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Exergoeconomically—aided evolution strategy applied to a combined cycle power plant

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Abstract

Evolution strategy has been combined with a particular exergoeconomic method to yield an optimization technique called Exergoeconomically—Aided Evolution Strategy. Its application to the optimization of a combined cycle power plant is examined to demonstrate, whether the exergoeconomic method can be used to improve the evolutionary optimization technique. It is shown, that there is a benefit on the optimization progress under certain conditions. However, there are generally so many uncertainties associated with the exergoeconomic method that it cannot be recommended as a universal tool for widely computerized process optimization. It remains, however, a useful tool for an interactive application by an experienced engineer.

Keywords: Exergo economics; Evolution strategy; Combined cycle powerplant

1. Introduction

An appropriate optimization technique is required for the economic optimization of thermodynamic processes. Conventional mathematical techniques often cannot be utilized for two major reasons. First, the optimization technique may converge into local optima and, second, the objective function is often available as a black-box simulation only, which some optimization techniques are not able to cope with. With developments in computer technology, evolution strategies have become more popular as an alternative in recent years. In principle, they have the ability to overcome local optima and particularly, they belong to the derivative-free methods [1]. Only the objective function value is needed for optimization. On the other hand, the required computing time can be very high due to the large number of simulation runs, if complex processes are considered. Therefore, it is desirable to reduce the number of simulation runs implementing suitable knowledge about the process.

Exergoeconomics can, in principle, yield this information. The heuristic benefits of exergoeconomics as an engineering tool for the improvement of existing plants or the synthesis of complex system structures are well known. It has also been applied as an interactive optimization technique for real-valued parametric optimization [2]. Evaluating certain exergoeconomic parameters, the optimizing engineer decides on the appropriate variation of the decision variables to improve the process configuration in the next optimization step. Therefore, this exergoeconomic method seems to be appropriate to exploit useful information about a successful variation of the decision variables when using evolution strategies. In order to investigate the usefulness of this certain exergoeconomic method as a tool for improving the performance of the evolution strategies, the evolution strategies have been combined with this exergoeconomic method. This new method is referred to as exergoeconomically—aided evolution strategy. To illustrate the results, a combined cycle power generation system has been chosen. The same model system was used in a previous publications [3,4].

The paper is organized as follows. The relevant features of evolution strategies are presented in Section 2. The principles of the exergoeconomically—aided evolution strategy are described in Section 3. In Section 4, the results for the combined cycle power generation system are summarized and the question, whether the exergoeconmic method can be utilized as a universal tool for improving the performance of the evolution strategies, is discussed.

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Nomenclature

B, n	constants of cost function	
$\dot{C}$	cost rate	$\$\cdot h^{-1}$
c	cost per unit of exergy	$\$\cdot MJ^{-1}$
$\dot{E}$	exergy flow rate	$MJ\cdot a^{-1}$ or MW
I	investment cost	\$
n	number of decision variables	
p	pressure	MPa
r	relative cost difference	
T	temperature	K
x	decision variable	
z	random number	

Greek symbols

α	generation counter
δ	step size
ξ	exergetic efficiency
κ	capital factor
λ	number of offspring
μ	number of parents
ξ	strategy parameter
Π	$= p_1/p_0$ pressure ration

Subscripts

C	compressor
F	fuel
i	counter
k	component k
O	offspring
P	parents
R	result

Superscript

opt	optimum

2. Evolution strategies

Evolution strategies (ES) are based upon the paradigms of biological evolution. In each generation (optimization step), there is a population of many individuals, each representing a particular set of the n decision variables $\{x_1, \ldots, x_n\}$. Evaluating the objective function, a certain fitness value can be associated to each individual. On the basis of fitness the μ best individuals of the present generation are selected as parents from which λ individuals, the so-called offspring, of the next generation are produced by the mechanisms of mutation and recombination.

Depending on the chosen variant of the ES, the parents are either removed from the new population and thus excluded from the selection (so-called "comma strategy") or they compete with their offspring in the next generation (so-called "plus strategy") with the associated notations (μ, λ)-ES or $(\mu + \lambda)$-ES, respectively. A mixing of comma and plus strategy can be applied by introducing a general deterioration factor for parents. If a parent stays longer than κ generations in the population, its fitness value will be impaired. The corresponding strategy notation is (μ, λ, α)-ES.

The mutation mechanism is crucial to the combination of ES and exergoeconomics. The natural mutation is imitated by using normal distributed random numbers z and step sizes δ. These step sizes are themselves subject to a self-adapting step size control, which itself uses the mechanism of mutation [1]. The normal distributed random numbers z make sure that offspring are produced which in the majority of steps do not differ much from their parent. The use of a step size control is of considerable importance as this is the most significant item that distinguishes the ES from the entirely statistical Monte Carlo method. One single decision variable x_i of the offspring O is determined from the parent value P as follows

$$\begin{aligned} x_{O,i} &= x_{P,i} + \delta_{O,i} \cdot z_i \\ \delta_{O,i} &= \delta_{P,i} \cdot \xi, \quad i = 1, \ldots, n \end{aligned} \tag{1}$$

Offspring are thus produced with both enlarged and reduced step sizes, as generated from the parents' step sizes by a strategy parameter ξ. Those offspring whose step size is best adapted to the objective function will be selected. This implies that information about optimum step sizes is transported to the next step. Hereby, offspring are not created entirely at random but rather in a way adequately adapted to the topology of the fitness function.

The normal distributed random number z is the factor which will be affected by the information of the exergoeconomic analysis, which gives a recommendation on the direction to which a particular decision variable should be changed. If a decision variable should be increased, only positive values for z are allowed, and vice versa.

3. Exergoeconomically—aided evolution strategy

The task of cost optimization as it is considered in this paper is the minimization of the total annual costs,

$$\dot{C}_F + \kappa \cdot \sum_k I_k \to \min \tag{2}$$

The fuel costs $\dot{C}_F$ are determined by the market price of fuel, while the investment costs I_k for each system component k are quantified by cost functions like those given in Appendix A. The model of economic analysis is taken into account by the capital factor κ considering both the annuity factor and the operating and maintenance expenses, which are assumed to be proportional to the investment costs.

3.1. Exergoeconomic analysis

The exergoeconomic analysis is used to provide the optimization algorithm, i.e., the evolution strategy, with information that is supposed to accelerate the optimization process. The basic concept of exergoeconomics is the relation between costs and exergy. This is represented by the cost per exergy unit c_i. Since costs are associated with each stream i, an exergy-related cost flow can be traced throughout the whole process by solving certain cost balances for each system component. In formulating the cost balances the capital costs are taken into account as source terms.

Defining carefully the result and the fuel of each system component, certain exergoeconomic parameters can be evaluated to describe the system components' thermodynamic and economic character. For more details see [2] or [4]. Generally, the exergetic efficiency of component k is defined as

$$\zeta_k = \frac{\dot{E}_{\mathrm{R},k}}{\dot{E}_{\mathrm{F},k}} \tag{3}$$

where $\dot{E}_{\mathrm{R},k}$ represents the exergy flow rate of product and $\dot{E}_{\mathrm{F},k}$ the exergy flow rate of fuel. The cost per exergy unit of fuel $c_{\mathrm{F},k}$ and product $c_{\mathrm{R},k}$ for each component result from the cost balances and the definition of fuel and product [2]. Especially, $c_{\mathrm{F},k}$ is used to define the costs of exergy loss of each system component k by

$$\Delta\dot{C}_{\mathrm{L},k} = c_{\mathrm{F},k} \cdot \Delta\dot{E}_{\mathrm{L},k} \tag{4}$$

By the term "exergy loss" in this paper the thermodynamic inefficiencies are meant that other authors call exergy destruction.

Therewith, the absolute cost difference of each component k can be determined by adding up the costs of exergy loss and the capital costs

$$\Delta\dot{C}_k = \kappa \cdot I_k + \Delta\dot{C}_{\mathrm{L},k} \tag{5}$$

Another exergoeconomic parameter is the relative cost difference r_k, which describes the ratio between the cost increase per exergy unit and the cost of fuel

$$r_k = \frac{c_{\mathrm{R},k} - c_{\mathrm{F},k}}{c_{\mathrm{F},k}} \tag{6}$$

These parameters are evaluated in order to provide the optimizer with useful information about the further strategy. Basically, the absolute cost difference is used to rank the components in descending order of cost production under simultaneous consideration of the relative cost difference. Following this ranking, the exergetic efficiency for each component is compared to a target value at each step of the ES. The decision variables are changed in such a way as to approach the exergetic efficiency of a component in a particular step of the optimization to its target value. These target values are determined by applying an exergoeconomically isolated optimization of each component. This implies that the exergy flow rate of product and the cost per exergy unit of fuel of the system component are held constant as an approximation.

3.2. Exergoeconomically isolated optimization of each component

In order to determine target values for each component's exergetic efficiency, a component is isolated from the remaining process. The exergetic efficiency has been chosen, because there is a relation to both fuel and capital costs. Fig. 1 illustrates the most common case, that the fuel costs increase with decreasing exergetic efficiency, while the capital costs increase rapidly with increasing exergetic efficiency. Therefore, an optimum of the total costs exists and can be found easily. The corresponding optimum exergetic efficiency ζ^{opt} is taken as the target value for the guided optimization of the whole process. In order to determine the optimum exergetic efficiency, the component's cost function I_k, which in fact depends on the decision variables associated with this component, is approximated as a simple function of the exergetic efficiency by applying a general equation introduced by Tsatsaronis [2], just slightly modified here,

$$I_k = B_k \cdot \left(\frac{\zeta_k}{1-\zeta_k}\right)^{n_k} \tag{7}$$

Since this approximation is only valid for small variations in the associated decision variables, one single decision variable is slightly varied in each optimization step in order to determine the constants B_k and n_k.

The fuel costs follow from Eq. (4) with some transformations to yield

$$\dot{C}_{\mathrm{F},k} = c_{\mathrm{F},k} \cdot \frac{\dot{E}_{\mathrm{R},k}}{\zeta_k} \tag{8}$$

Since exergoeconomic isolation implies constant cost per exergy unit of fuel and exergy flow rate of product, Eq. (8) describes the linear representation of the fuel costs shown in Fig. 1. The optimum exergetic efficiency can be calculated analytically to give [2]

$$\frac{\zeta_k^{\mathrm{opt}}}{1-\zeta_k^{\mathrm{opt}}} = \left(\frac{c_{\mathrm{F},k} \cdot \dot{E}_{\mathrm{R},k}}{\kappa \cdot B_k \cdot n_k}\right)^{1/(1+n_k)} \tag{9}$$

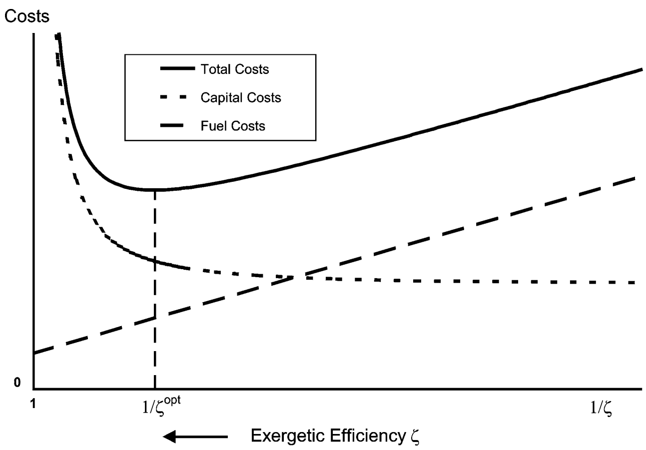

Fig. 1. Costs of a system component as a function of the exergetic efficiency.

Certainly, due to the inherent assumptions and simplifications, these target values are not identical with the final optimum exergetic efficiencies within the process, but they are assumed to have the potential to guide the optimization algorithm on the way to the global optimum in the early steps.

3.3. Key design variables

The exergetic efficiency of a system component depends upon more than one decision variable. Therefore, a decision has to be made which of them should be guided by the information gained from the exergoeconomically isolated optimization of a component. These variables, which are assumed to be most promising for the optimization of one component, are called key design variables. In principle, there are as much key design variables as there are combinatorial variants to combine system components and decision variables. In practice, this number of key design variables has to be reduced considerably before the beginning of optimization. Some can be ruled out easily on the basis of thermodynamic considerations. Others require some process simulation runs to prove their use as key design variables. Particularly, it has to be verified that the capital costs increase and the fuel costs decrease with increasing exergetic efficiency. Otherwise the optimization of a single component along the lines of Fig. 1 is impossible.

Defining key design variables is an important but also a time-consuming task. The interactive exergoeconomic optimization technique as introduced by Tsatsaronis [2] does not require this proper definition of key design variables, since the engineer as optimizer is expected to react when the suggested variation of a certain decision variable fails to improve the process.

3.4. Algorithm for guiding the optimization

The following scheme summarizes the use of an exergoeconomic analysis for guiding automatically the Evolution Strategy.

- Rank the components in descending order of cost production using the absolute cost difference $\Delta\dot{C}_k$ under simultaneous consideration of the relative cost difference r_k.
- The system components heading this list are treated first by an exergoeconomically isolated optimization.
- Determine the target values of the exergetic efficiencies following the methodology described in Section 3.2.
- Vary the actual exergetic efficiency ζ_k by varying the key design variable in order to approximate its target values. Find out the direction in which the key design variable shall be changed. This information is passed on to the mutation operator of the ES.

It should be mentioned, that this procedure is different from the interactive methodology proposed by Tsatsaronis in so far, as the optimizing engineer does not intervene in the optimization process. Considering the interactive methodology, he can introduce his knowledge and evaluate the information gained by exergoeconomics. He can, in particular, overrule this information whenever it fails to give reasonable results. On the contrary, the computer depends on reliable information provided by the exergoeconomic analysis without subsequent evaluation. Consequently, the combination of exergoeconomics and ES will reveal the true potential of the exergoeconomic method used in this paper.

4. Application to a combined cycle power plant

In this section the exergoeconomically—aided ES is illustrated by the application to a combined cycle power generation process.

4.1. The combined cycle power generation process

The scheme of the 100 MW power plant is shown in Fig. 2. The plant employs a simple gas turbine system fuelled by methane, consisting of an air compressor, a combustion chamber and a turbine. To adjust the exhaust gas temperature T_3 at the turbine's inlet, a part of the compressed air bypasses the combustion chamber and is mixed with the hot exhaust gas leaving the combustion chamber. The expanded gas is led to a heat recovery steam generator (HRSG) with two pressure lines. The feed water is heated, evaporated and superheated at high pressure in the HRSG. After expansion in the high pressure turbine the steam is re-superheated in the HRSG and conducted to the low pressure turbine. Finally, the expanded steam is condensed in the condenser.

The thermodynamic model consists of the independent mass and energy balances and the equations for evaluating the thermodynamic properties. Additionally some restrictive conditions on the basis of the second law of thermodynamics are implemented in the thermodynamic simulator, which have to be checked during process simulation. If at least one restriction is not fulfilled, the values of the fitness function are set to very high pseudo-values. For this reason those parameter configurations will be removed from the current population of the ES by selection.

In this case, 8 real-valued decision variables (temperatures and pressures) are to be optimized, which have been defined as follows:

- compressor pressure ratio $\Pi_C \leqslant 16$;
- exhaust gas temperature entering the gas turbine $T_3 \leqslant 1650$ K;
- exhaust gas temperature leaving the HRSG $T_6 \geqslant 433$ K;
- steam pressure entering the high pressure steam turbine $p_7 \leqslant 200$ bar;
- steam temperature entering the high pressure steam turbine $T_7 \leqslant 850$ K;

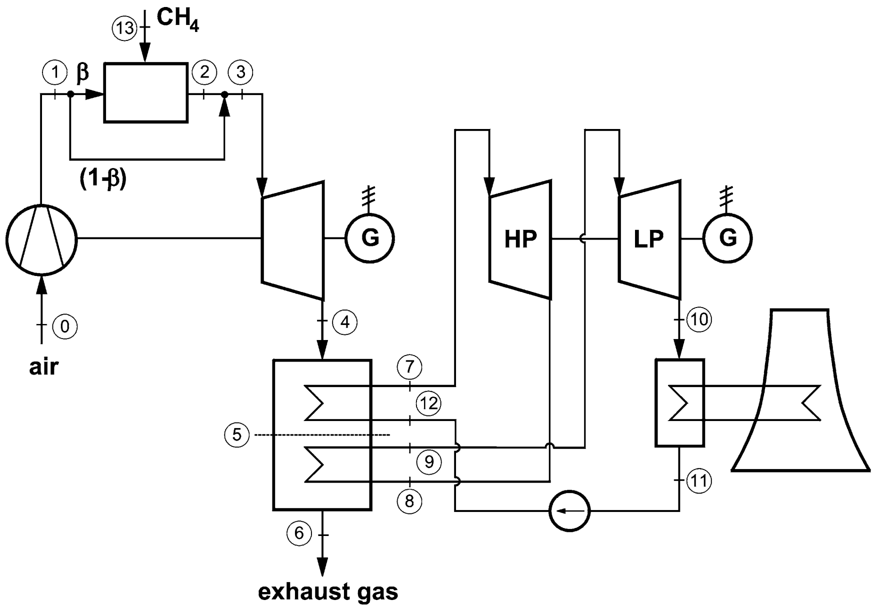

Fig. 2. Design of the combined cycle power plant.

- steam pressure entering the low pressure steam turbine $p_9 \leqslant 200$ bar;
- steam temperature entering the low pressure steam turbine $T_9 \leqslant 850$ K;
- condenser pressure $p_{10} \geqslant 6$ kPa.

The decision variables' lower or upper boundaries are given, too. They result from material and physical restrictions.

The investment costs of the power plant are calculated on the basis of certain cost functions for each plant component depending on relevant process parameters [5], see Appendix A. The annual fuel costs are determined using 3 US-$\$\cdot\mathrm{GJ}^{-1}$ as the unit cost of fuel based upon the fuel's lower heating value which is multiplied by the mass flow rate of fuel.

4.2. Process optimization using ES

The process under consideration can be optimized by applying a conventional ES. Since the optimization of the combined cycle power plant is a rather complex optimization problem, a more sophisticated ES than a simple $(1,\lambda)$-ES is required in order to determine the global optimum more reliably and exactly. Here, a $(15, 100, 1)$-ES has been chosen, which represents a standard choice [1], leading to an optimum configuration with costs of 5446 US-$\$\cdot\mathrm{h}^{-1}$ in this case. Approximately 15 hours computing time is required using a Pentium II 333 MHz. Parallelization could effectively reduce the computing time, but was not used in this study. The corresponding optimum values for the decision variables are

$$\Pi_C = 11.798,\quad T_3 = 1527.21\ \mathrm{K},\quad T_6 = 433\ \mathrm{K}$$
$$p_7 = 79.35\ \mathrm{bars},\quad T_7 = 806.15\ \mathrm{K},\quad p_9 = 2.56\ \mathrm{bars}$$
$$T_9 = 433.90\ \mathrm{K},\quad p_{10} = 6\ \mathrm{kPa}$$

The optimum, which has been determined with the $(15, 100, 1)$-ES, is used as benchmark for the results of the exergoeconomically—aided ES, which is supposed to reduce the required computing time significantly. Since the information provided by the exergoeconomically isolated optimization can only affect the mutation mechanism, a simple $(1,\lambda)$-ES has been applied in the following comparison. This strategy only uses mutation for determining the offspring. In this way, the exergoeconomically—aided ES can clearly be assessed disturbing the comparison by features of a more sophisticated ES.

4.3. Process optimization using exergoeconomically—aided ES

In this section the application of the exergoeconomically—aided ES is illustrated. First at all, the selection of the key design variables is described. Afterwards, the results of the optimization process are presented for a selected set of key design variables. Finally, a statistical evaluation gives further insight in the perspectives of the exergoeconomically—aided ES.

4.3.1. Selection of key design variables

The definition of key design variables is an important prerequisite, as their variation in each optimization step is controlled by the information of the exergoeconomic analysis. In the process under consideration, there are 64 combinatorial variants to define a key design variable for a particular component. Some of these combinatorial variants can easily be repudiated. For example, the performance of the steam turbine is independent of the compressor pressure ratio's value. In other cases, it has to be verified, that the capital costs and the fuel costs show the pattern of Fig. 1. If not, the exergoeconomically isolated optimization will not

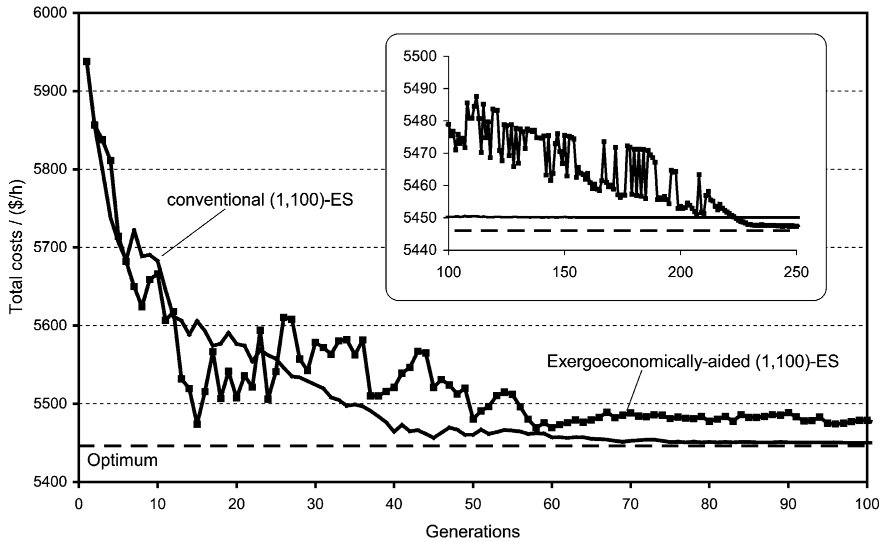

Fig. 3. Visualization of the optimization process.

yield reliable information on varying this decision variable. This cannot be proved a priori, so that some simulation runs of the whole process are required. This supplementary expenditure of computer time limits severely the benefits of the exergoeconomic analysis.

Considering the costs of the air compressor depending on variation of the compressor pressure ratio, for example, it is found, that the fuel costs are not in agreement with the ideal curve shown in Fig. 1. Therefore, the compressor pressure ratio cannot be defined as key design variable, although it has a significant influence on both the thermodynamic and the economic model of the compressor. The exergoeconomically isolated optimization would yield a target value which leads in the proper direction at best by chance. This is fatal for the automated exergoeconomically—aided ES, since it could not be eliminated and would mislead the algorithm. This fact is due to a deficiency of the particular exergoeconomic method applied in this work.

In fact, the 64 combinatorial variants of key design variables can be reduced systematically to 9 sensible key design variables, i.e.,

- Gas turbine: T_3;
- Heat recovery steam generator: T_3, T_6, T_7, T_9, p_7, p_9;
- High pressure steam turbine: T_7;
- Low pressure steam turbine: T_9.

These key design variables cannot be used all simultaneously for the exergoeconomically—aided ES, but also they cannot be reduced systematically any further. Their impact on the optimization progress remains to be tested empirical. This is a serious draw back, not only for the automated but also for the interactive version of exergoeconomics. The theory cannot guarantee to yield information with successful impact on the optimization progress.

4.3.2. Results

The results described in this section are obtained by using the most successful key design variables, i.e., p_7 and p_9 for the heat recovery steam generator, T_7 for the high pressure steam turbine and T_9 for the low pressure steam turbine. Fig. 3 shows the optimization process of the exergoeconomically—aided $(1,100)$-ES plotted versus the number of generations in comparison with the results of a conventional $(1,100)$-ES.

It is obvious, that the exergoeconomically—aided ES arrives at a value close to the optimum after 16 steps. The conventional ES, on the contary, needs about 40 generations to reach a value of about the same quality. Thus the optimizer is led to an almost optimum value in the early steps, as also found in the interactive approach. This depends on the proper selection of the key design variables. Other sets of key design variables than the one used here do not lead to an equally favorable performance [6].

In the following generations the exergoeconomically—aided ES is misled by the information from the exergoeconomically isolated optimization, as the target values of the exergetic efficiencies differ from their real optimum values. While the conventional ES yields more favorable values from step to step, the exergoeconomically—aided optimization process is led away from the optimum. However, the conventional ES is confined to a local optimum at 5450 $\$\cdot h^{-1}$, which is close to the global optimum due to the flat topology of the fitness function there. This is illustrated by the small figure in Fig. 3, which represents the generations from 100 up to 250. On the other side, the exergoeconomically—aided optimization is able to pass the local optimum in this case and finally yields the global optimum of 5446 $\$\cdot h^{-1}$ after about 1000 generations.

4.3.3. Statistical evaluation

A statistical evaluation demonstrates the impact of different start populations of the ES on the final results. Fig. 4

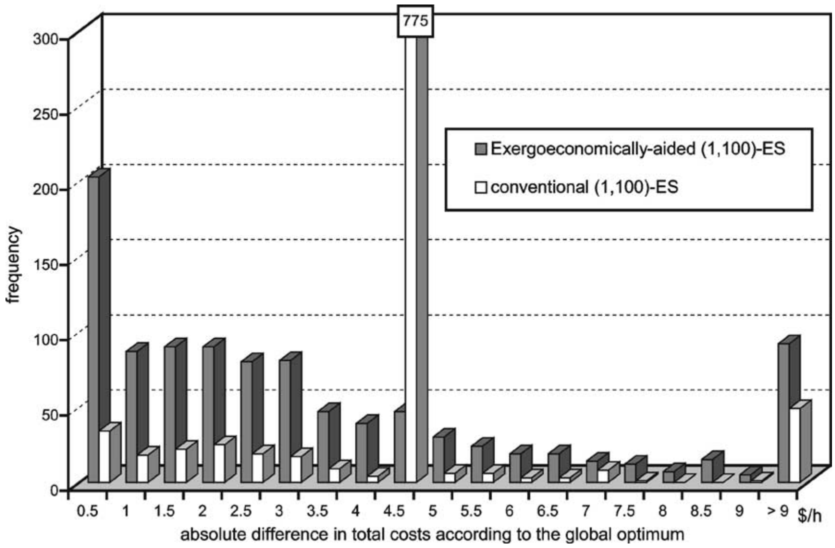

Fig. 4. Statistical evaluation.

shows the absolute differences in total costs with respect to the global optimum for one thousand applications of the conventional ES and the exergoeconomically—aided ES. The individuals in the start population are chosen randomly. The same set of key design variables has been used as described in Section 4.3.2.

It is found, that the conventional ES is confined within the local optimum in most of the cases (77.5%). Only 3.4% of 1000 optimization runs reach the global optimum in sufficient accuracy, whereby about 15% yield values between the global and the local optimum.

The statistical evaluation reveals the benefits of the exergoeconomically—aided ES in this special case. Fig. 4 shows, that almost 80% of the runs result in configurations, which differ only at most 4.5 $\$\cdot\mathrm{h}^{-1}$ from the global optimum. About 20% of all optimization runs reach the global optimum.

Therefore, exergoeconomics can have a notably positive influence on the optimization process compared to the results of the conventional ES. But in Fig. 4 it is also obvious, that more optimization runs yield a deviation from the global optimum of more than 5 $\$\cdot\mathrm{h}^{-1}$, when using the particular exergoeconomic method for guiding the ES than without it. This underlines, that the information obtained from this exergoeconomic method is not reliable. This is true for both the interactive and the automated methodology. In fact, a qualified criterion is missing to assess the proposed variation of a certain decision variable except trial and error. While this can be accomodated in the established interactive application it is rather fatal in combination with a computerized algorithm.

5. Conclusions

The aim of this study was to analyze the potential of a particular exergoeconomic method for process optimization with evolution strategies (ES). For this purpose, this exergoeconomic method has been combined with the evolution strategies. This exergoeconomically—aided ES demonstrates the feasibility of applying the exergoeconomic method in an automated optimization procedure without any engineer's intervention, contrary to the established interactive exergoeconomic optimization [2].

It has been shown, that exergoeconomics has the potential to accelerate the optimization process in the early steps, if a well defined set of key design variables has been determined before starting the optimization. This requires to analyze the process rather thoroughly including some additional process simulation runs.

Furthermore, it has been found, that the exergoeconomic method applied in this work cannot guarantee to yield information with successful impact on the optimization process. There is no qualified criterion to assess the proposed variation of a certain decision variable.

Therefore, it may be concluded, that the particular exergoeconomic method cannot be utilized as a reliable tool for process optimization. Maybe future work will lead to some modifications or additions to the exergoeconomic methodology that improve its reliability. However, the exergoeconomic method can be used for analyzing processes. This analysis yields useful hints for interactive optimization.

Appendix A. Cost functions (see [3])

Air compressor

$$C_{\mathrm{AC}} = c_{11} \cdot \dot{m}_{\mathrm{air}} \cdot \frac{1}{c_{12} - \eta_{\mathrm{sC}}} \cdot \Pi_{\mathrm{C}} \cdot \ln(\Pi_{\mathrm{C}}) \tag{A.1}$$

Combustion chamber

$$C_{\mathrm{CC}} = c_{21} \cdot \dot{m}_{\mathrm{air}} \cdot \bigl(1 + \exp\bigl(c_{22} \cdot (T_{\mathrm{out}} - c_{23})\bigr)\bigr) \times \frac{1}{0.995 - p_{\mathrm{out}}/p_{\mathrm{in}}} \tag{A.2}$$

Gas turbine

$$C_{\mathrm{GT}} = c_{31} \cdot \dot{m}_{\mathrm{gas}} \cdot \frac{1}{c_{32} - \eta_{\mathrm{sT}}} \cdot \ln\left(\frac{p_{\mathrm{in}}}{p_{\mathrm{out}}}\right) \times \left(1 + \exp\left(c_{33} \cdot (T_{\mathrm{in}} - c_{34})\right)\right) \tag{A.3}$$

Heat recovery steam generator

$$C_{\mathrm{HRSG}} = c_{41} \cdot \sum_i \left(f_{\mathrm{p},i} \cdot f_{\mathrm{T,steam},i} \cdot f_{\mathrm{T,gas},i} \cdot \left(\frac{\dot{Q}_i}{\Delta T_{\mathrm{ln},i}}\right)^{0.8}\right) + c_{42} \cdot \sum_j f_{\mathrm{p},j} \cdot \dot{m}_{\mathrm{steam},j} + c_{43} \cdot \dot{m}_{\mathrm{gas}}^{1.2} \tag{A.4}$$

$$f_{\mathrm{p},i} = 0.0971 \cdot \frac{p_i}{30\ \mathrm{bars}} + 0.9029 \tag{A.5}$$

$$f_{\mathrm{T,steam},i} = 1 + \exp\left(\frac{T_{\mathrm{out,steam},i} - 830\ \mathrm{K}}{500\ \mathrm{K}}\right) \tag{A.6}$$

$$f_{\mathrm{T,gas},i} = 1 + \exp\left(\frac{T_{\mathrm{out,gas},i} - 990\ \mathrm{K}}{500\ \mathrm{K}}\right) \tag{A.7}$$

Steam turbine

$$C_{\mathrm{ST}} = c_{51} \cdot P_{\mathrm{ST}}^{0.7} \cdot \left(1 + \left(\frac{0.05}{1 - \eta_{\mathrm{sST}}}\right)^3\right) \times \left(1 + 5 \cdot \exp\left(\frac{T_{\mathrm{in}} - 866\ \mathrm{K}}{10.42\ \mathrm{K}}\right)\right) \tag{A.8}$$

Condenser and cooling tower

$$C_{\mathrm{C}} = c_{61} \cdot \frac{\dot{Q}_{\mathrm{Cond}}}{k \cdot \Delta T_{\mathrm{ln}}} + c_{62} \cdot \dot{m}_{\mathrm{CW}} + 70.5 \cdot \dot{Q}_{\mathrm{Cond}} \times \left(-0.6936 \cdot \ln\left(\overline{T}_{\mathrm{CW}} - T_{\mathrm{WB}}\right) + 2.1898\right) \tag{A.9}$$

Feed water pump

$$C_{\mathrm{P}} = c_{71} \cdot P_{\mathrm{P}}^{0.71} \cdot \left(1 + \left(\frac{0.2}{1 - \eta_{\mathrm{sP}}}\right)\right) \tag{A.10}$$

Table 1 shows the constants used in the cost functions. The costs are calculated in US-$ based on the year 1996.

Table 1
Constants used in the cost functions

Air compressor	$c_{11} = 44.71$ \$·(kg/s)$^{-1}$	$c_{12} = 0.95$
Combustion chamber	$c_{21} = 28.98$ \$·(kg/s)$^{-1}$	$c_{22} = 0.015\ \mathrm{K}^{-1}$
	$c_{23} = 1540$ K	
Gas turbine	$c_{31} = 301.45$ \$·(kg/s)$^{-1}$	$c_{32} = 0.94$
	$c_{33} = 0.025\ \mathrm{K}^{-1}$	$c_{34} = 1570$ K
Heat recovery steam generator	$c_{41} = 4131.8$ \$·(kW/K)$^{-0.8}$	$c_{42} = 13380$ \$·(kg/s)$^{-1}$
	$c_{43} = 1489.7$ \$·(kg/s)$^{-1.2}$	
Steam turbine	$c_{51} = 3880.5$ \$·kW$^{-0.7}$	
Condenser	$c_{61} = 280.74$ \$·m^{-2}	$c_{62} = 746$ \$·(kg/s)$^{-1}$
	$k = 2200$ W·(m^{2}K)$^{-1}$	
Feed water pump	$c_{71} = 705.48$ \$·(kg/s)$^{-1}$	

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