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GAS PATH ANALYSIS AND GAS TURBINE RE-MAPPING

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ABSTRACT

The paper deals with the relevant problem of establishing the statuses of degraded performance of Gas Turbine based Power Plant Components and with the remapping of the simulator models.

The methodology is based on physical models including Reality and Actuality Functions that modify the model source terms of the Governing Conservation Equations.

Inverse calculations based on Neural Networks are illustrated and the application to two GE LM6000 PA aeroderivative Gas Turbines is widely discussed.

Keywords: Gas Turbine based plants, Inverse Problems, Status Recognition, Diagnosis, Neural Networks.

NOMENCLATURE

ACRONYMS

AF	Actuality Function
ANN	Artificial Neural Network
CHP	Combined Heat and Power
CPU	Central Processing Unit
DB	Database
DCS	Distributed Control System
EP	Extraction Pump
F, D	Functions
FP	Feed Water Pump
GA	Genetic Algorithm
GPA	Gas Path Analysis
GT	Gas Turbine
HPC	High Pressure Compressor
HPT	High Pressure Turbine
HRSG	Heat Recovery Steam Generator
LPC	Low Pressure Compressor
LPT	Low Pressure Turbine
M	Number of constraints, Number of measured points
MSE	Mean Square Error
N	Number of measured quantities
N&C	New&Clean
RF	Reality Function

VARIABLES

af	Vector of plant AFs
d	Vector of boundary conditions
g	Vector of geometric and global quantities
n	Order of the polynomial
ρ_{ji}	Reality Function Coefficient
rf	Vector of plant RFs
y	Plant dependent variable array
Y	Variable reference
z	Vector of process and state quantities
α_{ji}	Actuality Function Coefficient
ξ	Vector of quantities specifying the Plant Operating Point

Subscripts

i, j, k *Index*

Superscripts

*i, *, +, -* *Index*

Operators

U	Union of sets
~	Complement of a subset

INTRODUCTION

Gas Turbine (GT) based power plants are playing an even more significant role in the field of electric power production. Such plants usually operate in combined gas-steam arrangements. Reasons for such an increasing popularity are the high operational flexibility and maintainability, the relatively low investment costs and the high electrical efficiencies which altogether lead to competitive electricity production costs.

To increase profitability plants owned by independent producers are often designed to supply both electricity and heat to factories to feed industrial processes and to sell electric power on the free energy market.

Optimum plant management is a rather complex task especially when the plant is made of several groups operating in parallel arrangements and various objectives (i.e. economy, energy saving, pollution and so on) have to be achieved. One of the major issues is that the overall objective function is also constrained by the instantaneous behavior of the various plant groups. In order to set up really effective optimization tools the above constraints substantially representing the plant simulators have to take into consideration the actual statuses of machines and apparatuses. In order to reduce operating and maintenance costs, Plant Users should be able to identify how the plant behaves in terms of component performance and how the deterioration of each component affects the overall plant efficiency. Cerri developed a methodology for CHP plant optimum management which includes the above aspects. A detailed description is given in [1, 2]

Over the last decades, significant efforts have been devoted to the development of status recognition and performance diagnostic methodologies for GT based power plants. Although these techniques first made their appearance in the seventies [3] they are still a lively research area. Comprehensive reviews on Gas Turbine diagnostic techniques are provided by Li [4] and Marinai et Al. [5]

Gas Path Analysis (GPA) based methods aim to evaluate some parameters (efficiency, flow capacity, effectiveness, etc.) chosen to account for performance deterioration occurring inside plant components. A plant simulator establishing a relationship between input and output quantities through the above performance parameters is required. Actual values of performance parameters are evaluated by an inverse solution of the plant simulator given a set of measured quantities (temperatures, pressures, speeds, powers and so on). Performance deterioration of plant components is given in terms of deviations of the above parameters from their reference values which are those for N&C (healthy) conditions.

Main difficulties in assessing the actual statuses of plant components are represented by the small number of measured data and by errors in measurement (noise, sensors bias).

Researchers have investigated methods based on both linear and non-linear approaches. A comprehensive comparison between linear and non linear approaches is given in [6]. The former assume a linear relationship between performance parameter deviations and shifts of measured data [7, 8]. Non-linear methods take into account that implicit relationships between measured quantities and performance parameters are highly non-linear in most of the cases. The higher accuracy makes up for the higher computational complexity. The assumption of linearity leads to inaccuracy when high performance degradation levels cause relevant shifts from the reference N&C conditions. In order to overcome such a limitation recently Xia et al. [9] proposed a methodology to improve linear Gas Path Analysis. They start from the consideration that the actual engine operating point is defined by the matching of components whose maps change due to deterioration phenomena. Matching coefficients are introduced to isolate and eliminate the matching deviations which are a consequence of deterioration but should not contribute to the estimation of the engine health indexes.

Kalman Filter based methods are widely used in GT diagnostics. A comparison between various Kalman Filter approaches for the evaluation of aircraft engines health is given in [10]. The Author concludes that the Extended Kalman Filter appears the best choice for engine health parameters estimation taking both accuracy and computational effort into consideration. The introduction of constraints on health parameters together with the adoption of quadratic programming techniques able to manage the above constraints seems to bring benefits in terms of stability and accuracy [11]

Generally speaking the issue of status recognition is treated as an optimization problem. Parameters introduced to take into account degradation phenomena are evaluated by minimizing the difference between predicted and measured data. Usually a sum-of-square of errors is assumed as objective function. This approach has been adopted by Cerri et al. [12] to simulate the actual behavior of axial compressors. The method is based on the stacking of re-shaped generalized stage characteristic curves. The effect of deterioration phenomena on compressor performance is taken into account by introducing shape factors which modify N&C stage characteristic curves. Shape factors are evaluated by minimizing MSE between measured and calculated quantities.

Methods are still being proposed to improve diagnostic capabilities. Advanced techniques such as Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) have opened new opportunities in the field of on-line, real-time diagnostic.

Artificial Neural Networks based techniques have been introduced in Gas Turbines diagnostics in the late 80's. ANNs have the capability to establish a relationship between input and output quantities by storing the knowledge during a training process and making it quickly available for applications. ANNs have been successfully applied in a number of engineering problems which are highly non-linear in nature. In Gas Turbine diagnostics ANNs are used to replace physical-empirical plant simulators in order to reduce the computing time required by iterative solutions and CPU occupancy [13]. Another relevant advantage of ANNs in Gas Turbine diagnostic applications is represented by their tolerance to noise affecting measurements.

ANNs have been applied by Cerri et Al. [14-17] to evaluate accurately thermodynamic process quantities avoiding iterations and to perform real time load allocations on machines and apparatuses constituting complex CHP plants taking the actual performance level of the various plant components into consideration. DePold and Glass [18] and Kobayashi and Simon [19] investigated ANN applications to Gas Turbine prognostics and diagnostics. More recently a unified non linear adaptive approach including engine neural modeling for detection and isolation of engine faults has been presented [20].

As stated before, the identification of component performance parameter can be treated as an optimization problem. Genetic Algorithms (GAs) are emerging as powerful tools in Gas Turbine diagnostics due to the ability of searching the global minimum, the capability to retain full non-linearity and deal with measurement noise [21-23]. It has to be pointed out that GA based techniques are more computationally burdensome than the abovementioned approaches.

Finally, hybrid techniques conjugating features of ANNs and GAs show interesting potentialities as reported in [19].

The paper deals with an innovative methodology to set up GT based plant simulators capable of replicating the real plant behavior in the whole field of operations. This is achieved by introducing into the plant simulator suitable Reality and Actuality Functions. Such functions act on the mechanism of modeled phenomena occurring inside the plant components (work and heat transfer, losses, flow capacities, etc.) allowing the modification of the operating maps.

Reality Functions (RFs) are introduced to replicate the plant behavior at a reference condition (usually N&C). Actuality Functions (AFs) allow to update the model of each plant component to account for performance degradation with operations. Both RF and AF coefficients are calculated on the basis of measured data according to Gas Path Analysis technique.

An application of the proposed approach to a real plant is given and discussed.

SCIENTIFIC BACKGROUND

In order to achieve an effective plant management performance deterioration of components has to be taken into account. Accordingly a crucial aspect is to establish a plant simulator capable to replicate instant by instant the real plant behavior.

The set up of the plant simulator is based on a modular description at level of components in a really broad sense. Each module can represent a single component or a group of them. The module library allows a really easy configuration.

Each component module contains the physical-empirical behavior that mathematically can be expressed by a set of linear and non linear equations which represents the conservation of Mass, Energy, Momentum, Entropy and includes constitutive and auxiliary equations. The last ones describe processes and phenomena occurring in the machines and apparatuses allowing the calculation of quantities related to source terms in the conservation equations. A library of component models suitable to arrange Gas Turbine based power plant has been established.

Models of compressors, combustion chambers, gas and steam expanders, heat transfer devices, pumps, mixers, valves, connections, splitters, junctions, electric generators etc. have been developed. The above models are generic in nature and can be applied to commercially available and "ad hoc" designed components.

For each component model quantities are evaluated at relevant stations (e.g. at the exit of each compressor or expander row, upstream and downstream the filter, and so on). Three dimensional flow features at each station are taken into account by lumping into a single value the distributions of the various quantities of interest (pressure, velocity, temperature, etc.).

Component models include databases (DBs) containing shapes, architectures and related correlations (for example profile cascade features and related losses and deviations, finned tube bundles features and related heat transfer coefficients). Such DBs are adopted to select arrangements on the basis of manufacturer information or default choices. Moreover boundary conditions as well as surface qualities and geometric data are required to set up the model.

Sizing of Components

If all the constructive details and empirical relations characterizing each component were known, this model would represent correctly all the thermo-fluid-dynamic phenomena occurring in the real component. However, when building a model usually only some of the geometric data, shapes and correlations are available and quantities involved in the process (i.e. work and heat exchanged, losses, velocity distributions, etc.) are evaluated through empirical correlations applying similarity concepts.

The identification of unknowns quantities is performed by solving a first level inverse problem where component performance quantities are constraints. Such an inverse problem leads to a "slack" solution due to the fact that the model DBs do not necessarily fit exactly the real machine details. This means that imperfect similarity exists between elements of the real machine or apparatus and the DB shapes and correlations. As a consequence, the characteristic curves of the component fit only one or few points while no agreement exists in the remaining range of operations.

To fully establish the model of each plant component two concepts have been introduced: Reality Functions (RFs) which account for the deviation of the response of the model from the real situation observed in a reference condition (usually N&C) and Actuality Functions (AFs) which allow the model to reproduce the real component behavior in any situation characterized by a certain level of performance degradation.

Reality Functions

As stated before, a vector of RFs is introduced in the model to adapt the DB correlations to reproduce the real component behavior. Suitable RFs affecting correlations describing relevant processes occurring inside each plant component (heat and work transfer, entropy production, flow functions, etc.) are defined. Polynomials whose order is usually less or equal to two are adopted:

$$\mathrm{rf}_j = \sum_{i=0}^{n} \rho_{ji} Y^i \tag{1}$$

being ρ_{ji} the coefficients of the j-th RF, Y a relevant quantity influencing the process (e.g. temperature, power, a suitable flow quantity, etc.) and n the order of the polynomial.

RF coefficients are calculated by solving a minimization problem whose objective function is a MSE, errors representing differences between measured and calculated quantities. The former can be obtained by carrying out "ad hoc" campaigns or at least collected at acceptance tests. The assumption that component statuses do not change during such tests leads to the reference N&C model.

After the sizing is performed and the RFs are determined, the model is capable of replicating N&C behavior of a specific real component. As the manufacture of the machine terminates with the acceptance test, which establishes the true N&C map, so the making of its simulator, which represents the virtual "real" machine, terminates with the model RF calculations by using the acceptance test data.

Actuality Functions

Plant component performance changes during their life due to phenomena like fouling, corrosion, erosion of parts etc., affecting the actual behavior of plant units.

This means that going on with operations instant by instant different machines and apparatuses exist. Accordingly, characteristic curves of components and performance maps are continuously changing, thus they need to be continuously re-established inside the model if an accurate plant operation management is to be accomplished.

AFs have been introduced to represent the actual plant status. Since really slow changes occur in plant component features and since in a really short time a complete set of data is available, such set actually represents an instantaneous operating point of the plant monitored components. Such data are appropriate to identify the actual behavior of the previously established N&C real component.

Theoretically there is the possibility of using AFs for every single phenomenon typology (e.g. wakes, tip and secondary vortices, turbulence enhancement, etc), but in that case their number would be too high to be handled. In the adopted models the choice of using global AFs influencing component performance has been made. More specifically, AFs allow the model to reproduce the behavior of the real actual plant component with reference to:

- work exchange (afw) and heat transfer (afq)
- dissipative phenomena related to internal friction and coupling between fluid and surfaces (afl)
- effective flow function modifications (afb)

Actuality Functions are conceived in a way that their value is less than 1 when the actual performance is degraded with respect to a reference status (e.g. N&C status or after a major overhaul).

For each component or a portion of it (e.g. single rows in turbomachinery) a vector of **af** coefficients can be found depending on the number of available monitoring data. This affects also the polynomial form of the Actuality Functions utilized, that can be generalized by Eq. (1'):

$$\mathrm{af}_j = \sum_{i=0}^{n} \alpha_{ji} Y^i \tag{1'}$$

being *n* the order of the polynomial generally comprised between 0 and 2 and *Y* a relevant variable like temperature, power, mass flow, etc. AFs formulation is similar to that adopted for RFs. However, it should be pointed out that their implementation, number and location in the model formulae are not necessarily the same. They depend on various issues, such as test and monitoring data availability and model (and real component) complexity.

The AFs allow to re-establish the actual component characteristic curves and performance maps into the model. The instant by instant knowledge of the actual plant statuses is really useful to perform:

- the short term load allocation (or re-allocation) taking into account the present health statuses of power generation groups;
- the assessment of performance deterioration trends when dealing with long term production planning.

SOLUTION METHODOLOGY

The physical-empirical plant simulator is made up of assembled component models. Plant behavior is described by a set of equations:

$$\mathbf{F}\,(\mathbf{g}, \mathbf{z}, \mathbf{d}, \mathbf{rf}, \mathbf{af}) = 0 \tag{2}$$

and inequalities :

$$\mathbf{D}\,(\mathbf{g}, \mathbf{z}, \mathbf{d}, \mathbf{rf}, \mathbf{af}) \geq 0 \tag{3}$$

representing conditions establishing the feasibility domain. Vector **g** contains geometric and global quantities calculated after the preliminary sizing of components, **z** being a vector of process and state quantities such as pressures, temperatures, mass flows, fluid compositions, flow angles, rotational velocities, stresses and so on defined at characteristic stations. **d** represents the vector of boundary conditions, namely site pressure, temperature and relative humidity, temperature of cooling water and so on. When economic aspects are treated also costs of consumables, prices of electricity, tariffs and so on are included in **d**. **rf** is the vector of plant RFs and **af** is the vector of plant AFs.

The plant physical-empirical simulator represented by Eq. (2) and Eq. (3) can be applied to solve both direct and inverse problems, such as the RFs and **af** coefficient identification.

Direct problem solution is aimed at plant performance analysis or optimum management. Model parameters and boundary conditions are given: $\mathbf{g} = \mathbf{g}^*$, $\mathbf{rf} = \mathbf{rf}^*$, $\mathbf{af} = \mathbf{af}^*$, $\mathbf{d} = \mathbf{d}^*$. The array **z** can be subdivided into two subsets $\boldsymbol{\xi}$ and **y**. $\boldsymbol{\xi}$ contains the quantities required to specify the plant operating point (i.e. loads allocated on machines and apparatuses). $\mathbf{y} = \boldsymbol{\xi} \sim \mathbf{z}$ is the plant dependent variable array.

The identification of RF coefficients leads to the solution of a RMSE minimization problem. RF coefficients refer to N&C condition so **af** are set equal to one. Measured data referring to M plant operating points are available after acceptance test campaign. For each point, a set of N plant quantities $\mathbf{z}^*_k$ is measured together with boundary conditions $\mathbf{d}^*_k$. The array of plant variables $\mathbf{z}_k$ related to k-th operating point can be expressed as $\mathbf{z}_k = \mathbf{z}^+_k \cup \mathbf{z}^-_k$, $\mathbf{z}^+_k$ being a subset whose elements correspond to those of $\mathbf{z}^*_k$ measured quantities.

The problem is stated as follows:

Search **rf** that minimizes:

$$MSE = \frac{1}{M}\sum_{k=1}^{M}\left[\frac{1}{N_k}\sum_{i=1}^{N_k}\left(1-\frac{z^+_{ki}}{z^*_{ki}}\right)^2\right] \quad 4)$$

with the constraints represented by the M direct problem equations:

$$\left.\begin{aligned} &\mathbf{F}\,(\mathbf{g}^*, \mathbf{d}^*_k, \mathbf{af}^*, \mathbf{rf}, \mathbf{z}_k) = 0 \\ &\mathbf{D}\,(\mathbf{g}^*, \mathbf{d}^*_k, \mathbf{af}^*, \mathbf{rf}, \mathbf{z}_k) \geq 0 \end{aligned}\right\} \quad k = 1,2,\ldots,M \qquad (5)$$

Since calculations for RFs identification are performed few times - after acceptance test or after a massive overhaul - computational time is not so relevant. The Authors have investigated the potentialities of hybrid techniques based on Natural Evolutionary Algorithms coupled with deterministic ones [12]. The AFs identification is always based on a single measured point because it has to be done in real time using DCS data. $\mathbf{g}=\mathbf{g}^*$, $\mathbf{d}=\mathbf{d}^*$ and $\mathbf{rf}=\mathbf{rf}^*$ are given. Plant DCS provides a set of monitored quantities $\mathbf{z}^*$ corresponding to a subset of plant variables $\mathbf{z}^+ \subseteq \mathbf{z}$. The unknowns to be determined are $\mathbf{x} = \mathbf{z} \cup \mathbf{af}$.

Three situations may occur:

1) The monitored data for every component are in excess in respect to the number of **af** coefficients. In this case a minimization problem based on MSE has been adopted to solve the inverse problem for the identification of **af** coefficients:

Search **af** that minimize:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(1-\frac{z^+_i}{z^*_i}\right)^2 \qquad (6)$$

with the equality constraints:

$$\mathbf{F}\,(\mathbf{g}^*, \mathbf{d}^*, \mathbf{rf}^*, \mathbf{af}, \mathbf{z}) = 0 \qquad (7)$$

and inequalities:

$$\mathbf{D}\,(\mathbf{g}^*, \mathbf{d}^*, \mathbf{rf}^*, \mathbf{af}, \mathbf{z}) \geq 0 \qquad (8)$$

2) The monitored data are sufficient to establish for every component a set of non-linear equations whose number equals the **af** coefficients. In this case there is only one physical solution. Thus **af** coefficients identification is performed by solving the system of Eq. (7) and Eq. (8) with the additional conditions:

$$\mathbf{z}^+ = \mathbf{z}^* \qquad (9)$$

3) In the case that data are not sufficient to establish the right set of equations for every component (i.e. the data are fewer than the number of **af** coefficients) the problem has been solved by analyzing component by component the available data and reducing the order of polynomials or as a last resort setting equal to one the related AFs. Of course the availability of measured Y quantities related AFs introduced in the model leads to a decision on the above. This occurs in plants with reduced capacity monitoring systems. The difficulty related to this situation can be overcome upgrading the monitoring system by implementing new stations for the measure of relevant quantities. The best should be to bring back the problem to that of situation 1.

In determining **af** coefficients, that have an instantaneous value connected to a particular operating point, ANNs are used in order to obtain in short times information on component actual performance and status to estimate component efficiency and availability and to decide prompt and appropriate maintenance interventions.

PLANT NEURAL SIMULATOR

An ANN derives its computing power from the ability to capture from experience and to represent highly non-linear input/output relationships. The physical knowledge of the plant with its mathematical complexity is stored in the ANN during a training phase and can be successively extracted in a very short computing time. The plant physical-empirical model is utilized to generate the input-output map (database) needed for ANN training and testing. Single-layer feed-forward networks are trained with a back-propagation algorithm. The application of physical models to generate training databases allows providing

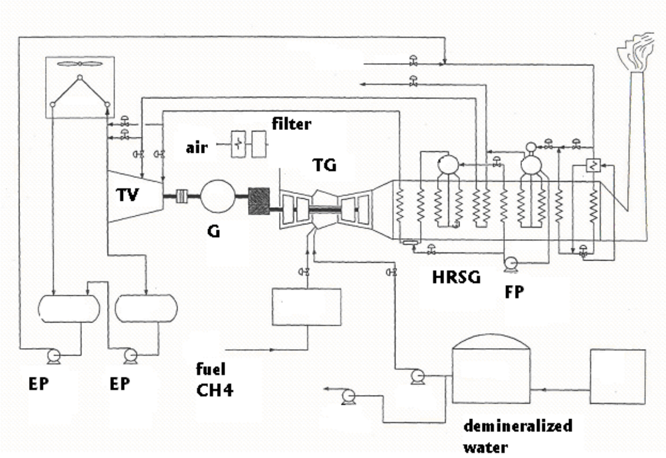

Fig.1 – LM6000 Combined Cycle typical plant arrangement

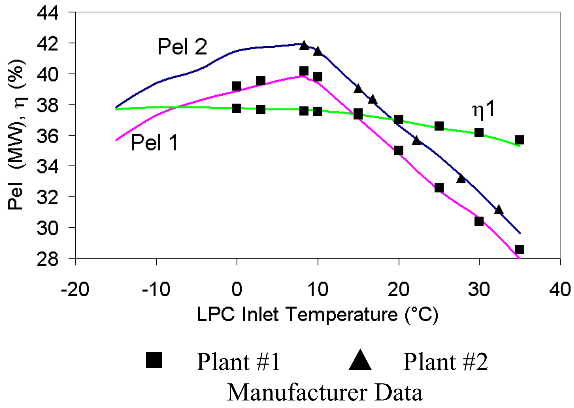

Fig.2– Plant #1 and Plant #2 GT electric output and efficiency versus LPC inlet temperature. Comparison between manufacturer data and model results.

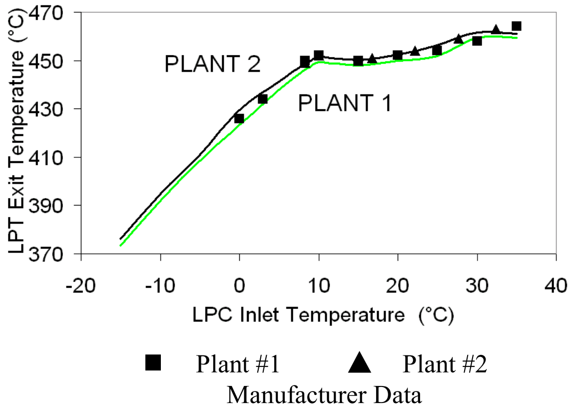

Fig.3– Plant #1 and Plant #2 LPT Exit Temperature versus LPC inlet temperature. Comparison between manufacturer data and model results.

ANNs with large amount of training data. This made it possible to produce reliable ANNs with one hidden layer only.

In order to reduce the massive computational effort required to generate the plant training database, a peculiar approach based on intermediate neural models of plant subsections used in cascade arrangement has been pursued. The adopted approach is extensively discussed in [16]. ANN performance depends heavily on the size of the database used for training it and on other relevant parameters such as Learning Rate and number of Hidden Neurons.

The database is populated by solving in direct mode the physical-empirical plant simulator as described in the previous chapter. Input quantities are ξ^*, $\mathbf{d}^*$ and $\mathbf{af}^*$, randomly spread in a suitable domain. ξ^*, $\mathbf{d}^*$ and plant simulator dependent variables $\mathbf{y}$. The database constituted by strings of input and output:

$$\xi \cup \mathbf{d} \cup \mathbf{y} \cup \mathbf{af} \tag{10}$$

is utilized for the training phase selecting as NN input the quantities:

$$\xi \cup \mathbf{d} \cup \mathbf{y} \tag{11}$$

and as output the **af** coefficients. In order to minimize the global Mean Square Error optimum number of Hidden Neurons, Learning Rate and Training Epochs is searched. The trained NN is validated to verify its general performance with a new set of data (testing process). Errors are calculated as difference between the values obtained by the NN and the desired ones calculated by the physical-empirical simulator. From previous experience has been found that the majority of ANN errors are in the range of ±1% [24, 25].

CASE APPLICATION

Hereafter the previous methodology is applied to a real case. In order to highlight the relevance of reproducing accurately the plant behavior in a reference situation (e. g. New and Clean) two combined plants of the same kind installed in different sites have been taken into consideration. Both plants are based on an aero-derivative General Electric LM6000 PA Gas Turbine and equipped with a two-pressure level Heat Recovery Steam Generator (HRSG) and a steam turbine. The combined cycle arrangement is schematically depicted in Fig. 1. For each plant performance curves at base load operation corrected on the basis of acceptance test data were provided by the manufacturer.

Tab. 1 – Percentage errors between manufacturer's curves and calculated values after RFs identification

LPC inlet temp. [°C]	Electric. Power	Efficiency	LPT exhaust temperature
Plant#1			
0	-0.76	+0.08	-0.68
3	-0.51	+0.13	-0.48
8.3	-0.75	+0.32	-0.84
10	-0.72	+0.26	-0.62
15	-0.66	+0.13	-0.44
20	-0.57	-0.11	-0.44
25	-0.61	-0.33	-0.46
30	-0.65	-0.28	+0.31
35	-0.75	-1.06	-1.01
Plant#2			
8.3	+0.24	+0.13	-0.16
10	+0.03	+0.48	-0.07
15	+0.02	+0.40	+0.04
16.8	-0.26	+0.11	+0.01
22.2	+0.06	-0.13	+0.02
27.7	+0.48	-0.41	+0.04
32.4	-0.64	-0.88	-0.43

The above curves give GT electric output, efficiency and LPT exhaust temperature versus LPC inlet temperature. Such data have been used to carry out RFs identification, expressed as a function of LPC inlet temperature. Details about RFs and the values found for the two plants are reported in [25]. It has to be pointed out that the modeling of machines of the same type has lead to different values of RFs to account for peculiar features due to manufacturing and installation which make the real machines, to some extent, different.

In Fig. 2 calculated and given electric power at base load operation vs LPC Inlet Temperature are compared. The introduction of RFs in the plant model has led to a really satisfactory agreement with manufacturer curves. The relevant difference in electric output between the two plants is due to quite different site conditions.

For clarity only Plant #1 electric efficiency curve has been reported in Fig. 2, Plant#2 electric efficiency curve being practically superimposed to that of Plant#1. Figure 3 shows for both plants the good agreement achieved between calculated and given exhaust temperatures at GT expander exit.

Percentage errors between given and calculated quantities are reported in Tab. 1. It can be noticed as the absolute value of errors is almost well below 1%.

The physical empirical simulator of the whole plant has been established according to the developed methodology. For sake of brevity the discussion will be focused on the Gas Turbine section.

An investigation concerning the degradation of GT performance and the related AFs describing the actual machine has been carried out. Such an investigation has regarded the capability of the theoretical approach to model the performance deterioration by the AFs. A set of 17 measured quantities were

Tab. 2 – Plant #1: GT Actuality Function recognition from DCS data and comparison with Plant Simulator solution

Boundary conditions				
		Unit	Measured	
1	Ambient Pressure	bar	0.972	-
2	Ambient Temperature	°C	17.4.0	-
3	Relative Humidity	%	67.0	-
4	LPT Exit Pressure *	bar	0.996	-
Gas Turbine Operating Quantities				
		Unit	Measured	Simulator
1	LPC Inlet Pressure	bar	0.968	0.971
5	LPC Inlet Temperature	°C	17.4	17.4
3	LPC Exit Pressure	bar	2.47	2.43
4	LPC Exit Temperature	°C	118.2	119.4
5	Fuel Mass Flow	kg/s	2.01	2.03
6	HPC Exit Pressure	bar	27.20	26.95
7	HPC Exit Temperature	°C	541.7	541.7
8	LPT Inlet Pressure	bar	6.11	6.13
9	LPT Inlet Temperature	°C	783.5	782.6
10	LPT Exit Temperature	°C	444.0	446.1
11	Electric power	MW	33.93	33.95
12	HP rotational speed	rpm	9853.0	9864.0
13	LP rotational speed	rpm	3602.0	3600.0
Actuality Function values				
1	afl_fil	0.720		
2	afl_LPC	0.952		
3	Afb_LPC	0.992		
4	Afw_LPC	0.972		
5	afl_HPC	0.972		
6	Afb_HPC	0.996		
7	Afw_HPC	0.985		
8	afl_LPT	0.987		
9	Afb_LPT	0.997		
10	afw_LPT	0.983		
11	afl_HPT	0.982		
12	afb_HPT	0.996		
13	afw_HPT	0.991		

available from Plant#1 DCS. Such data allowed the adoption of 13 zero order AFs, i.e. one for the inlet filter and three for each machine constituting the Gas Turbine (i.e. LPC, HPC, HPT and LPT). An ANN for AFs identification has been set up according to the previously described procedure.

A set of data collected at a certain instant (listed in Tab. 2) by plant DCS has been used to calculate the thirteen **af** coefficients also reported in the lower part of Tab. 2. Results achieved inputting such **af** values into the model are given in the simulator column of the table. As it can be seen the reproduction of measured data is excellent.

The computing time required to perform AFs identification is of some 50 μs by using an Intel Pentium IV based personal computer. As an example of the satisfactory accuracy of the ANN in identifying the status of the various components, GT performance has been re-calculated by using the direct simulator, given the boundary conditions and AFs. Results reported in the last column of Table 1 show a good agreement between calculated and measured data.

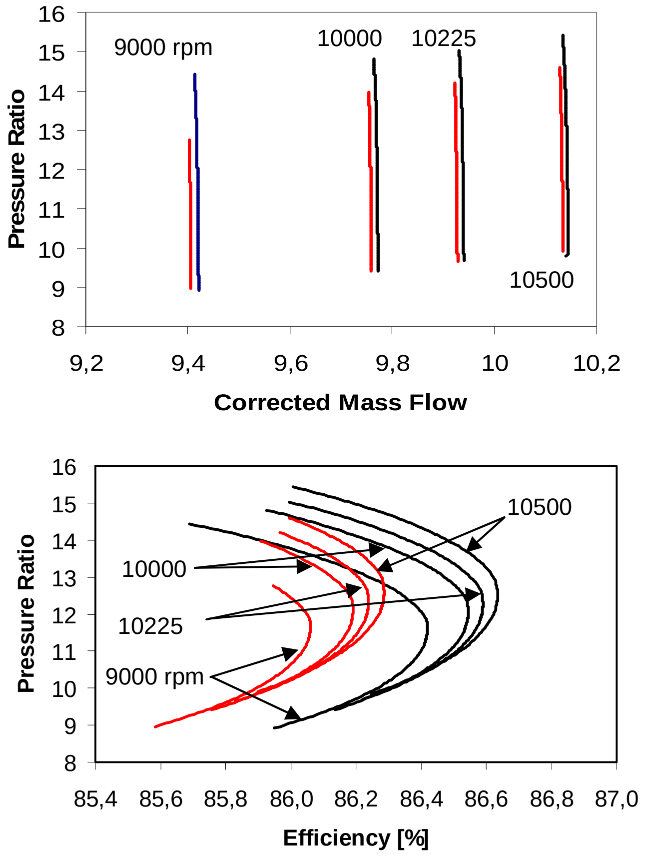

Fig.4– Actual (red lines) and New&Clean (black lines) High Pressure Compressor characteristic curves

AFs allow to re-establish into the plant simulator the actual performance maps. Figures 4 gives HPC performance maps evaluated for the actual operating condition taken into account (red lines) and maps evaluated at New and Clean condition (black lines). The loss of performance at various speeds in terms of flow capacity, pressure ratio and efficiency are clearly put in evidence. Finally the effect of components deterioration of GT base load performance are shown in Fig. 5.

CONCLUSIONS

Innovative techniques capable of making possible to set up models to replicate the real plant behavior in the whole Domain of Definition of the Plant Degree of Freedom and boundary conditions have been presented. Reality Functions allow to establish the N&C plant behavior replica interacting with the mechanisms of modeled phenomena that describe the work and heat transfer, the dissipation due to irreversibility (entropy

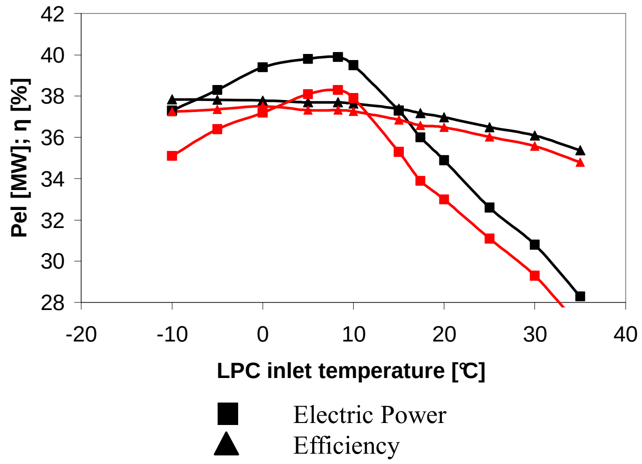

Fig.5– Actual (red lines) and New&Clean (black lines) base load performance curves.

production) and to the fluid flow blockage inside channels and orifices.

The adoption of Neural Models established for inverse and direct solutions shows fast calculations to allow evaluations in real time.

The identification of **rf**s and **af** coefficients poses two inverse engineering problems which ask for different strategies and solution techniques. In general, RF identification from available acceptance test data leads to a problem of error function minimization. Among the applicable solution techniques those based on hybrid Evolutionary-Deterministic Algorithms have been selected.

Component status recognition (i.e. identification of **af** coefficients) is based on a single measured point because it has to be done in real time using DCS data. In order to meet the requirement of a fast and sufficiently accurate solution ANNs have been proposed and successfully applied. This satisfactory accuracy and the really short computational time required (some 50 µs) show the potentialities of the neural approach for on-line or quasi on-line applications to support plant management decisions.

The case studies applied to two plants based on GE LM6000 PA aeroderivative Gas Turbine have demonstrate the capabilities of the methodology.

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