems [16, 19].

8.3 Comparative analysis of results

Tables 6 and 7 show, respectively for Cases 1 and 2 of the CP-24 problems, the present results obtained using Powell's method and the genetic algorithm together with the results obtained by Vieira et al. [16, 19] using the flexible polyhedron method by Nelder and Mead. A global analysis of Tables 6 and 7 reveals an important outcome: the method of Powell systematically leads to the smallest values of the objective function and of the number of simulator calls for all the investigated CP-24 scenarios.

Regarding the integrated mathematical optimization strategy, the number of evaluations of the objective function for the flexible polyhedron method is 3.6 to 8.5 times greater than that for the method of Powell. Also, for the genetic algorithm, N_C is about 8 times greater than that for the method of Powell. While Powell's scheme and the genetic algorithm essentially agree in the final values of *OF*, the average 7%

difference for the flexible polyhedron method appears consistent with the more significant discrepancies among the corresponding final values of the decision variables.

With the EIS approach, the final values obtained for *OF* are approximately equal, with discrepancies below 1.5%. Across all optimization techniques, relatively low discrepancies are also obtained among the final values of the decision variables. The method of Powell is 2 to 3 times faster than the flexible polyhedron method, and 6 to 7 times faster than the genetic algorithm. While Alternative 1 leads to smaller values of *OF* for all methods (except in Case 2, by a slim margin, with the flexible polyhedron method), Alternative 2 is consistently faster; in fact, the overall fastest performance occurs with Powell's method used in Alternative 2 applied to Case 1.

Despite some discrepancies verified in the final values of the decision variables, all schemes perform robustly: in all cases, they considerably reduce the value of the objective function, and they lead to the same global behavior of the plant CP-24. In fact, the gas turbines sizes and loads are reduced, while the operating pressures and temperatures of the HRSGs are increased [16, 19]. The condenser pressure is seen to be unimportant. The cooling tower range is increased, but the approach is reduced. Finally, as already pointed out, distinct treatments are given to the extraction pressure of the steam turbine by the mathematical and EIS approaches.

It is interesting to note that, contrary to what is observed with the flexible polyhedron method, the mathematical optimization with either the Powell's method or the genetic algorithm attains a lower value of the objective function, and sometimes at lower computational costs, compared to Alternatives 1 and 2 of the EIS approach. The differences encountered may be attributed in part to the fact that the improvement process does not modify appreciably some decision variables, because the associated exergoeconomic analyses indicate that they will have relatively little impact on the objective function. This is in accordance with the EIS philosophy, which does not aspire to obtain the mathematical optimum of the system. It must also be noted that the values of the parameters used in the improvement exercises are the same as those used originally by Vieira et al. [16, 19] with the flexible polyhedron method. No attempt has been made in this study to accelerate the EIS' performance, either by optimizing parameters values, or by employing advanced exergetic analysis.

Table 6. Results obtained in this work and in Refs. [16,19] for Case 1 of the optimization and improvement problems for system CP-24

Decision variable	Case 1								
	EIS, Alternative 1			EIS, Alternative 2			Mathematical optimization		
	Ref. [16]	Powell	Genetic	Ref. [16]	Powell	Genetic	Ref. [19]	Powell	Genetic
GT01.kW (kW)	40001	40000	40601	40001	40000	40601	40001	40008	41407
GT01a.kW (kW)	40001	40000	41097	40001	40200	41097	40157	40000	42162
GT01.f	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.74	0.53
GT01a.f	0.75	0.75	0.75	0.75	0.75	0.74	0.75	0.75	0.71
S09.p (bar)	120.0	117.7	110.5	120.0	117.7	105.9	76.3	119.8	108.2
S14.p (bar)	3.0	3.0	3.0	3.0	3.0	3.0	6.3	10.0	9.4
S08.t (^{o}C)	500.0	500.0	500.0	500.0	500.0	500.0	496.1	519.0	519.9
S08a.t (^{o}C)	500.0	500.0	500.0	500.0	500.0	500.0	505.9	519.0	522.2
S16.p (bar)	0.08	0.08	0.08	0.08	0.08	0.08	0.17	0.08	0.08
Range (^{o}C)	7.7	9.3	9.1	8.9	9.1	9.1	6.1	9.9	9.3
Approach (^{o}C)	5.0	3.4	5.0	5.0	3.6	2.7	5.6	3.1	3.9
OF (US$/MWh)	44.97	44.64	44.98	44.73	44.68	44.98	45.80	43.01	43.46
N_C	1796	723	5400	1241	455	2700	1700	475	4000

Table 7. Results obtained in this work and in Refs. [16, 19] for Case 2 of the optimization and improvement problems for system CP-24

Decision variable	Case 2								
	EIS, Alternative 1			EIS, Alternative 2			Mathematical optimization		
	Ref. [16]	Powell	Genetic	Ref. [16]	Powell	Genetic	Ref. [19]	Powell	Genetic
GT01.kW (kW)	40001	40000	41097	40001	40001	45493	42261	40094	41026
GT01a.kW (kW)	40001	40001	41097	40001	40000	41097	40337	40094	42162
GT01.f	0.75	0.75	0.74	0.74	0.75	0.76	0.85	0.74	0.53
GT01a.f	0.75	0.75	0.75	0.74	0.75	0.76	0.79	0.79	0.64
S09.p (bar)	120.0	116.0	118.8	106.3	119.5	118.8	70.1	119.5	109.3
S14.p (bar)	2.0	2.0	2.0	2.0	2.0	2.0	6.6	10.0	9.1
S08.t (^oC)	521.0	518.8	515.4	522.0	518.8	516.2	489.1	520.8	505.3
S08a.t (^oC)	502.6	518.8	502.4	521.5	514.0	516.3	475.6	518.8	522.2
S16.p (bar)	0.08	0.08	0.08	0.08	0.08	0.08	0.21	0.08	0.08
Range (^oC)	9.1	9.2	9.5	9.2	9.0	9.1	7.5	10.0	9.8
Approach (^oC)	3.6	3.4	3.1	4.2	3.6	5.0	6.0	2.6	2.6
OF (US$/MWh)	44.73	44.71	44.85	44.88	44.83	45.29	46.32	43.16	43.52
N_C	2985	930	6750	2365	828	1950	4654	547	4000

9. Conclusions

Integrated mathematical optimization and exergoeconomic improvement of a complex energy system modeled in a professional thermodynamic process simulator has been successfully carried out, using the direct search method of Powell and a genetic algorithm. In the optimization and improvement exercises, the method of Powell attained the best performance when compared to both the genetic algorithm and the flexible polyhedron method. Both the integrated tool and its evaluation are important, in view of the growing concern with the efficient design and operation of energy systems. Additionally, in the present study, Alternatives 1 and 2 of the EIS exergoeconomic improvement approach did not perform better than the mathematical optimization with Powell's and genetic methods, as opposed to what was observed when the flexible polyhedron method had been used. Still, the EIS approach has performed both robustly and efficiently, and it should thus be useful in exergoeconomic applications by the energy community at large. As indications for future research, the EIS approach may be further improved by optimization of parameters values, and/or by employment of advanced exergetic analysis.

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