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Optimizing the start-up operations of combined cycle power plants using soft computing methods

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Abstract

In this article we present a study on the application of soft computing methods for the start-up optimization of a combined cycle power plant. In particular, we use fuzzy sets in order to get a fitness function providing the effectiveness in the lattice [0,1] (zero bad, one excellent) of the given start-up regulations. Then we applied a genetic algorithm to find the best start-up regulations. Experimentation shows that the solution found remarkably improves the solution given by the process experts.

Keywords: Multiobjective optimization, fuzzy sets, genetic algorithms, power plants management.

1 Introduction

Combined cycle power plants (CCPPs) are a combination of a gas turbine and a steam turbine generator for the production of electric power in a way that a gas turbine generator generates electricity and the waste heat is used to make steam to generate additional electricity via a steam turbine. For such plants, one of the most critical operations is the start-up stage because it requires the concurrent fulfilment of conflicting objectives (for example, minimize pollutant emissions and maximize the produced energy). The problem of finding the best trade-off among conflicting objectives can be arranged like an optimization problem. This class of problems can be solved in two ways: with a single-objective function managing the other objectives, like thermal stress, as constraints, and with a multi-objective approach.

At present, the problem of CCPP start-up optimization has been tackled in the first way using simulators. As example, in [1] through a parametric study, the start-up time is reduced while keeping the life-time consumption of critically stressed components under control. In [2] an optimum start up algorithm for CCPP, using a model predictive control algorithm, is proposed in order to cut down the start-up time keeping the thermal stress under the imposed limits. In [3] a study aimed at reducing the start-up time while keeping the life-time consumption of the more critically stressed components under control is presented.

In the last decade the application research of soft computing (SC) methods has become one of the most important topics in industrial applications. In particular, in the field of industrial turbines for energy production, fuzzy set theory [4] has been mainly applied to fault diagnosis [5–9], sensor fusion [10] and control. Particularly, in the last area in [11] it is proposed a fuzzy control system in order to minimize the steam turbine plant start-up time without violating maximum thermal stress

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limits. In [12] it is presented a start-up optimization control system which can minimize the start-up time of the plant through cooperative fuzzy reasoning and a neural network making good use of the operational margins on thermal stress and pollutant emissions. Moreover, Evolutionary Algorithms (EAs) have already been applied to the CCPPs optimization. [13] proposes an application of an evolutionary algorithm to the minimization of the product cost of complex CCPPs where both the design configuration (process structure) and the process variables are optimized simultaneously. [14] applies an evolutionary algorithm to optimize the feedwater preheating section in a steam power plant from a thermodynamic viewpoint. [15] is concerned with the techno-economic optimization of investments in combined cycle gas power plants.

In all the reported examples the global start-up optimization is never handled, therefore, in order to solve this problem, in this work we propose a new approach based on SC methods where we combine fuzzy sets and EAs. Thus, for each single objective we define a fuzzy set and then we properly combine them in order to get a new objective function taking into account all the operational goals. Then we used it as the objective function of an EA and we compared the solution found with the one given by the process experts.

The article is structured as follows: in Section 2 we describe the problem we are dealing with, Sections 3 and 4 report the details of the method we carried out, Section 5 shows experimental results and finally Section 6 draws the conclusions.

2 The CCPPs

Gas and steam turbines are an established technology available in sizes ranging from several hundred kilowatts to over several hundred megawatts. Industrial turbines produce high-quality heat that can be used for industrial or district heating steam requirements. Alternatively, this high temperature heat can be recovered to improve the efficiency of power generation or used to generate steam and drive a steam turbine in a combined-cycle plant. Therefore, industrial turbines can be used in a variety of configurations:

- Simple cycle (SC) operation which is a single gas turbine producing power only
- Combined heat and power (CHP) operation which is a simple cycle gas turbine with a heat recovery heat exchanger which recovers the heat in the turbine exhaust and converts it to useful thermal energy usually in the form of steam or hot water
- Combined cycle (CC) operation in which high-pressure steam is generated from recovered exhaust heat and used to create additional power using a steam turbine (Figure 1).

The last combination produces electricity more efficiently than either gas or steam turbine alone because it performs a very good ratio of transformed electrical power per CO_2 emission. CC power plants are characterized as the 21st century power generation by their high efficiency and possibility to operate on different load conditions by reason of the variation in consumer load. CC plants are highly complex systems but with availability of high powerful processors and advanced numerical solutions, there is a great opportunity to develop high performance simulators for modelling energy systems in order to consider various aspects of the system.

The start-up scheduling is as follows (Figure 2). From zero to time t_0 (about 1200 s) the rotor engine velocity of the gas turbine is set to 3000 rpm. From time t_0 to t_1 the power load is set to 10 MW and then the machine keeps this regime up to time t_2. All this initial sequence is fixed. From time t_2 to t_3 (about 3600 sec) the machine must achieve a new power load set point which has to be set optimal and then the machine has to keep this regime up to time t_4. The time lag t_4–t_3 is variable

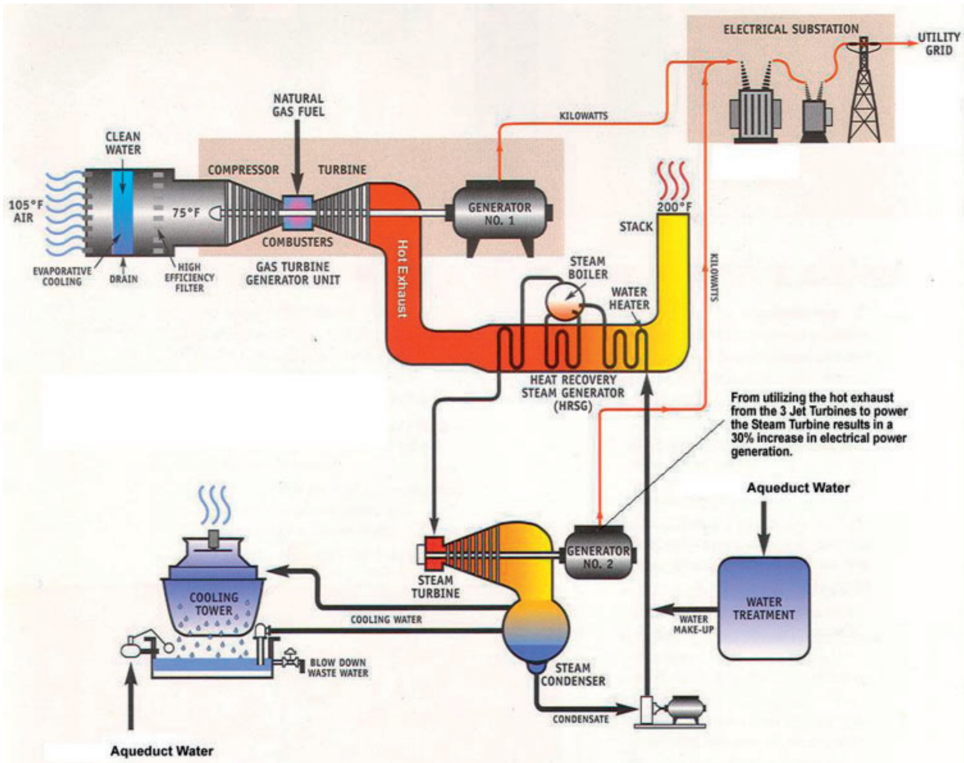

FIG. 1. CCPP.

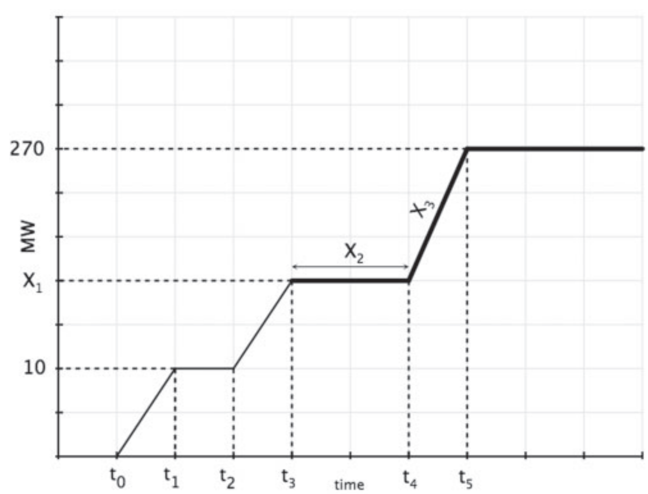

FIG. 2. CCPP start-up operations.

TABLE 1. Input control variables

Variable	Meaning	Operating range
X1	Intermediate power load set point (MW)	[20–120]
X2	Intermediate waiting time (s)	[7500– 10000]
X3	Gas turbine load gradient (MW/s)	[0.01–0.2]
X4	Steam turbine load gradient (%/s)	[0.01–0.2]

TABLE 2. Output variables

Variable	Meaning	Operating range
Y1	Start-up time (s)	[11700–29416]
Y2	Fuel consumption (Kg)	[53000–230330]
Y3	Energy production (KJ)	[$6.45*10^8$–$4.56*10^9$]
Y4	Pollutant emissions ($Mg*sec/Nm^3$)	[12, 32]
Y5	Thermal stress	[8, 3939]

TABLE 3. Fuzzy sets

Fuzzy set	Membership function $\mu_{Fi}(y_i)$	Variable	Weight w_i	t	c	Goal
F1	1-Sigmoid	Y1	0.2	8000	110000	Min
F2	1-Sigmoid	Y2	0.1	800	16200	Min
F3	Sigmoid	Y3	0.1	$0.4*10^9$	$1.8*10^9$	Max
F4	1-Sigmoid	Y4	0.3	2	25	Min
F5	1-Sigmoid	Y5	0.3	20	150	Min

and during this interval the steam turbine starts with the rotor reaching the desired velocity. Then the turbines have to reach at time t_5 the normal power load regime (270 MW for the gas turbine) according to two load gradients which are variable depending on the machine.

In Tables 1 and 2, we report the process control variables (input) and the output variables to be monitored.

Therefore, the problem we are tackling has four inputs and five outputs and in order to optimize the overall start-up operations, the following objectives need fulfilling:

- minimize time
- minimize fuel consumption
- maximize energy production
- minimize pollutant emissions
- minimize thermal stress

3 Fuzzy sets definition

In this paragraph, we describe how with the support of the process experts, we defined the single fuzzy sets (Table 3) over the output variables (Table 2) and how we composed them in order to get a cost function ranging in the lattice [0,1]. Therefore, we got an index representing the global start-up performance (0 = bad, 1 = excellent).

Where c and t are the parameters of the sigmoid function

$$\text{Sigmoid} = \frac{1}{1+e^{\frac{c-x}{t}}} \tag{3.1}$$

Different membership functions with several parameter settings have been tried out over a data set of diverse starting conditions where, for each of these, each objective was marked by the experts. Thus, the choice reported in the previous table is the one which best fitted, after fine manual parameter tuning, the marks given by the experts.

Consequently, the fuzzy sets have been composed through a weighted sum and the result is a fuzzy set whose membership function is

$$\mu(y_1, y_2, y_3, y_4, y_5) = w_1\mu_{F1}(y_1) + w_2\mu_{F2}(y_2) + w_3\mu_{F3}(y_3) + w_4\mu_{F4}(y_4) + w_5\mu_{F5}(y_5) \tag{3.2}$$

This composition has been finally chosen because we found out that for this problem the intersection was too restrictive (only one objective with a low value is sufficient to severely affect the whole performance) and the union was too lazy (only one objective with a high value is sufficient to have a high global performance). Thus, we have eventually applied the weighted sum operator, which is an intermediate composition between intersection and union, which gives a global performance proportional to the optimality degree of each single objective.

The values of the weights w_i has been given by the process experts according to the importance of the corresponding objectives.

4 Evolutionary optimization

With the class of evolutionary computation (EC) we refer to a population-based stochastic optimization process inspired by the principles of natural evolution. EC have been successfully used in many optimization problems, their ability to perform a parallel search exploring the solution space and exploiting the best solutions found is critical for the most complex problems. In this case the genotype represents a start-up sequence encoding the variables described in Table 2.

We implemented a real-coded genetic algorithm (GA) with a number vector's genotype representing the normalized process input variables. We choose real values for encoding because of the continuous search space and in this way we avoided the discretization due to binary coding. The normalization of the input variables, between 0 and 1, is to make mutation operators parameters heterogeneous given that the input variables differ strongly in magnitude (see Table 2).

A Gaussian mutation operator is implemented adding to the genotype genes a random value following a normal distribution, i.e.:

$$g_m^i = g^i + N(0, \sigma) \tag{4.1}$$

where g^i is the i-th gene and σ is the standard deviation of the gaussian distribution. We used a Uniform Crossover with a binary Tournament Selection and then as fitness function we use the fuzzy function shown in (3.2), which is within the range [0, 1]. Two termination criteria have been set for this algorithm: maximum number of generations and a target fitness value.

TABLE 4. GA parameters

Parameter	Value
Population Size	20
Mutation Rate	0.5
Mutation Amplitude	0.1
Crossover Rate	0.9
Tournament Pool Size	2
Maximum number of generations	1000
Target fitness value	0.83

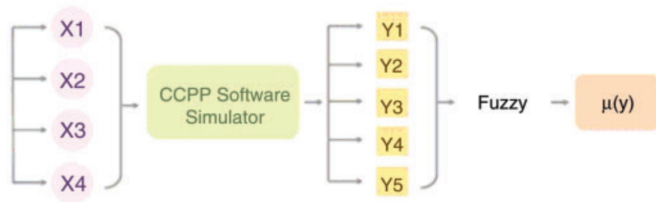

FIG. 3. Fitness evaluation.

The selected algorithm parameters after a set of experimentations are shown in Table 4.
Fitness is calculated according to (3.2) using a software simulator (Figure 3):

5 Experimentation

Experimentation has been carried out by means of a software simulator carried out by AnsaldoEnergia[1], a Finmeccanica company, which is the Italian leading thermoelectric power plants producer.

We performed 400 runs of the algorithm using the GA interfaced with the software simulator used to compute the fitness function value. In Figure 4 it is shown the distribution of the best solutions fitness values at the end of the experimentations and the same for the number of generations.

The average number of generations is 414, i.e. the number of function calls is 8280 because at each generation a number of fitness evaluations equal to the population size is performed.

In Table 5, we compare the solution given by the experts (Exp) to the optimal one (Opt) given by the proposed approach.

The nominal variation of the last row is calculated as

$$\frac{Y\mathrm{opt}_i - Y\mathrm{exp}_i}{\max_i - \min_i} * 100 \tag{5.1}$$

where Yopt_i is the outcome of the optimal solution, Yexp_i the outcome of solution given by human experts, $\max_i$ and $\min_i$ are the maxima and minima operating range values of the five output variables (Table 2).

At first glance, it is clear that from these results the overall start-up performance has been remarkably improved (from 0.53 to 0.83). This is mainly due to the fuzzy fitness function which properly combines different conflicting objectives providing the optimization algorithm with the good directions to search. Without it the EA wouldn't have achieved the optimal balance among contradictory

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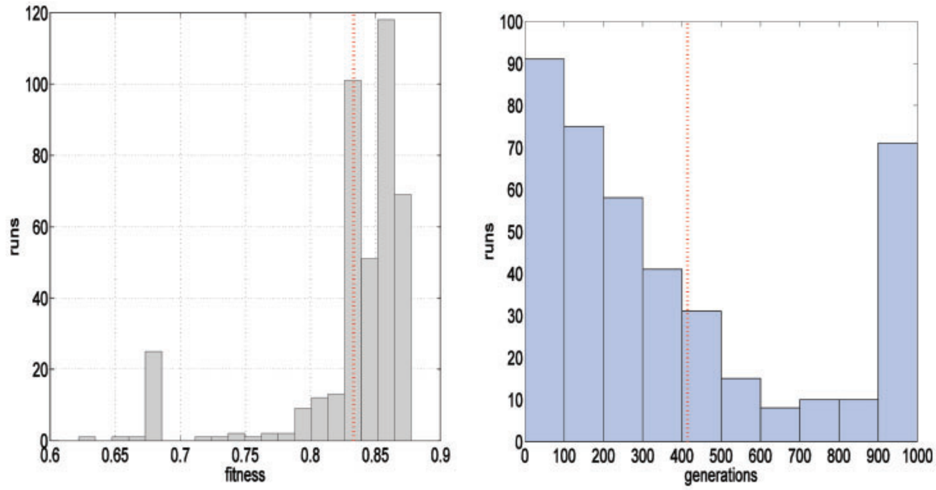

FIG. 4. GA: Distribution of fitness values (left) and number of generations (right).

TABLE 5. Output comparison

	Y1	Y2	Y3	Y4	Y5	Performance
Exp	21070	143557	$2.5*10^9$	25	10	0.53
Opt	14800	99282	$1.5*10^9$	21.6	54	0.83
Nominal Variation	−35%	−25%	−25%	−17%	+1.0%	+0.3

goals. Moreover, it would be interesting to compare the proposed EA with the fuzzy performance to other optimization techniques with the same fitness definition as well as with a performance modelled by crisp sets.

In particular, the solution found cuts considerably down the start-up time (−35%), consumption (−25%) and emissions (−17%) keeping the thermal stress very low. This solution has been actually acknowledged by the experts as the optimal balance for the start-up problem.

At present, the main drawback of the proposed method is the use of a complex software simulator each time the GA performs a fitness evaluation. Thus, the execution of the algorithm turns out to be very time consuming because the number of fitness evaluations, needed to explore the solution space and find the optimal solutions, can be very high. In applications where fitness function is particularly time-consuming, like the one in this work, the solution can be that of carrying out fitness approximation methods.

6 Conclusion

In this article, we presented a study on the application of soft computing methods for the overall optimization of the CCPPs start-up. Our method is based first on the fuzzyfication of the output process variables, in order to get a fitness value in the lattice [0,1] providing the effectiveness (zero bad, one excellent) of the given solution (start-up regulations), and then to run a genetic algorithm in order to find out the optimal solution.

In the problem we faced, human operators are able to optimize only one objective, the one which is the most critical (in CCPPs this is the thermal stress), but the problem is multi-objective. Therefore, the main novelty of the work is the proposed application of fuzzy sets in order to handle all the objectives and thus to optimize the global start-up operations.

We tested the methodology on a software simulator and we found a solution (0.83) which remarkably improves the solution given by the process experts (0.53). The main reason for this is mainly due to the fact that the fuzzy fitness definition keeps into account all the objectives and the solution found has been acknowledged by the experts to be the optimal balance among conflicting objectives.

As future work, we are willing to compare the proposed approach to multi-objective genetic algorithms as well as to carry out fitness approximation methods in order not to use the complex software simulator that we used for this experimentation.

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