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Pareto optimization of a combined cycle power system as a decision support tool for trading off investment vs. operating costs

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Abstract

The monetary optimization of thermodynamic processes may be approached by inherently thermodynamic frameworks like exergoeconomic analysis, or a rigid direct cost evaluation is applied. This paper, treating the optimization of a combined cycle power plant, follows the second path. Operation and investment costs are usually treated as a combined value by means of an annualization factor. Due to the rather far-stretching time horizon of turbine energy conversion systems, differing behaviour of those contributions with time, and varying subjective weighting and assumptions of future developments, this conventional subsumption is not necessarily a sensible one to identify the best solution for a given decision situation. It is therefore favorable to address both costing goals independently and identify the pareto set of the problem prior to a final decision on which parametrization of the system should be chosen. A numerical pareto optimization technique based on an evolutionary base strategy is discussed that addresses this type of problem in an efficient and easy to adapt manner.

Keywords: Pareto optimization; Evolution strategy; Combined cycle power plant

1. Introduction

Upon closer scrutiny the optimization of a power plant, like most practical optimization problems, is to be defined as multi-criterial, i.e., more than one target function is to be pursued in the process of system amelioration.

Addressing this multi-criteriality, the dubiousness of subjective weight functions is obvious in target values for different scaling, like cost and, e.g., pollutant emission. In such a trade-off the relative weighting depends heavily on the attribution of values by the definer and cannot be considered objective. Even when investigating just pure costs of a technical system, annualized investment costs may be compared to operating costs only after a somewhat arbitrary setting of the factor of annualization. It is therefore generally desirable to independently but simultaneously pursue each target function during the optimization process. Such an approach usually does not yield a single optimal solution but a tradeoff set of so-called pareto-optimal solutions, as most target functions show conflicting behaviours when considered simultaneously. Typical examples are efficiency vs. power output of thermodynamic systems, total costs vs. pollutant emission of combustion systems, or investment vs. operating costs for almost any practical process.

Even though only one system design will be put into practice, the determination of the pareto set is of practical importance: Knowing it a relative weighting of the targets can be questioned with respect to small losses in one and potential great gains in another single target by shifting it appropriately. Thus pareto optimization puts any particular selection on a rational basis.

As a demonstration process for the pareto optimization approach we investigate the costs of a combined cycle power generation system, separated into investment and operation costs, whose performance depends on eight configuration variables. The optimization is performed by an evolutionary parameter optimizer coupled black-box-wise to a system simulator. The investigated process serves as a computationally rather simple test bed for our evolutionary approach. Since only real-valued configuration variables are to be optimized a mostly homogeneous and smooth pareto set may

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Nomenclature

C	investment costs . . . . . US$	T	temperature . . . . . K
$\dot{m}$	mass flow rate . . . . . $kg{\cdot}s^{-1}$	ΔT_{ln}	logarithmic mean temperature difference . . . . K
p	pressure . . . . . MPa	*Greek symbols*	
P	mechanical power . . . . . kW	η_s	isentropic efficiency
$\dot{Q}$	heat transfer rate . . . . . kW	Π_C	compressor pressure ratio

be anticipated. Nevertheless the woes of optimizer tuning, automated population size adaptation, simulator-optimizer coupling, treatment of simulator instabilities, and similar may be investigated with such a problem, with more of those issues to appear in more difficult cases.

2. The combined cycle power generation process

A combined cycle power generation process has been chosen to illustrate the pareto optimization approach. The flowsheet of the 100 MW power plant is shown in Fig. 1. The plant employs a simple gas turbine system fueled by methane, consisting of an air compressor, a combustion chamber and a turbine. The methane is completely burned at constant air ratio of $\lambda = 1.1$. 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 remaining heat is discharged to the environment by cooling water and a cooling tower. The mechanical work of the gas turbine and the steam turbine is converted into electricity in one single generator.

In particular the thermodynamic model consists of the independent mass and energy balances and the equations for evaluating the thermodynamic properties. These have to be determined for the gaseous substances [7] and for water/steam [14]. Additionally some restrictive conditions on the basis of the 2nd 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 target functions are set to very high pseudo-values in order to render this solution proposition as non-competitive for the evolutionary algorithm.

Only eight real-valued configuration variables (temperatures and pressures) are to be optimized in the process under consideration, with the free parameters' lower/upper boundaries, due to material and physical restrictions, defined as follows:

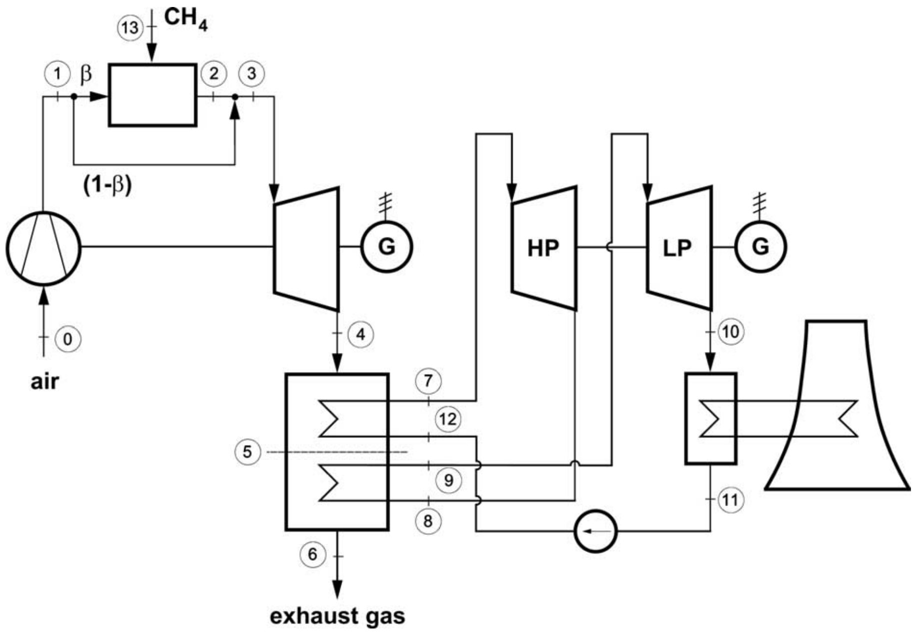

Fig. 1. Schematic of the investigated 100 MW combined cycle power plant.

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

The simulator includes both the thermodynamic model and the calculation of investment costs and fuel costs respectively. The simulator has been implemented as a C++ software program using classes for certain groups of plant components like heat exchangers etc.

3. Evolutionary pareto optimization

3.1. Concept of pareto set optimization

Multi-criterial optimization in general, and pareto optimization in particular have been discussed in so many papers (a collection of more than eight hundred, with a special focus on evolutionary computation even, may be found at [1]) that it seems futile to include a basic introduction to the concept in this paper. Only some non-exhausting and subject-related aspects will be given on that subject to alleviate reading.

The general idea of pareto optimization is not to weigh individual goals of an optimization problem prior to knowing its pareto set, being defined by *the complete set of parametric solutions in which one partial target value can only be improved by compromising on at least one other target*. This property of the pareto set must be viewed in concordance to the existing boundary conditions of the given problem, in the present case mostly imposed by technical restrictions like maximum temperatures or pressures, minimal flux rates, and the like. It is subject to change if new technical solutions like improved materials for turbine blades or new cooling mechanisms spring into existence. Therefore any given pareto set reflects the momentary state of the (technical) art, and needs to get re-calculated at changes of the latter.

The pareto set is a set and not just the only one solution for a given practical problem, as multiple target functions tend to fight each other. It is, however, a solid basis to draw serious conclusions and reflect on individual weightings of considered targets. In particular it unveils sensitivities in the trade-off of individual goals. As the pareto set of an optimization problem may show regions of stagnation in one target function accompanied by remarkable changes in another one, accepting just a minor change in the slowly varying target function may yield very favourable ones in (one of) the other.

3.2. Evolutionary approach

In contrary to conventional, analysis-based (single criterion) optimization algorithms evolutionary approaches do not try to identify a single (optimally estimated), direct approach to the optimal parameter settings of the problem in question. Instead, imitating nature, they utilize a set of system propositions defined by their respective configuration parameter values and characterized by their resulting target function value(s). Those system representations may be interpreted as a kind of biological "individuals".

Search steps are not calculated from discretized analysis-related steepest descent considerations but occur randomly, although not blindly, by taking the most promising individuals as originators of generation-wise new parameter test sets. Therefore the usual pitfalls of analytical optimization approaches for non-steady, non-derivative functions do not apply for this kind of proceeding. As numerous variants of evolutionary optimization algorithms have been published and studied extensively, both for single target function optimization (e.g., [2,8,11–13]) and for multi-criterial problem sets [1], we will restrict ourselves to the description of the particular evolutionary pareto algorithm chosen here for the combined cycle treatment and its specialties.

The basic toolbox adapted for the combined cycle optimization is EPO [9]. EPO is a rather simple generation based evolutionary optimizer for real-valued parameters. Already in its single-criterion variant it allows for several adaptations of the basic evolutionary strategy, though, and thus is a suitable basis for a multi-criterial extension.

The most prominent features of EPO are:

- Existence of recombination, i.e.: New parameter test sets are constructed by mixing two promising former variants, thus allowing for a parameter volume search, compared to a mutation originated random line search.
- Continuous change in between of "comma strategy" and "plus strategy" [11].
- Simple invocation subroutines for external (black box) linkage of simulation routines or stand-alone programs.

Depending on the settings of the applied evolution strategy parameters, a trade-off of parameter space volume vs. line search may be defined. It is found that, depending on the topology of the target function and on the maturity of an actual optimization run, differing strategical approaches seem best suited, but cannot be assessed beforehand. One main strategy ruler for this decision is the relative remanence of comparatively well-suited solutions in the set of reproducing individuals. Therefore in our approach we regard the soft switching between the extremes of comma and plus strategy as rather important, by introducing a general deterioration factor for parents in their competition with their offspring. The particular functions of EPO as discussed in [9] have proven to be appropriate for other sophisticated optimization problems [4–6,10].

EPOs basic strategy was modified for the pareto optimization with respect to the following issues:

Variable number of individuals in a generation. In a monocriterial optimization approach the size of the best list taken as parents for the generation of new parameter set variations mainly serves the purpose of genotypic variability. It aims at preventing the optimization run to get stuck in suboptimal solutions.

In pareto optimization the best list also serves the purpose of knowledge accumulation about the shape and extension of the pareto set. In order to represent the pareto set as densely as possible a variability of the size of the best list has been introduced, with every parameter set proposition exhibiting the pareto property in a given state of convergence being retained therein.

A new-found well-adjusted parameter set may outperform several former members of an older pareto set approximation. In that case it replaces all of the old members, leading to a shrinking of the best list.

Introduction of a pareto selection method. After determination of the target function values of all new parameter set propositions, a one-by-one paired comparison would be necessary for each target function to assess the relative merits of all sets correctly. This requires an extensive sorting effort for larger populations. On the other hand, after just some initial generations the detection of the pareto property is the only really interesting sorting criterion.

Therefore a fast classifying algorithm based on a ranking minimization system was developed that is designed to assess true pareto property solutions correctly. After the determination of all target function values for every new parameter set proposition in a given generational step the ranks of all parameter sets are set to zero. Next, the target function values of the first parameter set proposition are compared to those of every other proposition, but only with respect to being a relative pareto solution or not. In case one solution of the comparison pairs is found to be dominated by the other its rank is set to higher value than both former values. If neither of the two compared sets dominates the other the maximum value of both former ranks are given to both of them. The second parameter set needs only to be compared to the remaining $n - 2$ ones and so forth. In the end, only $n \cdot (n - 1)/2$ comparisons have to be performed to ascertain that the true pareto front parameter sets have the lowest possible ranking value of zero. Larger values give a rough idea about a parameter set's ranking with respect to the pareto property but do not claim to be well-defined.

Density balancing along the pareto front. The topological complexity in target function space and hence the difficulty in finding improved solutions may change along the pareto front. On the other hand, a more or less dense coverage of it is required to characterize it correctly. Therefore offspring are generated from the members of the best list on a (lack of) density of existing solutions basis: After determination of the members of the best list this list is sorted for average distances to the next neighbors, and individuals are taken predominantly from the more sparsely populated regions, thus probing those regions more extensively for better pareto front solutions. During the course of an actual optimization run one can clearly observe the impact of this strategy as sparsely populated regions become denser and denser with growing generation count.

Since the basic evolutionary algorithm does not draw any conclusions from the mathematical formulation of the models in question and their steadiness or derivative properties, it is possible to implement the actual acquisition of the target function value(s) as a black-box approach. It can be obtained from any simulation tool if an algorithmically organized interface between simulator and optimizer is available.

An important aspect of any numerical optimization approach is the tackling of simulation faults. With the exception of some very well-established and widely used computer codes most simulation tools have convergence and numerical stability problems, at least in certain regions of parameter space. For analysis-based line search strategies this poses a huge problem, as faulty or even no target functions returns will misguide the strategy into wrong interpretations or premature terminations. Evolution strategies, however, can cope with a certain amount of faulty target function returns as such settings will only be able to propagate in recombination with others—which usually will not work.

4. Obtaining the pareto set for the combined cycle process

For the combined cycle power plant optimization EPO was coupled to a custom simulator program. As both optimizer and simulator stem from different sources and utilize at least slightly different programming languages (C and C++) a fully disjunct program coupling via parameter and result files was preferred over a direct coupling, minimizing potential interferences of source codes.

As anticipated for such a custom built simulation environment the program was not completely stable and produced endless loops for some parameter settings. To overcome respective deadlocks (optimizer waiting for the simulation engine to return values before submitting a next set of differing parameters for calculation) a runtime inspection facility

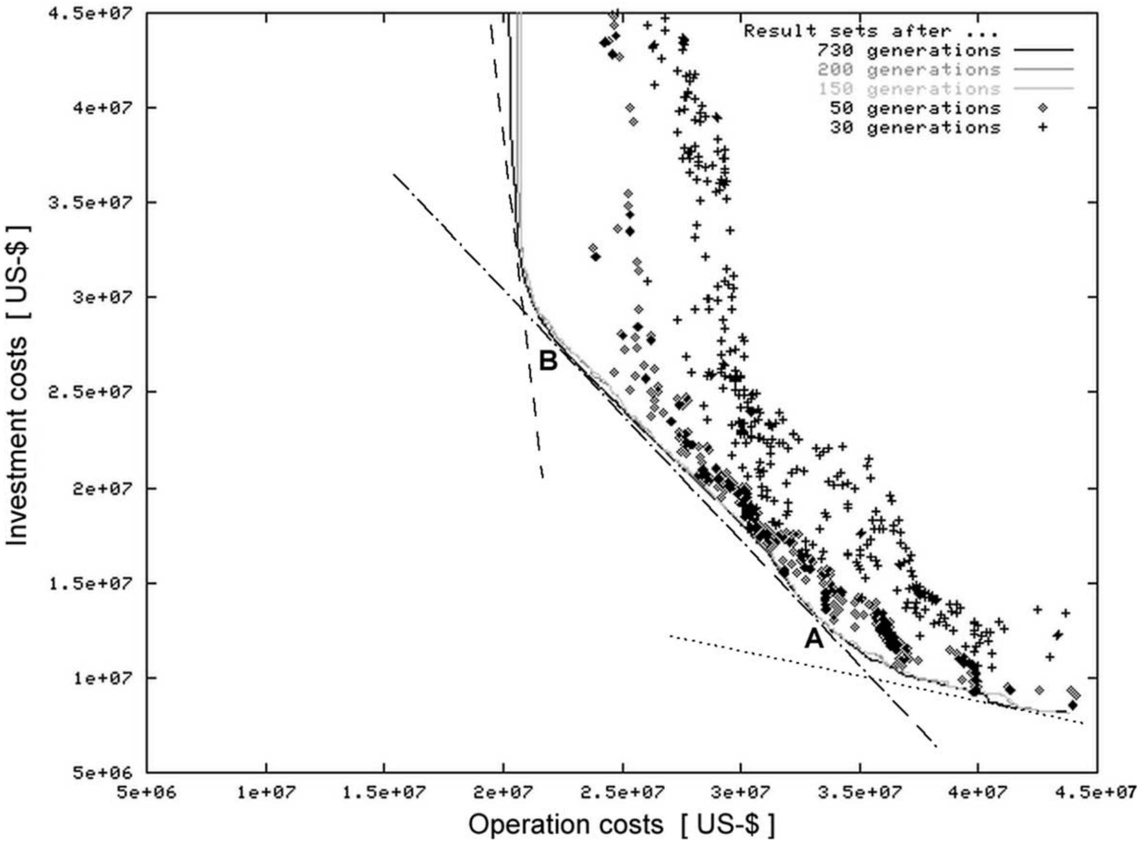

Fig. 2. Approaching the pareto set of the combined cycle power system in the course of evolutionary generations. The later generations are rendered as lines for clarity of presentation although they consist of individual points like the first ones.

has been introduced into the optimizer, limiting the maximum execution time of the simulator. If this is exceeded the simulation process is killed by the optimizer, the respective parameter set is discarded, and a different one is submitted for calculation instead. Infinite loop problems have been observed for several percent of submitted calculation runs, their frequency strongly depending on the investigated parameter space regions. The cost functions are calculated as detailed in Section 2.

The optimization process was started with an initial parent list size of 400 and an offspring of 200 per generation. The parent list size was allowed to expand to not more than 2000 individuals, with the number of new parameter sets per generation kept constant. The initial generation was defined by randomly set parameter values in the given allowed ranges.

During an optimization run (see Fig. 2) the first true pareto front develops after about 100 generations. Earlier generations just exhibit a best list distributed two-dimensionally in target function space, but more and more flattening out towards the sought trade-off curve of the target functions (Fig. 2, low generation counts). Due to the applied selection algorithm the number of individuals in the best list stays at the defined lower bound until the first true pareto front appears.

As solutions exhibiting a real pareto property are usually not eliminated from the best list it starts to grow as the front gets populated more and more densely with increasing generation number. For our problem this growth reduces by and changes into a fluctuation when approaching best list sizes of about 1500. At that point in convergence minimal changes in target value improvement tend to annihilate about the same number of former pareto front members as new ones are found.

The absolute improvement of target functions becomes smaller and smaller over the course of generations: While the advance of the pareto front is quite fast in the first tens of generations, the difference of generation 150 and 730, with a respective number of additional parameter sets having been probed, only provides a marginal improvement in most parts of the pareto set. Test runs with significantly more than 1000 generations only exhibited neglegible further improvements compared to the depicted one.

5. Discussion of the pareto set

The pareto front of the given combined cycle monetary pareto optimization shows a smooth, non-interrupted behaviour when viewed in target function space. This was not necessarily to be expected as some of the target function con-

Table 1
Comparison of two parameter settings leading to comparable aggregated cost values. Explanation see text

Target function/variable	Low investment cost variant A	Low operation cost variant B
Annual fuel costs	3.32×10^7 US$	2.20×10^7 US$
Total investment costs	1.32×10^7 US$	2.81×10^7 US$
Compressor pressure ratio Π_C	11.9	11.2
Exhaust gas temperature entering the gas turbine T_3	1516 K	1516 K
Exhaust gas temperature leaving the HRSG T_6	932 K	461 K
Steam pressure entering the high pressure steam turbine p_7	122 bar	84 bar
Steam temperature entering the high pressure steam turbine T_7	814 K	805 K
Steam pressure entering the low pressure steam turbine p_9	32.1 bar	2.2 bar
Steam temperature entering the low pressure steam turbine T_9	820 K	424 K
Condenser pressure p_{10}	0.06 bar	0.06 bar

tributions behave unsteadily when phase changes of water are involved in heat exchangers etc. Despite of these mathematical complications the pareto set was readily computed. At the finally determined pareto front the whole system does not seem to operate on phase change conditions as the resulting curve does not show unsteady points.

The shape of the curve represents the expected trade-off situation where investment costs are to be judged against operation costs. Reducing operation costs below about 2.2×10^7 US$ is either not possible or requires huge investment costs. On the other hand, a reduction of investment cost to less than 1×10^7 US$ will increase operating costs beyond sensible limits.

In the given case of pure monetary target functions one may use familiar economic relationships to aggregate operation and investment costs in the habitual way. Any such aggregation will define a linear superposition of the originally separate cost domains that may be expressed as a tilted new "optimization axis", equivalently expressed by arbitration iso-lines perpendicular to that axis. The angle of such iso-lines therefore may as well define the individual cost model. If, as an extreme example, only operation costs would be considered, the arbitration axis would coincide with the abscissa of our plot, and iso-lines would be parallel to the ordinate. Due to the uncertainties of cost modeling and subjective arbitration the superposition of the two cost contributions leaves quite a range of sensible monetary assumptions. Three exemplaric representatives of iso-line sets (dashed, dash-dotted, dotted) are given in the pareto diagram of the combined cycle process. Each of them identifies at the respective point of tangential touch the respective "optimal" achievable target function values.

If we start our investigation of the pareto set at the dotted line, which represents a relatively strong stress on investment costs, a slight change in arbitration in fond of operation costs will shift the relative contribution of target functions and hence the structure of the parameter propositions only slightly.

Tilting the arbitration iso-lines even more we eventually arrive at the dash-dotted situation where we observe a coincidence of aggregated quality for solutions quite separated in target function and in parameter space. Although yielding an identical aggregated quality those solutions differ significantly with respect to the relative contribution of operating and investment costs. As expected those solutions have quite different parameter settings, as detailed in Table 1. Scrutinizing the given parameter sets the plausibility of variant B, especially the low inlet pressure p_9 of the low pressure turbine, might be questioned. This is caused by the simulation model, though. There is no additional restriction implemented that would limit a further decrease of this free parameter for economic reasons. Only the thermodynamic feasibility is ensured by comparing this parameter to the condenser pressure. Therefore, the low value of the low pressure steam in case B is due to uncertainties of the apparatus cost modeling in interaction with thermodynamic reasons as a side effect of the way the water/steam is guided through the HRSG (see Fig. 1). In practice, the low pressure turbine would be omitted in this case.

The reduced fuel costs of the system propositions lying on the concave, almost linear section of the pareto curve are primarily based on the reduction of the exhaust gas temperature T_6 at the outlet of the HRSG. If this value falls below 600 K, respective low values for the low pressure steam are needed to use the exhaust gas optimally.

Laying even more stress on operation costs the pareto set solutions map to the aggregated cost function again in a rather unspectacular way of slowly shifting relative weights, the dashed line being a representative of this range. Here an exponential increase of the investment costs is found for individuals with a constant minimum temperature $T_6 = 433$ K. The increase is due to the remaining free parameter changes that have the greatest effect on costs in this constellation, like T_3, Π_C and p_7. Finally, all of them reach their maximum allowed values at the exergetic optimum, which marks the left end of the pareto curve, considering the given restrictions for the free parameters.

In our travel of changing relative weightings we never experienced a situation, though, where solutions at operating costs of about 3×10^7 US$ would be the ones to be chosen as optimal, due to a region of concavity in the trade-off curve. Nevertheless these solutions are members of the pareto set and do make sense to be determined and scrutinized: For any practical system to be constructed it may be most favorable to limit both operating and investment costs, even if the resulting solutions are slightly lower rated in a simple linear overall cost model. It may be a sensible means to bound the ill effects of uncertainties and flaws in any individual target function calculation by not following a very pointed construction proposition.

The mathematical representation of such a relative weighting may be constructed by non-linear models on the operation costs $f_{\mathrm{op}}(\vec{x})$ and investment costs $f_{\mathrm{inv}}(\vec{x})$ for any investigated parameter set $\vec{x}$, like

$$Q_{\mathrm{eff}} = \frac{\alpha f_{\mathrm{op}} + \beta f_{\mathrm{inv}}}{\alpha + \beta} + \gamma \cdot f_{\mathrm{op}} \cdot f_{\mathrm{inv}} \quad (\gamma < 0),$$

taking into account coincidence factors as $\gamma \cdot f_{\mathrm{op}} \cdot f_{\mathrm{inv}}$ contributing to the overall solution proposition quality. Resulting arbitration iso-lines are no more straight but more or less curved into the concave regions of the pareto set depending on the strengths of the non-linearity factor.

In any case, a pareto optimization performed prior to fixing the relative weights of target function attribution will capacitate the decision makers to reflect on the importance of the individual targets. It yields, at the same time, an immediate overview on disadvantages incurred by pronouncing a certain partial target function.

6. Conclusions and outlook

Evolutionary pareto optimization has proven to be applicable to parametrically defined combined cycle power plant models. The optimization method behaved robust in spite of occasional convergence problems of the applied simulation model. With typical model simulation times of less than one minute the problem could be solved during some hours on a simple single-CPU personal computer, but without any in-depth mathematical scrutinization of the underlying model.

The same pareto set could have been determined instead by sequential application of numerous aggregated individual weighting sets. In order to assess the merits of coinciding partial qualities, though, the investigation of pure linear superimposed relative weights would not suffice, thus rendering the required efforts for this “simple” approach as quite large. Furtheron the application of faster deterministic optimum search methods would have to cope with mathematical peculiarities of the target functions and would, in the course of a large number of automatically defined optimization runs, presumably not always proceed to the respective global optimum.

The result of the optimization process, the pareto set of the problem, yields an immediate choice of parameter sets for whatever relative weighting is considered as the most appropriate one for the actual design problem by the final decision makers. For any relative set of weights the stability of the resulting decision with respect to the configuration parameter set to be chosen may be investigated with respect to subjective differences and uncertainties of priority settings. Even if non-linear cost function superpositions are to be included in the set of sensible attribution the identified pareto set allows an estimate of the amount of non-linearity involved to yield further interesting solutions.

With more complex simulative calculations expected for more elaborate models the accumulating computing time will no doubt rise significantly, but as of now the most efficient absolute optimization time reduction potential, parallelization, has not yet been exploited. Every target function determination of an individual parameter setting is completely independet of any other, so the calculations may well be performed in parallel. With growing simulation time requirements the relative part of parallelizable code in a complete optimization iterative step becomes significantly larger, so according to Amdahl’s law the expected gain in performance grows as well. For demanding simulations with individual system simulation times of several minutes a speedup of several tens to several hundreds is realistic if an appropriate number of (cheap consumer system) processors is available.

Appendix A. Cost functions (see also [3])

Air compressor:

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

$c_{11} = 44.71\ \$\cdot(\mathrm{kg\cdot s})^{-1}$

$c_{12} = 0.95$

Combustion chamber:

$$C_{\mathrm{CC}} = c_{21} \cdot \dot{m}_{\mathrm{air}} \cdot \left(1 + e^{c_{22}\cdot(T_{\mathrm{out}} - c_{23})}\right) \cdot \frac{1}{0.995 - p_{\mathrm{out}}/p_{\mathrm{in}}}$$

$c_{21} = 28.98\ \$\cdot(\mathrm{kg\cdot s})^{-1}$

$c_{22} = 0.015\ \mathrm{K}^{-1}$

$c_{23} = 1540\ \mathrm{K}$

Gas turbine:

$$C_{\mathrm{GT}} = c_{31} \cdot \dot{m}_{\mathrm{gas}} \cdot \frac{1}{c_{32} - \eta_{sT}} \cdot \ln\left(\frac{p_{\mathrm{in}}}{p_{\mathrm{out}}}\right) \times \left(1 + e^{c_{33}\cdot(T_{\mathrm{in}} - 1570\ \mathrm{K})}\right)$$

$c_{31} = 301.45\ \$\cdot(\mathrm{kg\cdot s})^{-1}$

$c_{32} = 0.94$

$c_{33} = 0.025\ \mathrm{K}^{-1}$

Heat recovery steam generator:

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

$$f_{p,i} = 0.0971 \cdot \frac{p_i}{30\ \text{bar}} + 0.9029$$
$$f_{T,\text{steam},i} = 1 + \exp\left(\frac{T_{\text{out,steam},i} - 830\ \text{K}}{500\ \text{K}}\right)$$
$$f_{T,\text{gas},i} = 1 + \exp\left(\frac{T_{\text{out,gas},i} - 990\ \text{K}}{500\ \text{K}}\right)$$
$$c_{41} = 4131.8\ \$\cdot(\text{kW}\cdot\text{K})^{0.8}$$
$$c_{42} = 13380\ \$\cdot(\text{kg}\cdot\text{s})^{-1}$$
$$c_{43} = 1489.7\ \$\cdot(\text{kg}\cdot\text{s})^{-1.2}$$

Steam turbine:

$$C_{\text{ST}} = c_{51} \cdot P_{\text{ST}}^{0.7}\left(1 + \left(\frac{0.05}{1 - \eta_{s\text{ST}}}\right)^3\right) \times \left(1 + 5 \cdot \exp\left(\frac{T_{\text{in}} - 866\ \text{K}}{10.42\ \text{K}}\right)\right)$$
$$c_{51} = 3880.5\ \$\cdot\text{kW}^{-0.7}$$

Condenser and cooling tower:

$$C_C = c_{61} \cdot \frac{\dot{Q}_{\text{Cond}}}{k \cdot \Delta T_{\text{ln}}} + c_{62} \cdot \dot{m}_{\text{CW}} + 70.5 \cdot \dot{Q}_{\text{Cond}} \times \left(-0.6936 \cdot \ln(\overline{T}_{\text{CW}} - T_{\text{WB}}) + 2.1898\right)$$
$$c_{61} = 280.74\ \$\cdot\text{m}^{-2}$$
$$c_{62} = 746\ \$\cdot(\text{kg}\cdot\text{s})^{-1}$$
$$k = 2200\ \text{W}\cdot(\text{m}^2\cdot\text{K})^{-1}$$

Feed water pump:

$$C_P = c_{71} \cdot P_P^{0.71}\left(1 + \frac{0.2}{1 - \eta_{sP}}\right)$$
$$c_{71} = 705.48\ \$\cdot(\text{kg}\cdot\text{s})^{-1}$$

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