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PERFORMANCE OF GAS TURBINE POWER PLANTS CONTROLLED BY MULTIAGENT SCHEME

Lorenzo Dambrosio
DIMeG Sez. Macchine ed Energetica
Polytechnic University of Bari
Via Re David 200, 70125 Bari
Email: dambrosio@poliba.it

Marco Mastrovito
DIASS
Polytechnic University of Bari
Viale del Turismo 8, 74100 Tarantoi
Email: m.mastrovito@poliba.it

Sergio M. Camporeale
DIMeG Sez. Macchine ed Energetica
Polytechnic University of Bari
Via Re David 200, 70125 Bari
Email: camporeale@poliba.it

ABSTRACT

In latter years the idea of artificial intelligence has been focused around the concept of a rational agent. An agent is a (software or hardware) entity that can receive signals from the environment and act upon that environment through output signals. In general an agent always tries to carry out an appropriate task. Seldom agents are considered as stand-alone systems. Their main strength can be found in the interaction with other agents in several different ways in a multiagent system.

In the present work, multiagent system approach will be used to manage the control process of a single-shaft heavy-duty gas turbine in Multi Input Multi Output mode.

The results will show that the multiagent approach to the control problem effectively counteracts the load reduction (including the load rejection condition) with limited overshoot in the controlled variables (as other control algorithms do) while showing good level adaptivity readiness, precision, robustness and stability.

NOMENCLATURE

a agent action.
k iterative index variable.
o agent perception.
$\mathbf{u}$ fuzzy logic output vector.
$\mathbf{z}$ fuzzy logic input vector.
$\hat{z}$ mean value of the input fuzzy Gaussian membership function.
$\tilde{\mathbf{A}}$ antecedent fuzzy sets.
$\hat{A}$ mean value of the antecedent fuzzy Gaussian membership function.
N number of fuzzy logic rules.
R fuzzy logic base of rules.
β consequent fuzzy sets.
μ fuzzy logic membership function.
π agent policy function.
σ variance of fuzzy Gaussian membership function.
DARMA Deterministic Auto Regressive Moving Average.
FLS Fuzzy Logic System.
MAS Multi Agent System.
PID Proportional Integrative Derivative controller .
MIMO Multi Input Multi Output.
VCE fuel valve actuator.
VIGV Variable Inlet Guide Vanes.

INTRODUCTION

The dynamic behaviour of a Gas Turbine is inherently nonlinear and characterized by a large number of internal parameters. The design of the feedback characteristics of the control system generally requires a linearized model of the system in the *s-space* or in the state variable space. The linearized model is obtained for a steady-state point and is generally applicable only in a limited range around such a steady state condition (Ref. [1,2]). Typically the solution is based on the linearization of the system for various operating points and the controller parameters are found for these operating points using, e.g., linear quadratic regulator theory. Non-linear control algorithms are more suitable to determine the control law for regulating non-linear systems. In fact, for Gas Turbine power plant a number of such algorithms have been proposed. A few of them can be divided in two main branches: non-deterministic and knowledge-based. The One Step Ahead Adaptive and the Weighted One Step Ahead Adaptive (Ref. [3–5]) algorithms refer to non-deterministic family. Such algorithms employ the Least Square Algorithm parameter estimator in order to estimate the coefficients of a *DARMA* model of the controlled system. In particular, the One Step Ahead controller determines the control law from the *DARMA* model, trying to annihilate the control error one step in the future. On the other hand, the Weighted One Step Ahead Adaptive control algorithm considers a penalty associated with the control effort by means of an appropriate cost function (Ref. [5, 6]). In Ref. [7] a non-linear control technique for Gas Turbine based on self-tuning control parameters is described. Finally, Ref. [8, 9] deal with model reference predictive control algorithms.

As far as the knowledge-based methods are concerned, they usually are based on fuzzy logic system and artificial neural networks structure, or on the model reference approach. The first one employs a set of fuzzy rules (supplied by expert or by numerical/experimental data) that perform a mapping between the input and the output variables (Ref. [10,11]). The second method need to be trained (by means of input-output samples) in order to operate the input-output mapping (Ref. [12]). Finally, the latter employs a model reference of the controlled system in order to evaluate the appropriate control law (Ref. [13, 14]).

All the foregoing algorithms present, in different degree, good characteristics in terms of adaptivity readiness, precision, robustness stability, etc. Nevertheless, it is arduous that a centralized single algorithm shows good performance for all the foregoing features. Usually a compromise choice has to be made. A way to overcome such limitations is represented by the multiagent approach. Recently the idea of artificial intelligence has been focused around the concept of a rational agent. An agent is a (software or hardware) entity that can receive signals from the environment and act upon that environment through output signals. In general an agent always tries to carry out an appropriate task; such an agent is called a rational agent. Generally agents are not considered as stand-alone systems. Their main strength can be found in the interaction with other agents in several different ways. Therefore a system composed of a group of agents that can potentially interact with each other is called a multiagent system (*MAS*) (Ref. [15, 16]).

The *MAS* approach has been used to manage the control process of a single-shaft heavy-duty gas turbine. In particular, the *MAS* control scheme has been applied in Multi Input Multi Output (*MIMO*) mode. Indeed, in the single-shaft heavy-duty gas turbine application, the output variables are represented by the rotational speed (which is closely related to the power frequency) and by the stack temperature (which affects the overall efficiency); on the other hand the control variables are represented by the combustion chamber fuel flow *MAS*s and by the variable inlet guide vanes (*VIGV*), the plant being assumed to undergo sudden variations of the electric load.

The agents employed in the proposed *MAS* are based on a fuzzy logic scheme. Such a choice allowed the authors, on one hand, to deal with agents featured by an adequate level of flexibility, thanks to the fuzzy logic nature of each agent; on the other hand, since each agent has not to face the entire control problem, it has been possible to maintain a low level of complexity for the fuzzy logic structure of each agent.

In the Results section, it will be shown that the *MAS* approach to the control problem, applied to the single-shaft heavy-duty gas turbine effectively counteracts the load reduction (even during the load rejection condition) with limited overshoot in the controlled variables (as other control algorithms do) while showing good level adaptivity readiness, precision, robustness and stability.

MULTIAGENT SYSTEM

Agents constituting a *MAS* present a number features that affect the behaviour of the multiagent system. Such features deal with agent design, environment, perception, control and knowledge. For a complete description of all the agents characteristics refer to Ref. [15, 16].

The *MAS* approach provides a number of potential advantages with respect the single-agent approach:

- to decompose a problem, allocate subtasks to agents, and synthesize partial results;
- to offer a distributed perceptual information of the environment;
- to offer a decentralized control allowing an efficient coordination mechanisms among agents;
- to enable agents to properly react to the actions, plans, and knowledge of other agents.

As stated earlier, an agent is anything that can be viewed as perceiving its environment through input signal and acting upon that environment through output signal. Each agent has to accomplish such an action performing an appropriate task. The performance measure is typically defined by the user (the designer of the agent) and reflects what the user expects from the agent in the task at hand. In other words, an agent has to face a decision-making problem. This means that an agent must choose an action, a_t, basing, not only upon the current perception, o_t, of the world in which the agent is embedded, but also taking into account the past history of perceptions, o_τ, and actions, a_τ:

$$\pi(o_1, a_1, o_2, a_2, \ldots, o_{t-1}, a_{t-1}, o_t) = a_t, \tag{1}$$

where π is called *policy*. However, the complete history can consist of a very large (even infinite) number of perception action pairs, which can vary from one task to another. Such an approach would require large amount of memory, beyond the computational effort due to actual computation of π. To overcome such a computational complexity, it is possible to define simpler policies. A particular simple policy is represented by the so-called *reactive* or *memoryless* policy that takes the following form:

$$\pi(o_t) = a_t. \tag{2}$$

Agents using such a policy, called reflex agents, are employed in the proposed *MAS* .

An important issue regarding the way an agent works with is the definition of the policy function that carries out the mapping between perception and action. In the present paper, the authors defined the policy function as a fuzzy logic system. The reasons for such a choice lie on the two following aspects:

- to deal with agents featured by an adequate level of flexibility, thanks to the fuzzy logic nature of each agent;
- to maintain a low level of complexity for the fuzzy logic structure of each agent, since each agent has not to face the entire optimization problem.

In this context, the perception is considered by the fuzzy logic system as the input vector whereas the fuzzy logic output represents the agent action. In the following section a concise description of the fuzzy logic system will be outlined.

FUZZY LOGIC SYSTEM

The Fuzzy Logic System (*FLS*) employs a set of N fuzzy linguistic rules. These rules may be provided by experts or can be extracted from numerical data. In either cases, such rules are expressed as a collection of $IF-THEN$ statements. Therefore, a fuzzy rule base, R, containing N fuzzy rules can be expressed as:

$$\begin{aligned} &R = [Rule_1, \ldots, Rule_j, \ldots, Rule_N], \\ &Rule_j : IF\ \left[\mathbf{z}\,\mathrm{is}\,\tilde{\mathbf{A}}\right]\ THEN\ [\mathbf{u}(k)\,\mathrm{is}\,\beta_i], \end{aligned} \tag{3}$$

where k refers to the iterative index variable and $\mathbf{z} = [z_1, ..., z_l]^T$ are all of the l fuzzy inputs to the *FLS* (that coincide with the agents perception). On the other hand, $\mathbf{u}(k) = [u_1(k), \ldots, u_m(k)]^T$ and $\beta_i = \left[\beta_i^1, \ldots, \beta_i^m\right]^T$ are the *FLS* fuzzy output (agent output) and the consequent fuzzy set, respectively. In the antecedent of rule $Rule_i$, the term $\tilde{\mathbf{A}} = [\tilde{A}_i^1, \ldots, \tilde{A}_i^l]^T$ represents the vector of the fuzzy sets referring to the input fuzzy vector $\mathbf{z}$. The membership functions of both the antecedent and consequent, $\tilde{\mathbf{A}}$ and β, respectively, have been chosen to be Gaussian; the inference engine employs a *product inference* for the rule implication. Finally the fuzzification and defuzzification processes have been carried out by means of a Gaussian fuzzifier and a *height* defuzzifier, respectively. Gaussian fuzzifier, in particular, acts as a filter for the input uncertainties. Moreover Gaussian model for the fuzzy sets membership function allows a simple implementation for the fuzzy output as outlined in the following. On these basis the output variable, $\mathbf{u}(k)$, of the *FLS* can be obtained by means of the so called *fuzzy basis function*, as described in details by Mendel (Ref. [17]):

$$\mathbf{u}(k) = \frac{\sum_{i=1}^{N} \beta_i \prod_{j=1}^{l} \mu_{Q_i^j}[z_{j,max}(k)]}{\sum_{i=1}^{N} \prod_{j=1}^{l} \mu_{Q_i^j}[z_{j,max}(k)]}, \tag{4}$$

where,

$$\mu_{Q_i^j}[z_j(k)] = \mu_{z_j}(k)\,\mu_{\tilde{A}_j^i}(k) \tag{5}$$

and

$$z_{j,max}(k) = \frac{\hat{z}_j \sigma^2{}_{z_j} + \hat{A}_j^i \sigma^2{}_{\tilde{A}_j^i}}{\sigma^2{}_{z_j} + \sigma^2{}_{\tilde{A}_j^i}} \tag{6}$$

is the value of the *j-th* input that maximizes Eq. (5). The maximization of Eq. (5) represents the *supremum* operation in the *sup-star* composition of the *i-th* rule [17]. In Eq. (6) $\hat{z}_k$ and σ_{zk} are the mean value and the variance of μ_{zk}. Likewise, $\hat{A}_k^j$ and $\sigma_{\tilde{A}_k^j}$ are the mean value and the variance of $\mu_{\tilde{A}_k^j}$.

AGENT DESCRIPTION

In this section a brief description of the agents employed to manage the control process of a single-shaft heavy-duty gas turbine will be outlined. In particular, the *MAS* control scheme has been applied in *MIMO* mode, where the controlled variables are represented by the shaft rotational speed (power frequency) and stack temperature (related to the overall gas turbine efficiency); on the other hand, the fuel mass flow (*VCE*) and the Variable Inlet Guide Vanes (*VIGV*) have be chosen as control variables.

As illustrated in Fig. 1, the *MIMO* control problem has been faced by means of two independent *MAS*: *MAS1* and *MAS2*, for the rotational speed and stack temperature, respectively. Both the *MAS*es share the same internal structure (Fig. 2) composed by four agents based on a fuzzy policy function. For such reason, in

Figure 1. GAS TURBINE CONTROL SIGNAL LAYOUT.

Figure 2. MULTIAGENT SCHEME.

the following, a description of each agent composing the generic *MAS* will be outlined, omitting any direct reference to the shaft rotational speed and/or stack temperature control problem for the sake conciseness.

Starting from classical control applications which adopt ordinary (or scheduled) *PID* controllers, the first agent, called *AGENT1*, performs a fuzzy selection of the *PID* parameters according to the requested electrical power. In other words, considering a scheduled *PID* controller, whose parameters have been optimized, by using Ziegler-Nichols method, for different load conditions, the *AGENT1* operates a fuzzy mapping between the requested electrical load and the *PID* parameters. The *PID* parameters employed into the *AGENT1* base of rules have been optimized taking into account, not only the controller promptness and accuracy, but also the rate of approach of controlled variable to the reference value. In this perspective, the perception for the *AGENT1* is represented by electrical power demand whereas its action is the *PID* parameter selection (Fig. 2). Such a definition of the *AGENT1* allows to smoothly varying the *PID* parameters within the schedule intervals. For the present application *AGENT1* is featured by 4 and 5 fuzzy rules for the *IGV* and *VCE* controllers, respectively.

The second agent, called *AGENT2* , has been added to amplify the *PID* parameter in order to increase the controller promptness. However, such amplification cannot be the same in all the working conditions. In fact, as sketched in Fig. 2, *AGENT2* performs a mapping between the absolute value of relative control error and its first time derivative on one side and the amplification factor on the other side. In this way, e.g., if the control error is large and its first time derivative is positive (the control error is increasing), then the amplification has to be large in order reduce the control error. On the other hand, if the control error is large and its first time derivative is negative (the control error is decreasing), then the amplification has to be small in order to avoid undesired oscillating behaviour. Therefore, in *AGENT2* , the perception is represented by the control error and its first time derivative whereas the action consists in the selection of the amplification factor. *AGENT2* decisions are based on a 48 rules, which cover the range $[0,5]$ for absolute value of relative control error and $[-0.1,0.1]$ for its time derivative. The corresponding multiplier values range in $[1,2.8]$, $[0.02,2]$, and $[1,20]$, for proportional, integral and derivative actions respectively.

The third agent, *AGENT3* , presents the same perception of *AGENT2* , but it does not affect the *PID* parameters. On the contrary its action affects directly the control law. In fact, it performs a direct derivative action, adding an extra control effort only when the control error is large and its first time derivative is positive (the control error is increasing). In all the other conditions it presents no action. Its policy function is based on 107 rules, which cover the range $[0.8,1.2]$ for the relative control error and $k_1 * [-1,1]$ for the time derivative of its absolute value, where k_1 assumes the values 20 and 100 for the *VCE* and *IGV* controller, respectively. The corresponding output values ranges in $k_2 * [-0.1,0.1]$, where k_2 assumes the values 10 and 1 for the *VCE* and *IGV* controller, respectively.

The last agent, *AGENT4* , provides the steady state value of the control variable according to the electrical load demand. In other words, *AGENT4* , carries out an open-loop fuzzy mapping between the external load (disturbance) and the control variable, by means of 13 fuzzy rules. It does not present any feedback validation concerning the control error. Therefore, even if, on one hand, *AGENT4* promptly supplies almost the entire control effort needed in steady state condition for a given load variation, on the other hand, it is unable to generate appropriate control law during dynamic conditions or to annihilate static error. For these reasons *AGENT4* is complementary to the first three agents since the latter act meanly during transient conditions preventing un-

Table 1. SPECIFICATIONS OF ANSALDO-SIEMENS V64.3A ENGINE.

Shaft speed [rpm]	5420
Electrical power [MW]	67.8
Cycle efficiency	35.9
Inlet air flow [kg/s]	189.3
Pressure ratio	16.6
Turbine inlet temperature [K]	1581
Turbine outlet temperature [K]	867

desired static control errors, whereas the former promptly yields nearly the final value of the control variable.

Two final considerations are in order: firstly, the *MAS* structure presents four agents. They do not have the same perception and present a different action. Moreover, the first two collaborate to improve the readiness and the precision of the existing *PID*. On the other hand, the others act directly on the control law. Such a *MAS* does not present a master agent which governs the other agents. On the contrary each agent performs its task independently from each others. Besides, the two *MAS* structures work independently on the two controlled variables (one can says they constitute a larger *MAS*) and do not need of any uncoupling procedures that prevent from undesired mutual influence of the two controllers. Such an aspect is very interesting since allows to design a *MAS* independently from other *MAS* structure acting on the same environment.

MATHEMATICAL MODEL OF THE GAS TURBINE

A mathematical model previously developed by the authors (Ref. [18]) numerically simulates the V64.3A gas turbine single shaft gas turbine plant for electric power generation with a 17-stage axial flow compressor. The first four compressor stages are equipped with adjustable guide vanes (IGV) to improve performance at part-load. Seven of the eight turbine rows are cooled however in this work, for sake of simplicity, the last two stages have been considered as adiabatic. The design specifications of the V64.3A engine are summarized in Table 1. The turbine expander has been schematized making use of three different blocks. The first two blocks represent the cooled stage dynamic in which the model proposed by El Mastri (Ref. [19]) for cooled expansion has implemented. The third block simulates the last two adiabatic stages. A model validation is at the moment quite difficult for the lack of experimental data arising from transient test. Due to this obstacle, a part-load validation has been carried out on the basis of the experimental data published by Jansen et al. in Ref. [20].

Figure 3. GAS TURBINE LOAD HISTORY.

Moreover, the temperature transducer dynamic of shielded thermocouple has been simulated by means of a linear model in s-space characterized by one zero and two poles (Ref. [18]). As far as the variable inlet guide vanes is concerned, the authors simulate its actuator by means of a first order transfer function, limiting both the range extension and the maximum actuation speed.

Dynamic parameters such as temperature transducer transfer function, flame delay, combustion chamber volume, compressor discharge volume, fuel system transfer function, *IGV* actuator transfer function, shaft and gear inertia are taken from the literature and, when it was possible, from the technical specifications.

RESULTS

The Multiagent system control scheme described in the previous sections has been applied to the single-shaft heavy-duty Gas Turbine in *MIMO* mode. In the application, the controlled variables are represented by the shaft rotational speed (power frequency) and stack temperature (related to the overall gas turbine efficiency); on the other hand, the fuel mass flow (*VCE*) and the Variable Inlet Guide Vanes (*VIGV*) have be chosen as control variables.

In the simulation test, the plant is assumed to undergo to a prescribed time history variation of the electric load (Fig. 3) that, from the control point of view, represents the disturbance variable. As illustrated in figure 3, the turbine experiences different types of load variations: in the first part of the test, a full load rejection occurs whereas, in the second part it is subjected to increasing and decreasing linear ramps. The reason for such a prescribed time history variations of the electric load is explained as follows: the aim of the first part of test is not only to prove the capability of the proposed methodology to counterbalance sudden variations of the electrical load, but it is also to cover a wide area of working conditions. On the other hand, the second part of the simulation tests the capability of the *MAS* control scheme to reject more severe disturbance variations, represented by increasing and decreasing linear ramps. In particular the slope of such ramps has been chosen unusually high in order to provide a

Figure 4. COMPARISON *MAS* vs. *PID* APPROACHES: SHAFT ROTATIONAL SPEED RESULTS.

Figure 5. COMPARISON *MAS* vs. *PID* APPROACHES: STACK TEMPERATURE RESULTS.

more severe test.

A comparison between the proposed methodology, a standard *PID* controller optimized (in terms of promptness, accuracy and controlled variable rate of approach to the reference value) for the nominal working condition, and a conventional scheduled *PID* controller has been presented. Scheduled *PID* controller shares the same control parameter map with fuzzy *AGENT 1*. Figures 4 and 5 show the results obtained by the application of the *MAS* control scheme and the *PID* algorithms. Specifically, Fig. 4 illustrates the normalized turbine rotational speed and the control signal fed into the fuel valve actuator (*VCE*), whereas Fig. 5 refers to the normalized stack temperature (measured by means of a temperature transducer dynamic of shielded thermocouple) and the corresponding control signal to the variable inlet guide vanes actuator (*VIGV*). Such figures report not only the comparison between the *MAS* control scheme and *PID* controllers, but they also report each agent contribution to control variable value.

From Fig. 4 it is possible to note not only that the *MAS* control scheme reduce considerably the initial overshoot due to the load rejection (1.6% of the *MAS* scheme versus 2.5% of the *PID*-schemes), but it also modulate the approach velocity to the reference value preventing negative overshoot that arises in the standard *PID* applications. Moreover, even during the increasing and decreasing linear ramps *MAS* control methodology produces better results with respect to those of the *PIDs* in terms precision, promptness, and rate of approach to the reference value. A final consideration about the single agent contributions to the control law is in order. The *AGENT4* contribution derives from an open-loop fuzzy mapping between the external load (disturbance) and the control variable; for such reason, on one hand, it present a stabilizing effect on the shaft rotational speed, on the other hand, it is unable to promptly react during transients and to annihilate control static errors. On the contrary, the other agents take care of dynamic conditions ensuring a zero static error. In particular *AGENT1* and *AGENT2* collaborate tuning the *PID* components, whereas the *AGENT3* contribution, due to its derivative nature, modulates the approach velocity of the controlled variable to its reference value.

As far as the stack temperature is concerned, Fig. 5 reports not only the normalized value, measured by means of a temperature transducer dynamic of shielded thermocouple, and the corresponding *VIGV* signal, but it also shows, for completeness, the actual stack temperature evaluated by the gas turbine model for the *MAS* and *PID* approaches. In the first part of the test it possible to notice only minor differences between the performance of *MAS* and *PID* controllers. This is mainly due to the limitation of the maximum actuation speed of the variable inlet guide vanes. In fact, the load rejection causes all the controllers to rapidly close the inlet guide vanes, reaching the maximum allowed velocity. Nevertheless, a slightly different behaviour arises between the *MAS* and the *PID* controllers. Such a difference can be ascribed, on one hand, on the quite different behaviour of the rotational speed regulated by the *MAS* and *PID* approach; on the other hand, especially focusing on the actual stack temperature, it is possible to point out a better response of the *MAS* methodology in terms of promptness and accuracy. Right after the load rejection, all the controllers incur in a second inlet guide vanes limitation regarding the range extension. In fact, the *VIGV* control system (both *MAS* and *PIDs*) has to keep the exit temperature constant from 50% to 110% of nominal load; outside of this range the *IGV* position is kept constant. The final part of the test clearly demonstrates the better capabilities of the *MAS* system with respect the *PID* ones. In fact, the former presents nei-

Figure 6. FULL *MAS* vs. DISABLED AGENTS ON *VCE*: SHAFT ROTATIONAL SPEED.

Figure 7. FULL *MAS* vs. DISABLED AGENTS ON *VCE*: STACK TEMPERATURE.

ther overshoot nor oscillating behaviour whereas the scheduled *PID* shows a 7.9% overshoot and the standard *PID* is affected by a small oscillating behaviour. In spite of the small oscillations produced by the standard *PID* controller in terms of measured stack temperature, its real value experience a larger temperature variation which corresponds to a more severe thermal stress. Moreover, the *MAS* controller is also characterized by a faster approach to the reference value.

A further consideration is in order: from figures 4 and 5, it is worthy of notice that not all the agents of the *MAS* control scheme work in all the gas turbine working conditions. In particular, *AGENT2* and *AGENT3* are disabled whenever the first time derivative of the control error assumes small values. In such conditions only *AGENT1* and *AGENT4* are enabled and the *MAS* scheme behaves as a fuzzy system that provides smooth scheduled *PID* control parameters in which the steady state value of the control variable is provided by *AGENT4* . Therefore in quasi-stationary condition the *MAS* is equivalent to a scheduled *PID* with the same characteristic of precision, robustness and stability.

In addition, fig. 6 shows what happens when one or more agents are disabled. Specifically fig. 6 reports the results, in terms of shaft rotational speed, obtained by disabling, in the *VCE* controller, only *AGENT2*, both *AGENT2* and *AGENT4*, and, finally, *AGENT2*, *AGENT3*, and *AGENT4*. Such results, on one hand, assess the decentralized structure of the *MAS* controller; even if by disabling agents the overall performance decreases, the main tasks of the controller (*i.e.* control stability) is ensured. Moreover, the modular structure is reflected by the collaborative action of each agent which always contributes to accuracy improvements, independently from each other. Consequently, the design of the *MAS* controller is carried out by a modular approach since the single agent has not to face the whole control problem, but it has to accomplish a well defined task. The good level of robustness and accuracy is confirmed by fig. 7 which presents the stack temperature time history obtained by disabling the *VCE* controller agents. In this conditions, the *VIGV MAS* controller is still featured by all agents and therefore it is able to counterbalance the effects coming from *VCE* agents disabling. In fact, only minor differences may be observed between the diagrams reported in fig. 7, although the best performance is still to ascribe to the full *MAS VCE* controller.

CONCLUSIONS

In the present work, a multiagent system approach has been proposed to manage the control process of a single-shaft heavy-duty gas turbine. In particular, the, multiagent system control scheme has been applied in Multi Input Multi Output mode. Specifically, the controlled variables are represented by the shaft rotational speed (power frequency) and stack temperature (related to the overall gas turbine efficiency); on the other hand, the fuel mass flow and the Variable Inlet Guide Vanes have be chosen as control variables.

Multiagent system presents a number of potential advantages with respect the single-agent approach such as: decompose a problem, allocate subtasks to agents, and synthesize partial results; offer a distributed perceptual information of the environment; offer a decentralized control allowing an efficient coordination mechanisms among agents; enable agents to properly react to the actions, plans, and knowledge of other agents.

The results showed that the multiagent approach to the control problem, applied to the single-shaft heavy-duty gas turbine, not only effectively counteracts the load with limited overshoot in the controlled variables (as other control algorithms do), but is also shows good level adaptivity readiness, precision, robustness and stability.

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