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AN AUTOMATED TOOL FOR SINGLE- AND MULTI-OBJECTIVE OPTIMIZATION FOR DESIGNING COMBINED CYCLE GAS TURBINE POWER PLANTS

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Abstract. *Modern optimization methods based on evolutionary algorithms and game theory are employed for the design of optimal Combined Cycle Gas Turbine Power Plants with dual-pressure heat recovery steam generators. They will be supported by computational methods for their thermal analysis and a simple model for computing their capital cost. Results will be presented for two power plants, a diesel oil fired and a natural gas fired respectively, the latter involving an additional condensate preheater. In both plants, design parameters are those related to the Heat Recovery Steam Generator.*

1 INTRODUCTION

Combined Cycle Gas Turbine Power Plants (CCGTPPs) based on the Brayton cycle gas turbine and the Rankine cycle steam system, constitute an efficient and reliable power generation technology. Nowadays, CCGTPPs are in widespread use all over the world. In Greece, CCGTPPs became attractive alternatives for power generation after the introduction of natural gas to the Hellenic Energy System as an additional energy source. More particularly, instead of conventional lignite fired thermal power plants, natural gas fired CCGTPPs will be installed to cover new capacity demands. It is also worth noting that CCGTPP solutions are highly recommended for islands (Crete, Rhodes) with increased capacity demands, in which both light and heavy fuel oil are actually in use for power generation.

Thus far, Public Power Corporation (PPC) has installed three CCGTPPs. One unit is in operation in the island of Crete (132,2 MW ISO), with two Gas Turbines (GTs), two Heat Recovery Steam Generators (HRSGs) and one Steam Turbine (ST). Two more units have been installed in Lavrion; one of 173 MW net ISO capacity, with two GTs, two HRSGs and one ST; the other of 550.2 MW, with three GTs, three HRSGs and one ST. One more unit, of 477.3MW, is under construction in the Komotini Industrial Area, with two GTs, two HRSGs and one ST. The Lavrion and Komotini units are natural gas fired. It is worth noting that, since 2001, the Greek electrical power industry switched to unregulated business so individuals companies got permission for the construction and operation of natural gas fired power plants, based on CCGTPP technology.

According to what exposed so far, the design of thermo-economically optimal CCGTPPs is of primary importance for power producers. Thermal analysis of a CCGTPP is possible through software based on fundamental thermodynamic principles; on the other hand, cost prediction may rely on empirical correlations and/or available market prices. In this paper, a detailed thermal model and a quite simple economical model will be incorporated in an evolutionary search algorithm and an automated tool for the design of new CCGTPPs will be demonstrated. The search algorithm used is a Genetic Algorithm (GA) for single- and multi-objective optimization problems. The latter is handled through Game Theory inspired enhancements to the GA based search yielding the so-called optimal Pareto front. With two objectives (viz. electrical efficiency and investment cost), the Pareto front members can be envisaged as compromises between high-cost/high-efficiency and low-cost/low-efficiency designs. A series of papers appeared in the literature addressing the practical implementation of deterministic or stochastic optimization methods in relevant problems, [1], [2], [3], [4]. However, most of them are in the field of cogeneration and only a few papers deal with CCGTPPs. In the present paper, two CCGTPPs will be optimized, both of them equipped with dual-pressure HRSGs: the first is a diesel-oil fired plant of 100 MWe total power output and the second a natural gas fired plant of about 400 MWe. Emphasis will be given to the optimization of the HRSG.

2 CCGTPP THERMO-ECONOMIC ANALYSIS AND OPTIMIZATION – THEORETICAL ASPECTS

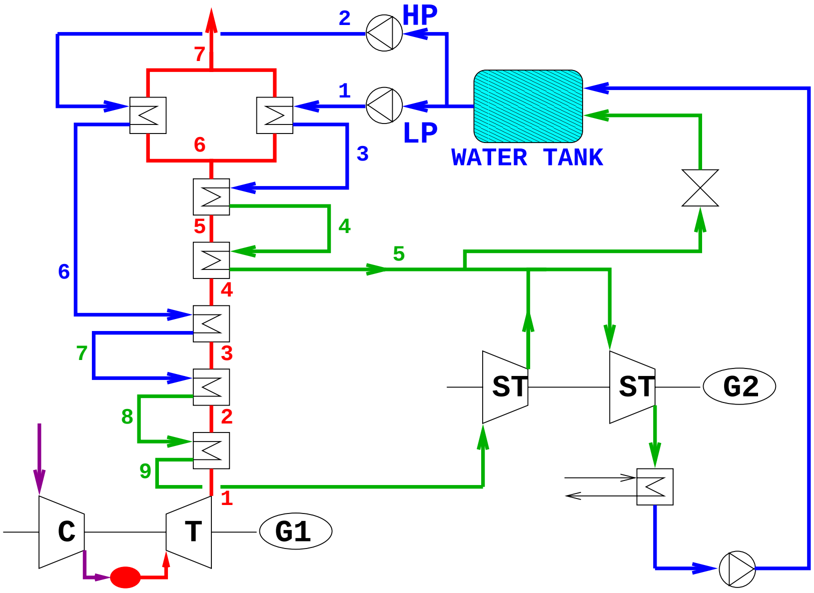

Fig. 1 Diesel oil fired, dual-pressure CCGTPP.

2.1 CCGTPP Configurations – Fixed Data and Design Variables Identification - Constraints

In this section, two CCGTPP configurations with dual-pressure HRSGs will be described. Fixed data as well as design variables involved in the optimization process will be identified. In the diesel oil fired CCGTPP, the flue gas is cooled in the HRSG by traversing seven high and low-pressure heat exchangers, from the GT exhaust up to the stack, as shown in the left part of fig. 1. In the HRSG, superheated high-pressure (HP) and low-pressure (LP) steam is generated, which is then expanded in the ST to produce mechanical work. The latter is finally converted to electrical power. After its expansion, steam is condensed and the condensate feeds the feedwater tank. From the tank, preheated water is driven by the HP and LP pumps to the HRSGs. The natural gas fired configuration (fig. 2) is further equipped with a condensate preheater and the steam fed to the water tank is extracted from a LP steam-turbine stage.

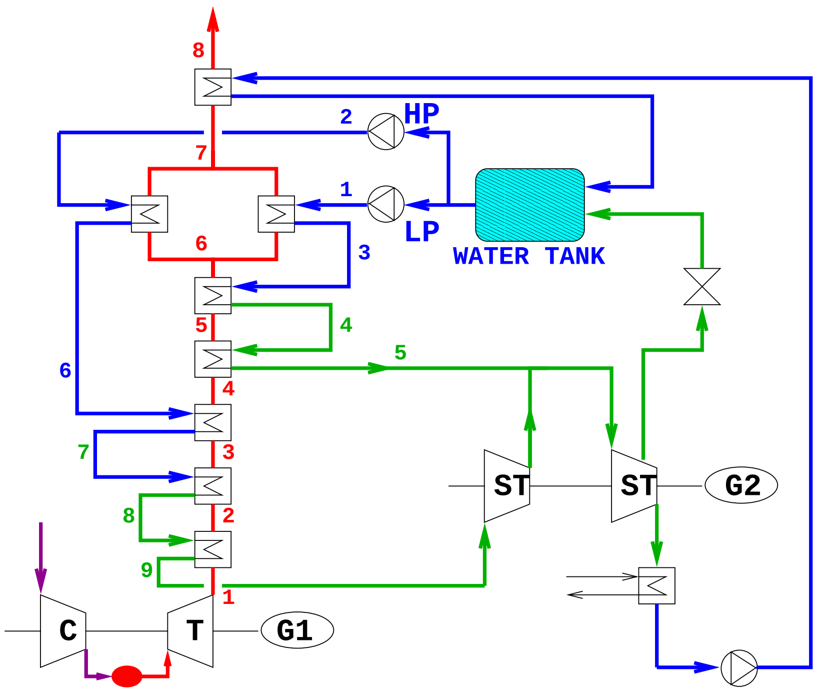

Fig. 2 Natural gas fired, dual-pressure CCGTPP with condensate preheater.

The power produced at the ST is calculated using a simple thermodynamic analysis of the water/steam cycle; energy and mass balance equations are written for all of the cycle components (heat exchangers, feedwater tank, ST, condenser). Thermodynamic properties of water, steam and exhaust gases are properly modeled [5].

In both design problems, the GTs are considered to be given; these have been chosen among the available market models.

For the diesel oil fired CCGTPP, two identical GTs are used. As previously stated, the GTs power output (70 MW, in total) as well as their electrical efficiency (40%) are fixed; fixed are also the exhaust gas mass flow (265 kg/sec) and its temperature (440^{o}C). The HP and LP steam turbine isentropic, mechanical and electrical efficiencies are fixed to typical market values. The steam pressure at the low-pressure ST outlet has a constant value which was computed a priori by considering the minimal waste heat in the condenser. In view of the above, the design variables in the diesel oil fired CCGTPP are listed below:

- HP steam pressure
- LP steam pressure
- superheated HP steam temperature

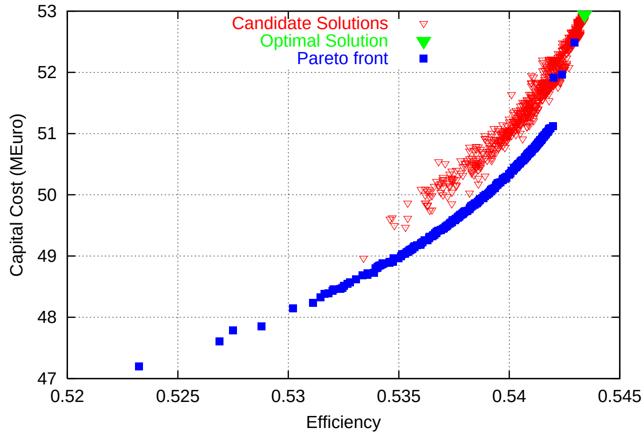

Fig. 3 Diesel oil fired CCGTPP: optimal Pareto front and optimal solution computed from the single-objective (CCGTPP efficiency) optimization; points marked as “candidate solutions” correspond to the configurations which have been evaluated in the course of the single-objective optimization.

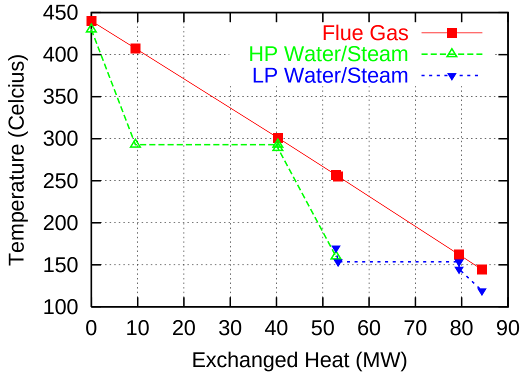

Fig. 4 Diesel oil fired CCGTPP: temperature plots at characteristic locations along the HRSG, for the optimal solution computed from the single-objective optimization tool; pinch points and the constraints satisfaction can be viewed.

- feedwater temperature at the inlet to the HP evaporator
- feedwater temperature at the outlet from the first HP economizer
- feedwater temperature at the inlet to the LP evaporator
- superheated LP steam temperature
- steam pressure fed to the water tank
- exhaust gas mass flow ratio (percentage of mass flowrate traversing the LP economizer)
- exhaust gas temperature at the HRSG outlet.

A number of constraints are implicit to such a thermal problem. These constraints are related to the requirement that flue gas temperatures should exceed (often, by a certain safety margin) the water or steam temperatures at characteristic points along the HRSG. For instance, requirements such as $T_{gas,3} \geq T_{water,7} + 8^o$, $T_{gas,6} \geq T_{water,3} + 8^o$, etc. are to be imposed. Solutions which violate these constraints are not feasible; however, as it will become clear below, during the optimization phase, constraints will be handled in a “relaxed” way.

For the second problem examined, viz. the natural gas fired CCGTPP, one GT of 260 MW power output and 38% electrical efficiency has been used. The exhaust gas mass flow is equal to 615 kg/sec at 600^{o}C. HP and LP steam turbine efficiencies are fixed to the same values as in the previous problem. Over and above to the design variables defined in the previous problem, the steam extraction pressure from the LP steam turbine and the exhaust gas temperature at the inlet to the condensate preheater are allowed to vary in the course of the optimization method, the latter being governed by a number of similar constraints.

2.2 CCGTPP Thermo-Economic Optimization

Both problems are first treated as single- and then as multi-objective optimization problems. In all the single-objective computations, the CCGTPP efficiency was considered to be the optimization target. The search

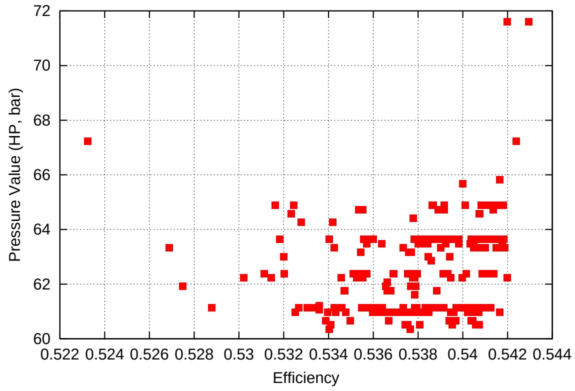

Fig. 5 Diesel oil fired CCGTPP: HP pressure values, for the optimal Pareto front solutions.

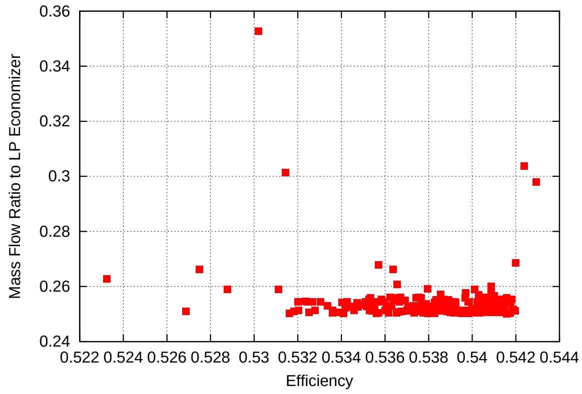

Fig. 6 Diesel oil fired CCGTPP: percentage of flue gas mass flow rate traversing the LP economizer, for the optimal Pareto front solutions.

of the optimal configuration was undertaken by Genetic Algorithms (GAs, [6]). GAs are search algorithms based on the theory of adaptive systems and the Darwinian theory for the evolution of species. They have found widespread use in a variety of applications (applications in aeronautics from the same research group can be found in [7]), using either real or binary coding for the free variables. During the evolution from generation to generation, individuals selected from the current population using deterministic (fitness value based) or stochastic criteria or even a combination of them are allowed to produce offspring through recombination. The simplest concept is to allocate reproductive trials to the current individuals in proportion to their fitness; however, fitness ranking, fitness scaling, etc may also be used. Recombination is based on crossover operators which control the exchange of parental segments. Finally mutation is applied which, with a quite small probability, allows for the random alteration of genetic material in the offspring.

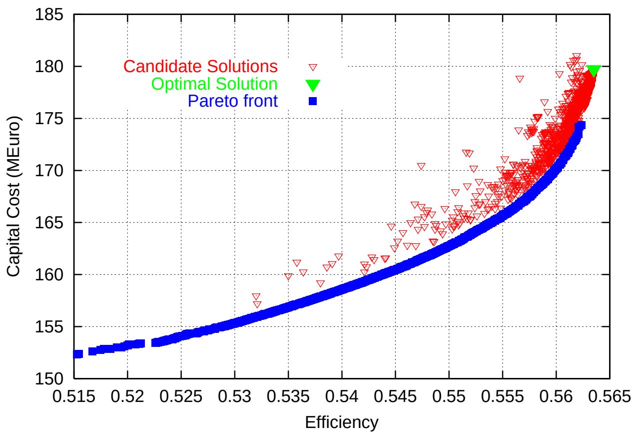

Fig. 7 Natural gas fired CCGTPP: optimal Pareto front and optimal solution computed from the single-objective (CCGTPP efficiency) optimization; points marked as "candidate solutions" correspond to the configurations which have been evaluated in the course of the single-objective optimization.

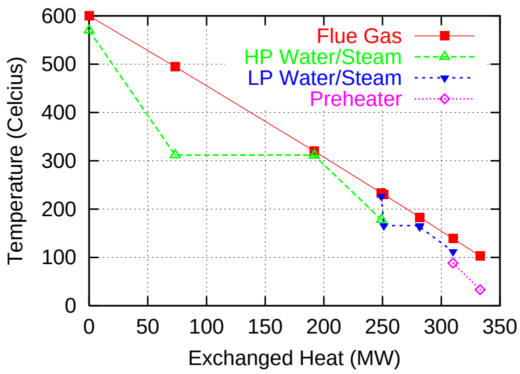

Fig. 8 Natural fired CCGTPP: temperature plots at characteristic locations along the HRSG, for the optimal solution computed from the single-objective optimization tool; pinch points and the constraints satisfaction can be viewed.

The widespread use of GAs can easily be explained due to their indisputable advantages. They are robust and may capture the global optimal solution, without being trapped to local optima. Any existing evaluation software can be incorporated and with no modification at all. The only known drawback of GAs is the high number of calls to the evaluation software they require; however this is not the case herein since, in our applications, the evaluation software bears almost negligible computing cost.

In the literature, we may find contradictory statements on the superiority of binary or real coding. According to the minimal alphabet coding rule, binary coding seems to offer the maximum number of schemata per bit of information. In contrast, the advantage of real coding is that high--cardinality alphabets theoretically contain more schemata and that problem--tailored genetic operators can be devised. In the present study, binary and real coding have both been tested and led to almost identical solutions (at least considering the stochastic nature of

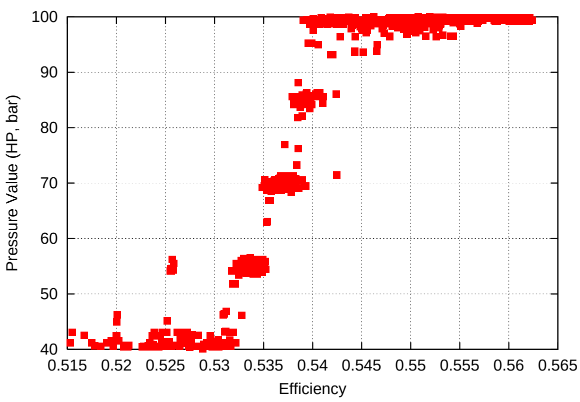

Fig. 9 Natural gas fired CCGTPP: HP pressure values, for the optimal Pareto front solutions.

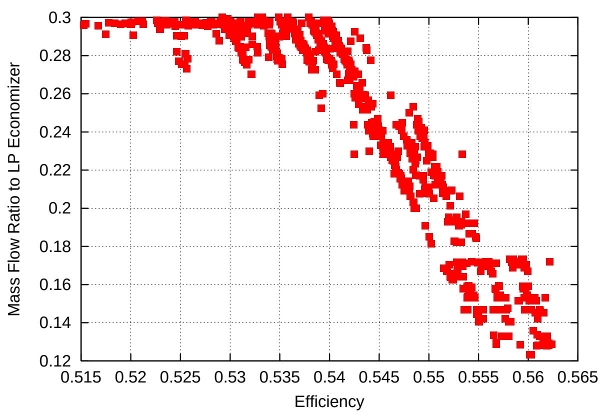

Fig. 10 Natural gas fired CCGTPP: percentage of flue gas mass flow rate traversing the LP economizer, for the optimal Pareto front solutions.

the search algorithm).

The two-objective optimization are carried out using GAs enhanced with Non-Dominated Sorting and Sharing Techniques [8]. This technique, which includes elements from Game Theory, provides a front of possible solutions to the problem, in the sense that none of them dominates over the rest with respect to all of the objectives. Sharing is used to spread solutions over the front (as in [7] or [8]); a sharing function, computed in the variable- or the objective-space, penalizes solutions over the same front that are close together and promotes diversity. So, practically, the two objectives (considering a minimization problem, these are the inverse of the CCGTPP efficiency and the capital cost) are first used to locate the non-dominated individuals by repetitively classifying them into a number of fronts. Non-feasible candidate solutions, i.e. CCGTPP configurations which violate one or more of the aforesaid temperature constraints, which certainly come out during the evolutionary process are not eliminated; they are taken into consideration after penalizing them by multiplying their efficiency by the ratio of the two temperatures involved in each inequality constraint.

In the two-objective computations, the capital cost of a plant to be erected is due. A first estimation of the total capital cost of a CCGTPP results from the investment cost of the main equipments of the plant, [8], viz. the GT, the HRSG and the ST. The cost of a GT is estimated from its power P_{GT} and it is equal to $C_{GT} \cdot (P_{GT})^{0.89}$ where C_{GT} is a constant value derived from the cost of known GTs. The cost of a ST is a function of its power P_{ST} according to the relation $C_{ST} \cdot (P_{ST})^{0.9}$. Finally, the cost of a HRSG is calculated from the total area of the heat exchangers of the HRSG according to the relation $C_{HRSG} \cdot (\text{heat exchanger area})^{0.85}$.

To calculate the total capital cost of the CCGTPP the sum of GT, HRSG and ST costs is multiplied by an empirical coefficient so as to include also the cost of the additional electromechanical equipment as well as the cost of civil works. Since this multiplier is constant, it does not affect the results of the optimization process and is used only in order to present realistic figures of investment costs.

3 CCGTPP DESIGNS – RESULTS AND DISCUSSION

3.1 The Diesel Oil Fired CCGTPP

Fig.3 illustrates both single- and multi-objective optimization results. We recall that in the single-objective optimization runs, the objective is to minimize the inverse of plant efficiency. However, in fig. 3, the optimal solution is plotted using as ordinate the corresponding capital cost value, which was computed afterwards without taken it into consideration during the optimization task. The optimal solution for the diesel oil fired plant is shown as a single point in the upper-right corner of fig. 3 (see caption). It corresponds to 54.34% efficiency, 25.1 MW steam turbine power and 52.9 MEuro investment cost. In the same figure, the cloud of points terminating to the optimal solution corresponds to the numerous candidate solutions generated and evaluated during the genetic evolution. It is worth mentioning that the abscissa (i.e. efficiency) of some of these points does not necessarily correspond to the real value of the CCGTPP efficiency, since this might have been multiplied by one or more penalty factors (temperature ratios) if this configuration violates one or more of temperature constraints. For the single-objective optimal solution, flue gas-water and flue gas-steam temperature variations along the HRSG (vs. the exchanged amount of heat) are plotted in fig. 4. In the same figure, the satisfaction of constraints can also be observed along with the minimum temperature differences between flue gas and steam at the two pinch points.

Fig. 3 illustrates also the Pareto front computed with identical search space limits for the design variables, using the inverse of efficiency and the capital cost as the two objectives that are to be driven to their minimal values. This front consists of configurations with efficiencies in the range from 0.52 up to 0.545 and with capital costs in the range from 47 MEuro to 51 MEuro. None of the Pareto front members violates any of the constraints. As expected, the Pareto front envelops the candidate solutions generated using the single-objective GA. However, the front does not extend to the upper-right part of the graph, where the single-objective optimal solution is located. This is quite reasonable since the “strength” of the search algorithm is spread over so many solutions lying on the front.

Figs. 5 and 6 illustrate the HP steam pressure values (allowed to vary between 20 and 100 bar) and the flue gas mass flow ratio to the LP economizer (allowed to vary between 25% and 45%) computed for the Pareto front members. It can be seen that the HP steam pressure of the optimal front solutions varies within a range of values far from the allowed upper bound and increases only at the right most edge of the front, where maximum efficiency and cost are attained. On the other hand, the mass flow ratio to the LP economizer remains almost constant.

3.2 The Natural Gas Fired CCGTPP

Fig.7 summarizes the optimization results for the natural gas fired power plant through the single- and multi-objective handling software. As in the previous case, the optimal solution is located in the upper-right corner of fig. 7 and corresponds to 56.35% efficiency, 125.5 MW steam turbine power and 179.7 MEuro capital cost. This point is obtained upon completion of the evolution of the populations, i.e. after having examined numerous

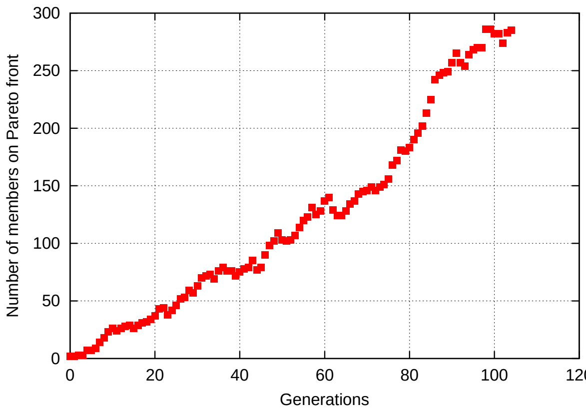

Fig. 11 Diesel oil fired CCGTPP: evolution of the number of solutions computed on the optimal Pareto front.

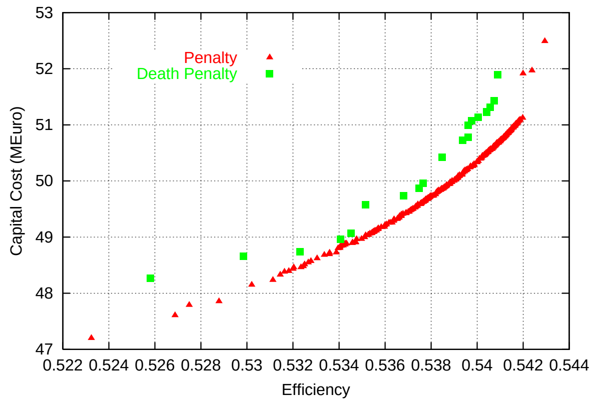

Fig. 12 Diesel oil fired CCGTPP: optimal Pareto fronts computed by (a) penalizing (lowering) the efficiency of infeasible solutions (marked as "Penalty") and (b) eliminating infeasible solutions (marked as "Death Penalty").

candidate solutions shown as a cloud of points in the same figure. The exchanged heat -temperature diagram for the HRSG is given in fig. 8, for the optimal solution.

The Pareto front computed using two objectives (inverse of efficiency and cost) is also illustrated in fig.7. For this case, the efficiency range of the Pareto front is 0.515 to 0.565 and the corresponding capital cost range 152 to 180 MEuro. Same remarks as in the diesel oil fired configuration are valid. However, it is interesting to examine the HP steam pressure values (fig.9) and the flue gas mass flow ratios to the LP economizer (fig.10) that correspond to the Pareto front members. In contrast to the diesel oil fired case, the HP steam pressure values of the left most Pareto front members approach the lower bound of the search space whereas, for the right most members, pressure values close to the upper bound are obtained. In between, there is an abrupt transition area from the lower to the upper bound. Concerning the flue gas mass flow ratios to the LP economizer of the Pareto front members, values near the upper bound are observed for efficiencies less than 0.54 whereas for higher efficiencies the ratio degrades linearly.

3.3 Discussion

In this section, a couple of issues related to the implementation of GAs in the single- and multi-objective constrained optimization problems will be discussed.

The diesel oil fired CCGTPP problem was examined using GAs with 50-member populations. The maximum number of evaluations was 5000, defining thus the stopping criterion for the algorithm. The optimal Pareto front obtained after 104 generations consists of 256 individuals. Fig. 11 illustrates the evolution of the front size vs. the number of generations; as it can be seen from this figure, the front size generally increases, though (about 4000-5000 evaluations) this has practically reached its "optimal" shape and any further enrichment in new front members simply yields a denser front.

For the same problem, the constraint handling is investigated further. Two different methods are compared.

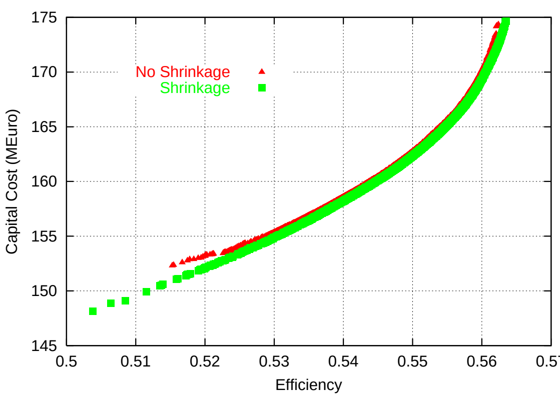

Fig. 13 Natural gas fired CCGTPP: Optimal Pareto fronts computed with and without shrinking the search spaces for the design variables.

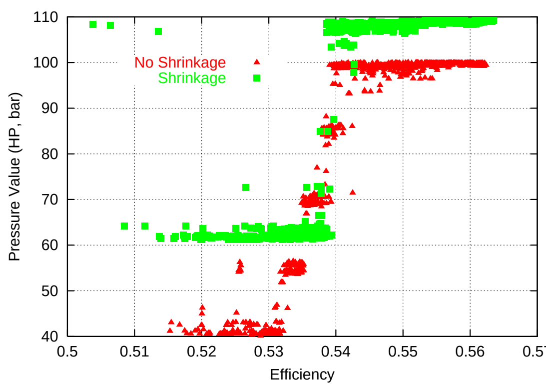

Fig. 14 Natural gas fired CCGTPP: HP pressure values, for the optimal Pareto front solutions, computed with and without shrinking the search spaces for the design variables.

The first (marked as "penalty", which is the one used to obtain any result presented thus far), is based on the multiplication of the plant efficiency by a penalty factor which is proportional to the ratio of temperatures involved in the non-satisfied inequalities. The second one is the so-called "death penalty", which eliminates any infeasible individual in the course of genetic evolution. The comparison of the resulting fronts, fig. 12, demonstrates the superiority of the first method. The so-computed front is very dense and dominates the sparse front members computed using the death penalty method. It is also important to mention that, during the test of the death penalty method, the population size was set to 300 (instead of 50) since otherwise the number of surviving feasible solutions during the first, highly explorative generations was almost zero and the GA could not afford the situation. However, the same test in the natural gas fired plant did not demonstrate the same behavior. Though results are not presented in this paper, it should be stressed out that almost identical fronts were obtained using both constraint handling methods. The different behavior of the two methods is attributed to differences in the configuration and to the differently defined search spaces.

The last issue that is worth discussing is the possible implementation of the so-called "shrinkage" technique in the genetic optimization. This stands for a technique developed and used in the past by the second author, [10], which allows the redefinition of the search space whenever the optimal solution lies close to the user-defined bounds and stagnates during a number of generations. The width of the new search space is a percentage of the current width (about 80% is a typical value) and the new search space is centered to the current optimal solution. The use of the shrinkage technique can be used in case that the search space is not strictly imposed by other factors. For the natural gas fired plant, figs. 13 and 14 compare results obtained with and without shrinking the search spaces. With the same computing cost (12000 evaluations) the use of shrinkage improved the quality of the optimal Pareto front which is now denser and dominates the Pareto front computed without this technique. One of the main reasons for improving the plant efficiency is that shrinkage allows the use of higher HP steam pressure values, as shown right most part of the front, fig. 14.

4 SUMMARY - CONCLUSIONS

In this paper, the use of GAs and game theory methods for the design of optimal Combined Cycle Gas Turbine Power Plants, either diesel oil or natural gas fired, was presented. Single-objective designs aimed at higher plant efficiency. Two-objective designs, however, aimed at the higher plant efficiency with the lower investment cost, which are in fact two contradictory targets. This problem was faced by delivering a front of feasible solutions, none of which was dominated by any other front member in terms of both objectives. The decision about what configuration to choose among them depends on various criteria, their discussion being beyond the scope of this paper. Constraints related to temperature differences at various locations within the Heat Recovery Steam Generator were handled by defining and using proportionate penalty factors. Thus, infeasible solutions which temporarily appeared in the evolution process were not eliminated but were free to participate in the formation of the next generation of candidate solutions, though with an artificially lower efficiency. This strategy proved to outperform the death penalty strategy, which might fail whenever a great number of infeasible solutions appear in the genetic evolution; this was the case of the diesel oil fired plant problem. Finally, through minor modifications, the present method gives also the possibility to work with loosely defined search space bounds and, through the shrinkage technique, to get optimal solutions outside the initially defined search spaces. Though such a treatment might not always be desired, in some cases (for instance in brand new designs) this might settle the matter of a priori unknown bounds.

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