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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.

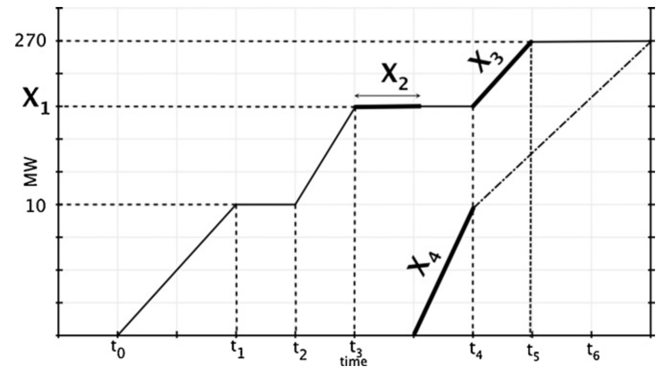

Fig. 1. Combined cycle power plant start-up operation.

- 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.

Variable	Meaning	Operating range	Unit measure
Input variables			
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			
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]	–