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Soft computing based optimization of combined cycled power plant start-up operation with fitness approximation methods

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ABSTRACT

This paper describes an application of fuzzy-logic and evolutionary computation to the optimization of the start-up phase of a combined cycle power plant. We modelled process experts' knowledge with fuzzy sets over the process variables in order to get the needed cost function for the genetic algorithm (GA) we used to obtain the optimal regulations. Due to the obvious impossibility to test the resulting inputs on the real plant we used a complex software simulator to evaluate the performance of the solutions. In order to reduce the computational load of the whole procedure we implemented for the genetic algorithm a novel fitness approximation technique, cutting by 98% the number of fitness evaluations, i.e. software simulator runs with respect to a genetic algorithm without fitness approximation. Moreover, solutions found by our methods remarkably improved the solutions given by the plant operators.

1. Introduction

Combined cycle power plants (CCPP) 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, minimise pollutant emissions and maximise 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 Ref. [1] through a parametric study, the start-up time is reduced while keeping the life-time consumption of critically stressed components under control. In Ref. [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 Ref. [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 fuzzy set theory [4] has become one of the most important topics in industrial applications. In particular, in the field of industrial turbines for energy production, it has been mainly applied to fault diagnosis [5,6], sensor fusion [7] and control. Particularly, in the last area in Ref. [8] it is proposed a fuzzy control system in order to minimize the steam turbine plant start-up time without violating maximum thermal stress limits. In Ref. [9] 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 NO_x emissions. In all the reported examples it is clear that the global start-up operations are not optimised. Therefore, in this work we propose an approach based on fuzzy sets in order to overcome the exposed drawbacks. 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. We applied this method to a large artificial data set of different start-up conditions and we compared the best solution we found with the one given by the process experts.

Our idea is to use an evolutionary algorithm in order to optimise the whole start-up process, this because EA will offer an easy and adaptable way to find an optimum in a complex function without the need of a deep knowledge of the process. This kind of algorithms are able to self-learn the trend of the objective function and seek for the best solutions in few steps compared with other optimization algorithms. In order to let the EA to work fine, we need to define a unique function that can represent the state of our process, considering a lot of variables (consumption, emissions, time, etc.) and

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merging them in a representative value. For this reason we have used a fuzzy set based fitness function which allows us to group many variables into a single value.

EAs, as stochastic techniques, need an high number of evaluations of the fitness function in order to find the optimal solution and when the function is expensive (computationally or economically), as in real-world applications, it could be approximated to reduce the number of time-consuming calls, see Ref. [10] for a survey about this kind of approach.

Evolutionary algorithms have already been applied to the combined cycles power plants optimization. An application of an evolutionary algorithm to the minimization of the product cost of complex combined cycle power plants is proposed in Ref. [11] where both the design configuration (process structure) and the process variables are optimized simultaneously. Ref. [12] applies an evolutionary algorithm to optimize the feedwater preheating section in a steam power plant from a thermodynamic viewpoint. A power plant design problem is analyzed in Ref. [13] and the optimization, concerning techno-economic aspects, is carried out through multiobjective evolutionary algorithms.

Our main contribution is the application of soft computing methods to the global start-up optimization of such plants with a method for reducing the computational load of the optimization process. This paper is organized as follows. Section 2 introduces the optimization problem, describing the start-up phase and the involved parameters. Section 3 describes the fuzzy sets modelling of the problem described in the previous section. Descriptions of the EAs approaches, with and without the approximation method, are given in Sections 4 and 5 and the results are presented in Section 6. Section 7 provides some concluding remarks.

2. The combined cycle power plant start-up optimization problem

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): a single gas turbine producing power only.
- Combined heat and power (CHP): 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.

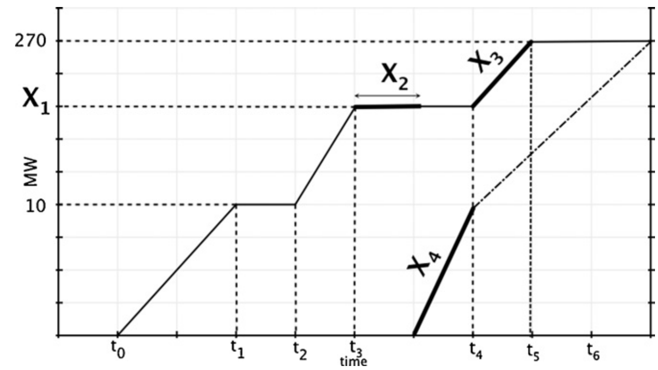


Fig. 1. Combined cycle power plant start-up operation.

- Combined cycle (CC): high pressure steam is generated from recovered exhaust heat and used to create additional power using a steam turbine.

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 plants are characterized by high efficiency and possibility to adapt operation to different load conditions but they are an highly complex system which need the availability of powerful processors and advanced numerical solutions to develop high performance simulators for modelling purposes.

2.1. Start-up phase

The start-up scheduling diagram is shown in Fig. 1. 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 s) the machine must achieve a new power load, the initial set point load indicated as X_1, 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 and is another variable to optimize, here called X_2, 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; the gradient for both, compressor and steam rotors, are the last optimization variable that we should use: X_3 and X_4. The sequence for that procedure is that first steam turbine grow up with X_4 gradient, then the turbine rotor can grow up following the X_3 gradient.

Table 1
Process input and output variables.

Input variables

Variable	Meaning	Operating range	Unit measure
X1	Intermediate power load set point	[20, 120]	MW
X2	Intermediate waiting time	[7500, 10,000]	s
X3	Gas turbine load gradient	[0.01, 0.2]	MW/s
X4	Steam turbine load gradient	[0.01, 0.2]	%/s

Output variables

Variable	Meaning	Operating range	Unit measure
Y1	Start-up time	[11,700, 29,416]	s
Y2	Fuel consumption	[53,000, 230,330]	Kg
Y3	Energy production	[6.45×10^8, 4.56×10^9]	KJ
Y4	Pollutant emissions	[12.24, 32.58]	Mg s/N m^3
Y5	Thermal stress	[8, 3939]	–

Table 2
Fuzzy sets.

Fuzzy set	Membership function (μ_{F_i})	Variable	Weight (w_i)	t	c	Goal
F1	1 – sigmoid	Y1	0.2	8000	110,000	Min
F2	1 – sigmoid	Y2	0.1	800	16,200	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

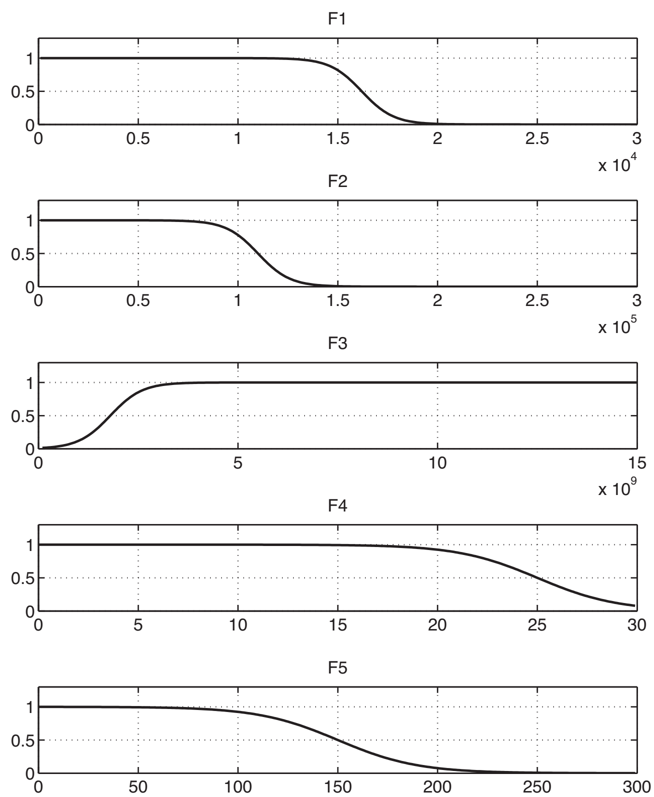


Fig. 2. Fuzzy sets diagram.

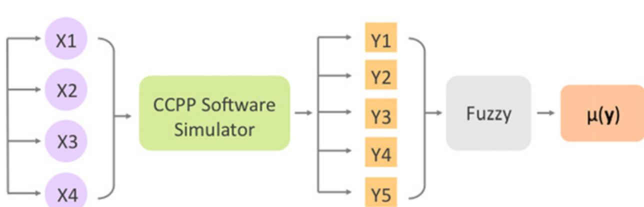


Fig. 3. Diagram of the fitness model.

In Table 1 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 optimise the overall start-up operations, the following objectives need fulfilling (Figs. 2–5):

1. Minimise startup time (Y1).
2. Minimise fuel consumption (Y2).
3. Maximise energy production (Y3).
4. Minimise pollutant emissions (Y4).
5. Minimise thermal stress (Y5).

In Fig. 6 a diagram with the correlation between each pair of objectives is shown, some linear relations are visually evident, e.g. between fuel consumption (Y2) and energy production (Y3).

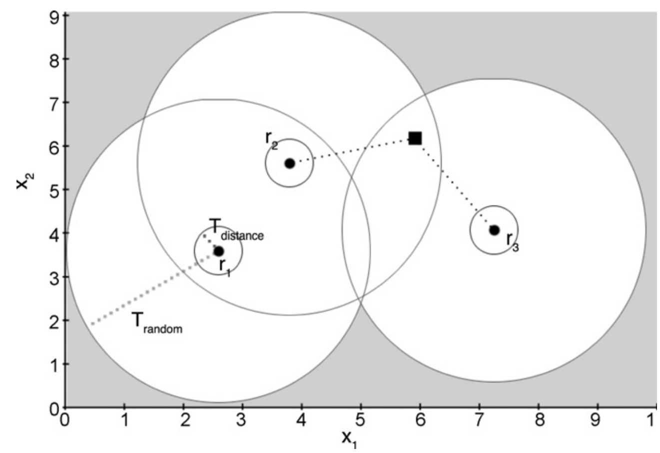


Fig. 4. Example of the proposed approximation method: fitness value of requested point (square) is computed interpolating the fitness value of its neighbours (r_2 and r_3), i.e. all the points below the RANDOM_THRESHOLD (T_{random}) radius. The grey space is the part of the solution space where fitness value is computed randomly. $T_{distances}$ represents DISTANCE_THRESHOLD.

3. Fuzzy sets definition

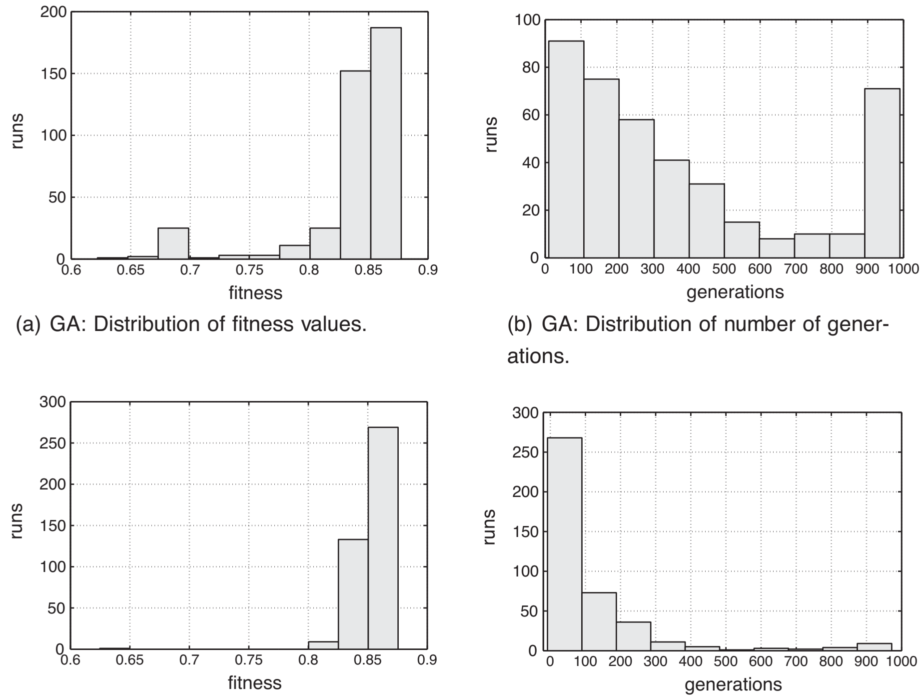
In order to allow a process of optimization through a black-box techniques such as evolutionary algorithms, we need to define a unique numerical quantity that can evaluate the whole process of start-up, giving an index of how the given configuration is effective, in harmony with the desired trend of the output values. The computed quantity will be used as a fitness value for our individuals in the evolutionary environment. In collaboration with process experts, we first defined the single fuzzy sets (see Table 2) over the output variables (see Table 1 and Fig. 2) and we composed them in order to get a cost function ranging in the range [0, 1]. Therefore, we got an index representing the global start-up performance. For every membership function, each linked to one of the process output, we used sigmoid membership functions with two parameters c and t:

$$\text{sigmoid}(x) = \frac{1}{1 + \exp(c - x/t)} \qquad (1)$$

These functions are used simply as they are, if we wish to maximize the value, or used in a complementary mode, if we wish to minimize the output. The resulting fuzzy output has the following

Table 3
GA parameters.

Parameter	Value
Population size	20
Mutation rate	0.5
Mutation amplitude (σ)	0.1
Crossover rate	0.9
Tournament pool size	2
Max. number of generations	1000
Target fitness value	0.83



(a) GA: Distribution of fitness values.

(b) GA: Distribution of number of generations.

(c) GA with Fitness Approximation: Distribution of fitness values.

(d) GA with Fitness Approximation: Distribution of number of generations.

Fig. 5. Results of experimentations.

Table 4
Experimentation results.

Genetic algorithm (GA)	
Success rate	79%
Average number of generations	414
Average fitness value	0.83
Average CPU time per simulation	2070 h
GA with fitness approximation	
Success rate	98%
Average number of generations	144
Average fitness value	0.85
Average CPU time per simulation	36 h

form:

$$\mu(y_1, y_2, y_3, y_4, y_5) = \sum_{i=1}^{5} w_i \mu_{F_i}(y_i) \tag{2}$$

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 finally applied the weighted sum operator, which is a good trade-off between intersection and union, which gives a global performance proportional to the optimality degree of each single objective. To obtain the weight for each fuzzy set in the previous composition we worked with the designer of this kind of turbo gas, in order to achieve a good combination of weights that can represent the theoretical directions that they try to reach when working on the start-up of this kind of process. With this function we try to work in cooperation with human behaviour, learning from the experience, instead of replacing the human factor.

4. Optimization with evolutionary computation

In this section we describe the optimization of the cost function defined in the previous section by the means of an evolutionary algorithm.

Evolutionary computation methods have been used successfully in many optimization problems. The ability to perform a parallel search exploring in the solution space and exploiting the best solutions found is critical for the most complex problems. In our case the solution's genotype represents a start-up sequence encoding the variables described in Table 1.

We implemented a real-coded genetic algorithm with a number vector's genotype representing normalized process' input variables. We choose a real-values 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 inputs' variables differ strongly in magnitude (see Table 1). A Gaussian mutation operator is implemented adding a random value following a normal distribution to the genotype's genes, i.e.:

$$g_m^i = g^i + \mathcal{N}(0, \sigma) \tag{3}$$

where g^i is the ith 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 Eq. (2) (see Fig. 3 for a diagram of the fitness model), 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. Algorithm's parameters selected after a set of experimentations are shown in Table 3.

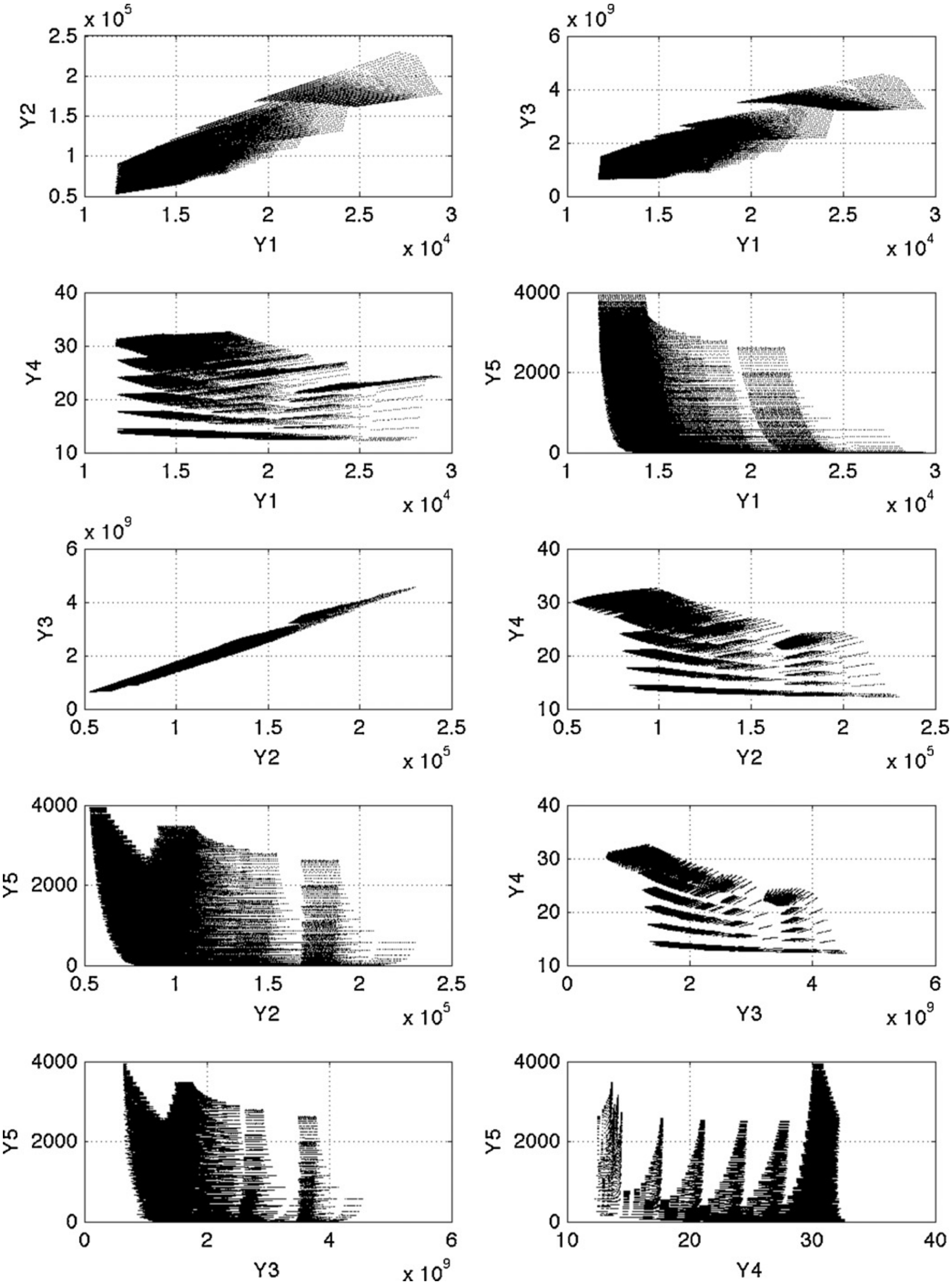


Fig. 6. Plot of relations between objectives.

Table 5
Comparison between solution provided by plants manager and best solutions of both approaches.

	Y1	Y2	Y3	Y4	Y5
Experts	21,070	143,557	2.5×10^9	25	10
GA (values)	14,800	99,282	$1\ 5 \times 10^9$	21.6	54.3
GA with FA (values)	16,569	115,070	1.86×10^9	18.8	78.4
GA (improvement)	35%	25%	−25%	17%	−1%
GA with FA (improvement)	25%	16%	−16%	30%	−2%

5. Approximating the fitness function for computation load reduction

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Algorithm 1Calculate Approximate Fitness $f(x)$
Require: point x, archive R
1:distance(x,R^x)< DISTANCE_THRESHOLD then
2: $j \leftarrow$ nearest (x,R^x) Get the index of the nearest point from x inside the archive $f(x) \leftarrow R_j^f$
3: $f(x) \leftarrow R_j^f$
4:**else**
5:distance(x,R^x)< RANDOM_THRESHOLD then
6:$N \leftarrow$ neighbourhood(x) Get the points which distance from x is below the threshold
7: $f(x) \leftarrow \sum_{i \in N} \frac{1}{1+\text{distance}(x, R_i^x)} R_i^f$
8:**else**
9: $f(x) \leftarrow$ random(0,1)
10: end if
11:end if

Evolutionary algorithms applied to computational expensive problems, like the one considered in this paper, could be time consuming due to their stochastic nature. To tackle this issue we implemented an approximation method (pseudo-code is shown in algorithm 5) for the fitness with the purpose of reducing the number of fitness function calls. All the points evaluated are stored into an archive R containing the point's n-dimensional coordinates and their fitness value in the last column, with the following form:

$$\mathbf{R} = [\mathbf{R}^x \mathbf{R}^f] = \begin{bmatrix} x_{11} & \dots & x_{1n} & f_1 \\ x_{21} & \dots & x_{2n} & f_2 \\ \vdots & \vdots & \vdots & \vdots \\ x_{k1} & \dots & x_{kn} & f_k \end{bmatrix} \tag{4}$$

When the fitness value of a new point is requested, a search within the archive is performed to find a similar point, considering two points similar if their euclidean distance is below a certain threshold (DISTANCE_THRESHOLD), in this case we assume for the requested point the same fitness value of the similar one already inside the archive. Differently, if there is not a similar point, the method computes the fitness values in two ways: randomly, if the nearest point inside archive distance is above a threshold (RANDOM_THRESHOLD), otherwise interpolating the fitness value of the nearest points (see Fig. 4). The interpolated fitness of the requested point is obtained from a weighted sum of the nearest points' fitness values considering weights inversely proportional to the euclidean distance of the points (see line 7 in algorithm 5). At the end of each generation the best individual of the population is evaluated with the real fitness function and added to the archive.

The archive represents the information we have collected on the fitness model and the proposed method tries to approximate new points' fitness with an interpolation unless the point is too distant. In such case, randomness represents the lacks of information about that part of the fitness space and a random value enhances the possibility of explore unknown areas with the probability related to the fitness of the best individual. In fact, especially at the beginning of the evolution, a random value has an higher probability to have a better fitness value than the best solution already into the population.

6. Results

We performed 400 runs of the algorithm using the GA interfaced with the software simulator used to compute the fitness function value. In Fig. 5 is shown the distribution of the best solutions' fitness values at the end of the experimentations and in Fig. 5 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.

The same number of runs is performed with the fitness approximation method, in Fig. 5(c) and (d) are shown respectively the distribution of the best solutions' fitness values and the same for the number of generations at the algorithm's stop. In Table 4 there is a comparison of the performance of both the approaches, with and without fitness approximation.

For DISTANCE_THRESHOLD and RANDOM_THRESHOLD we used respectively a value of 0.01 and 0.1, chosen after a set of preliminary tests.

In the fitness approximation scheme we perform a single fitness function evaluation for each generation (the best solutions at the end of the generation), in this way an average run needs only 144 fitness function calls instead of the 8280 needed without fitness approximation.

We compared the optimal solutions found by both approaches with the solution provided by the experts, in Table 5 we show the value of the five output variables (see Table 1) for each solution and improvement of such solution calculated as:

$$d_i = \frac{|Y_i - Y_i^e|}{\text{range}_i^{\max} - \text{range}_i^{\min}} \tag{5}$$

with Y_i^e is the ith output variable of the solution provided by experts, $\text{range}_i^{\max}$ and $\text{range}_i^{\min}$ the operative ranges of the ith variable (see Table 1). The sign of the deviation is put positive if the deviation is considered an improvement, negative vice versa.

7. Conclusions

When in an optimization problem the objectives are conflicting and subject to operational constraints, like in industrial applications, black-box approaches like evolutionary algorithms might give good performances due to their stochastic nature, assuming that an effective problem's representation could be found. Multi-objective optimization problems can be coped with two different methodologies: Pareto-based optimization and single-objective reduction with expert knowledge modelling. In the first case, considering all the objectives with the same priority, a Pareto front containing all the non-dominated solutions is obtained, in our case the application of this multi-objective approach was not considered successful due the complexity of the problem and other factors (see Ref. [14] for further details). Fuzzy logic-based approach permits to model the experts' knowledge, reducing the problem to a single-objective one which can be tackled with classical evolutionary algorithms.

A major drawback for stochastic algorithms such EAs can be the high number of fitness evaluations needed in order to explore the solution space and find the optimal solutions. In applications where fitness function is particularly time-consuming, like the one in this paper, we can try to interpolate the fitness value of the new points from the solutions already evaluated assuming a static environment where the fitness value of a solutions does not change during the time. Despite the interpolation we implemented is not complex it provides better performances in the application of a genetic algorithm, leading to a reduction of the overall number of fitness function evaluations avoiding the evaluations of similar or identical solutions.

In our tests we obtained a strong reduction of the number of fitness evaluations and a consequent decrease of the time needed for the optimization of the start-up phase from 2070 h to 36 for 100 simulations. However, both the approaches lead to a start-up sequence which is better than the already used one according to the plants operator and the results which show (see Table 5) an improvement in three objectives and a worsening (in energy production).

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