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METAMODELS OF A GAS TURBINE POWERED MARINE PROPULSION SYSTEM FOR SIMULATION AND DIAGNOSTIC PURPOSES

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Abstract:

The paper presents the application of artificial neural network for simulation and diagnostic purposes applied to a gas turbine powered marine propulsion plant. A simulation code for the propulsion system, developed by the authors, has been extended to take into account components degradation or malfunctioning with the addition of performance reduction coefficients. The above coefficients become input variables to the analysis method and define the system status at a given operating point. The simulator is used to generate databases needed to perform a variable selection analysis and to tune response surfaces for both direct (simulation) and inverse (diagnostic) purposes: two ANN are trained to reply simulator behavior in steady state conditions with considerably reduced calculation time (direct ANN), and to invert simulator inputs and outputs in order to obtain information on the system health state starting from measured variables (diagnostic ANN). The application of the methodology to the propulsion system of an existing frigate version demonstrate the potential of the approach for simulation and diagnostics: the simulation model behavior is replied with acceptable errors, while the health state of the propulsion system is successfully identified from the selected state variables by properly trained artificial neural networks.

Keywords: Monitoring , diagnostics, artificial neural networks, simulation, ship propulsion.

NOMENCLATURE

ANN	artificial neural network
Avg	average
BSFC	bore specific fuel consumption
CPP	controllable pitch propeller
eff	effective
eta	efficiency
GT	gas turbine
K	loss/fault coefficient
M	mass flow rate
MblC	turbine cooling air mass flow rate
MSE	mean square error
p	pressure
Q	shaft torque
S	shaft speed
T	temperature
TCS	gas turbine control system
TH	propeller thrust
V	ship speed
w	network weight
x	neuron input
y	neuron output
θ	neuron threshold
a	ambient

Subscripts

bl	cooling
C	compressor
Eng	engine
eta	efficiency
Err	error
Fr	friction loss
f	fuel
GG	gas generator
GT	gas turbine
HPT	high pressure turbine
hp	high pressure
Kq	propeller torque coefficient
in	inlet
lp	low pressure
out	outlet
PORT	portside
Prop	propeller
r	real
req	required
Sh	shaft
STBD	starboard
Kt	propeller thrust coefficient
T	turbine

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1. Introduction

Real time operation monitoring and effective fault diagnosis are crucial issues in plant management, in order to increase safety and reliability: uninterrupted availability, even if a fault occurs, is a desirable feature in almost any engineering application field. Several monitoring and diagnostic techniques have been developed, especially for industrial power plants and aeronautic propulsion systems. The general purpose of these techniques is to monitor the plant's operation through a number of experimental measures of an appropriate set of state variables, then to identify one or more diagnostic variables through a model, which can be based on various soft-computing techniques such as simulation, optimization algorithms, expert systems, response surfaces. This paper aims to present an analysis of a gas turbine powered ship propulsion plant, via simulation and response surface techniques using artificial neural networks. Gas turbine engines have found wide application in aircraft propulsion and power generation industry. Diesel engines are the most common engine type used in ship propulsion, however gas turbines (in two shafts configuration) are used for high performance applications, when a high power density and performance is required, mainly in military vessels and high speed ferries. Marine engines operate in aggressive corrosion conditions if compared to aeronautic or industrial applications: a diagnostic system can be useful to increase the reliability and safety of the ship. Moreover, a diagnostic system for ship propulsion needs to take into account effects due to gas turbine components corrosion, hull resistance increase, propeller performance decay, shaft line and gearbox wearing. In other words, the propulsion system needs to be considered in all its aspects in order to provide effective diagnoses. Simulation is a widely used method to obtain information in systems transient conditions. The authors have acquired significant experience in marine propulsion systems simulation and in developing computer codes to model the main marine engines (Benvenuto *et al*, 2005) and the overall ship propulsion plants (Benvenuto *et al*, 2000, Campora *et al*, 2003, Altosole *et al*, 2009).

The use of simulation for faults and diagnostic analysis have been tested in previous applications to propulsion systems (Altosole *et al*, 2010, Campora *et al*, 2011, 2013). The modeling of governor and control systems is a crucial issue for accurate simulation of transient load analysis, steady analysis at off-design conditions or in case of faults (Benvenuto *et al*, 2000, 2008, Campora *et al*, 2013). Referring to the propulsion system of the frigate version considered in this paper, an analysis of over time performance decay due to components performance deterioration (including hull resistance increase due to fouling) has been presented in Altosole *et al* (2014). On the other hand the use of a simulator for diagnostic purposes has two major shortcomings: intensive CPU time not acceptable for real-time analysis and a rigid input/output set of variables that does not allow reverse analysis using specific input variables from the system.

Artificial neural networks (ANN) are efficient function fitting tools that can be effectively used to speed up the simulation process when the numerical direct simulation is too expensive for real time analysis or for optimization purposes (Cravero *et al*, 2012, Cravero, 2013). ANN can also be effective for diagnostic purposes (Palmé *et al*, 2011) because of their ability in modeling the system as a black box without the need for specific and pre-defined relationships between input and output variables. In this paper, a ship propulsion system simulation model has been used to generate a database for ANN development. The model is able to simulate the plant operation in different fault and degradation conditions, through a set of fault coefficients implemented in the code as documented in literature (NATO RTO, 2007). For an effective ANN implementation, a design of experiment (DoE) analysis of the multivariate domain has been carried out to understand the effects of input variables to output data and to be able to make a selection of the most significant variables to reduce the problem dimensions. This target has been tackled with a Student's t-test analysis of a database generated by 1500 simulation runs with different input conditions, obtained with a pseudo-random domain filling algorithm. After having selected the optimum set of variables to describe the problem, the simulation data has been used to train two ANN, for simulation and diagnostic purposes respectively. Network sensitivity and robustness against random measure errors has been finally considered.

2. Ship Propulsion Plant Simulation Model

The main features of the ship are 140 meters of length, 5900 tons of displacement, and 27 knots of maximum speed. The ship propulsion plant scheme with the fundamental components is shown in Fig. 1. The main engine of the propulsion plant is the General Electric-AVIO LM 2500 gas turbine (GT), characterized by a two shafts arrangement. The gas generator is composed by the compressor (C in Fig. 1), the combustion chamber (CC) and the high pressure turbine (HP_T). The MCR (maximum continuous rating) power, delivered by the power turbine (LP_T), is 32 MW at 3600 rpm. This last moves, by a reduction gear (RG), two controllable pitch propellers (CPP). Fig. 2 shows the overall ship propulsion plant SIMULINK scheme. The simulator is organized in a modular arrangement, where each block models the performance of the pertinent propulsion plant component, by means of the component's geometrical data, performance characteristics maps, mechanical and thermodynamic equations (mainly: continuity, energy and momentum).

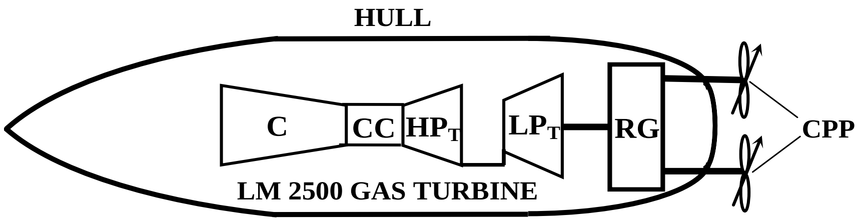

Fig. 1: Frigate propulsion plant scheme

The frigate propulsion plant is basically composed by a gas turbine (LM2500 GAS TURBINE block in figure) which drivers, through a reduction gear (GEAR), two controllable pitch propellers (STARBOARD and PORTSIDE PROPELLER blocks) for the ship propulsion. The performance of each system component, can be determined for different load conditions and components health status. This last is determined, for each component, by the value of the corresponding fault coefficient K (reported in red over the pertinent block in Fig. 2). The fault coefficients K are reported and described in Table 1. A brief description of the main subsystems and of the overall propulsion plant simulator operation logic is reported. A more detailed description of this plant and its components is given in Altosole *et al* (2014) and Capelli (2013).

The overall system is governed by the MAIN PROPULSION PLANT CONTROLLER block in Fig. 2, starting by the telegraph value (green block). The required propellers pitch value signal Prop_STBD/PORT PITCH is generated according to the telegraph value by the combinatory table and transmitted to the STARBORD/PORTSIDE PROPELLER blocks. The propeller model has been generated following the classical approach for the propeller performance prediction described in Benvenuto *et al* (2000), using the open water CPP diagrams for the propulsion thrust and propeller torque of the considered frigate. The propellers thrust K_T and torque K_Q coefficients can be determined from the open water diagram with the procedure described in Benvenuto *et al* (2000), given the advance coefficient J and the propeller pitch diameter ratio P/D value. The thrust (TH in figure) of both the propellers are transmitted to the HULL DYNAMIC block, that determine the ship speed (V in Fig. 2) by the dynamic balance between the frigate hull resistance force, determined as function of the ship speed and the propellers thrust.

Table 1: SIMULINK propulsion plant simulator fault components coefficients

K_pin	Compressor inlet filter fault coefficient
K_Ceta	Compressor efficiency reduction coefficient
K_Cm	Compressor mass flow rate coefficient
K_Thp	HP turbine fault coefficient
K_Tlp	LP turbine fault coefficient
K_dpout	GT outlet duct fault coefficient
K_etam	Mechanical efficiency gear coefficient
K_FrShPort	Friction increase due to bearing fault (portside shaft)
K_FrShStbd	Friction increase due to bearing fault (starboard shaft)
K_Kt	Propeller thrust loss fault coefficient
K_Kq	Propeller torque increase fault coefficient
K_PortErr	Portside propeller pitch actuator error [°]
K_StbdErr	Starboard propeller pitch actuator error [°]
K_HullRes	Hull resistance coefficient increase due to fouling

The propellers resistance torques Q, determined in the STARBORD/PORTSIDE PROPELLER blocks, are transmitted to the STARBORD/PORTSIDE SHAFT DYNAMIC blocks together with the GT speed S_GT to compute the propellers shaft rotational speeds S by means of the dynamic momentum equation. The reduction gear is simulated by a simple ratio between the incoming and outgoing rotating shafts speeds. In addition, the MAIN PROPULSION PLANT CONTROLLER block manages the GT load by the GT gas generator speed S_GT req signal, generated by a PID governor system. The LM2500 GAS TURBINE block, in blue in Fig. 1, is the most complex component, for this reason it is described referring a specific SIMULINK scheme reported in

Fig. 3. Once again the components health status is determined by the value of the fault coefficients K, reported in red over the pertinent block in the above figure.

The main engine of the propulsion plant is the General Electric-AVIO LM2500 GT. It is arranged in a two shafts configuration. The gas generator is composed by compressor (COMPRESSOR in Fig. 3), combustion chamber (COMBUSTOR) and the high pressure turbine (HP TURBINE) blocks.

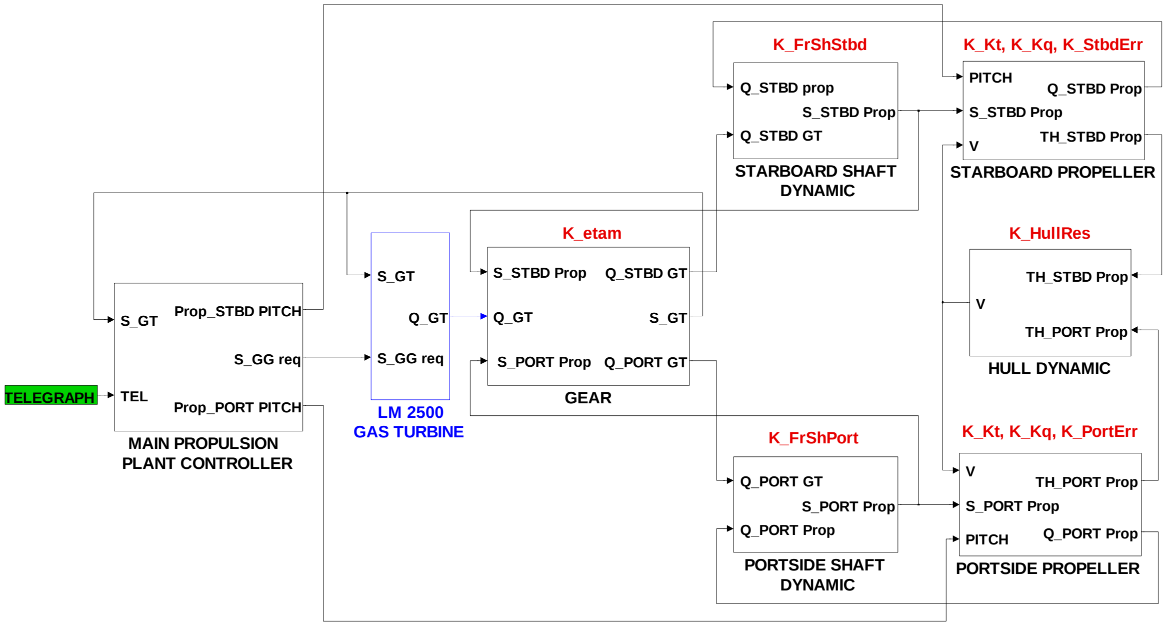

Fig. 2: Overall ship propulsion plant SIMULINK scheme with components loss coefficients (in red)

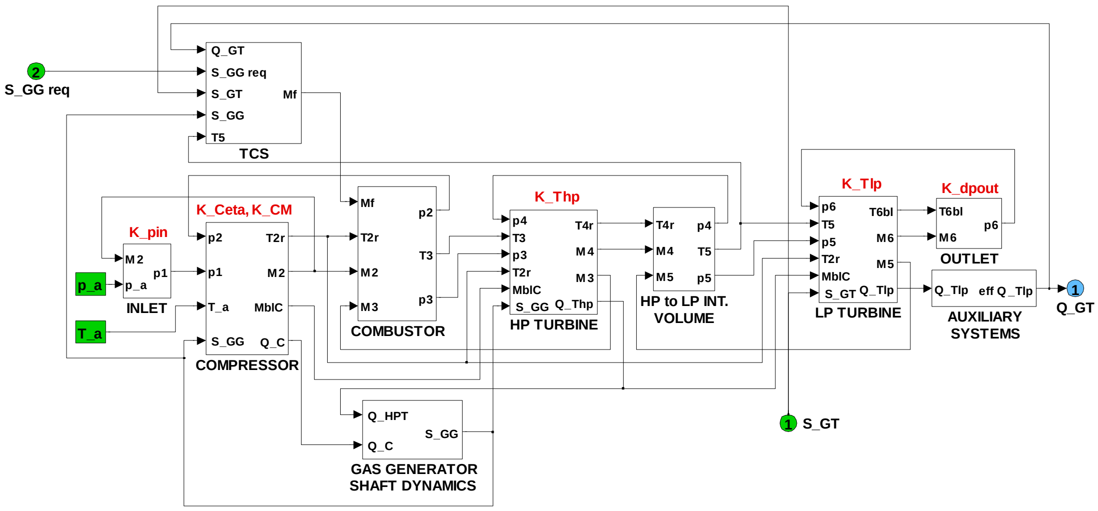

Fig. 3: Overall gas turbine SIMULINK scheme with components loss coefficients (in red)

As mentioned, the GT delivered power is governed by the MAIN PROPULSION PLANT CONTROLLER block (Fig. 2), through the required GT gas generator speed (S_GG req in Fig. 3), which is an input of the LM2500 GAS TURBINE block. An increase of this variable increases the GT delivered power. This last is the input signal of the effective GT governor block, named TCS (turbine control system) in figure. By means of a PID controller scheme, the TCS controls the fuel valve position, in order to manage the fuel mass flow rate Mf value which is transmitted to the COMBUSTOR block. The GT power is governed as reported by Tortarolo (2000) in order to obtain the required GT power turbine speed S_GT. As shown in Fig. 3, the TCS governor monitors a series of GT parameters. In case one of the TCS monitored variables reaches the maximum allowable value, the GT governor reduces the fuel mass flow in the GT combustor in order to preserve the GT components from overloads or over temperatures. The GT propulsion components modeled in the SIMULINK environment are briefly described while a detailed explanation is presented in Benvenuto *et al*, 2005. In the INLET module of Fig. 3, the GT inlet duct pressure loss is determined as function of air filter fouling, indicated by the pertinent constant loss (K_pin in red over the block). For the compressor simulation, typical steady state performance maps (Cohen *et al*, 1987) are used. In the COMPRESSOR module (Fig. 3), the component efficiency and the outlet air mass flow (M2 outlet of the block) are determined by the above mentioned steady state performance maps, as functions of the compressor pressure ratio and of the S_GG shaft speed. The gas generator shaft bearings losses are evaluated as function of the compressor shaft speed.

The performance and data regarding the two GT turbines (HP TURBINE and LP TURBINE blocks in Fig. 3) are determined in a similar way. For the combustor (COMBUSTOR and HP to LP INT. VOLUME modules in Fig. 3) performance estimation, the continuity and energy dynamic equations are used. The OUTLET block is simulated similarly to the INLET module. Finally, the AUXILIARY SYSTEM block takes into account the power absorbed by GT auxiliaries by means of a constant value that reduce the delivered GT torque Q_GT, that is the only output of the LM2500 GAS TURBINE block.

The above described overall frigate propulsion plant simulator has been validated comparing the numerical results with sea trials data, measured during the on board test campaign of the vessel, referred to steady state load conditions for different telegraph lever positions. In Fig. 4 the percentage errors between calculated and reference values of the most significant propulsion plant characteristics are shown in absolute values, referred to five steady state load conditions (38%, 47%, 67%, 80% and 90% of telegraph setting position), in case of perfect status for every component (all the faults coefficients are set to one). As can be seen from the data reported in Fig. 4, the errors between numerical and experimental data are acceptable for all monitored parameters, particularly at high engine loads. Higher errors are observed at very low engine loads in the gas generator sections, mainly due to lack of information regarding compressor and turbines maps at low running conditions. However, the errors do not affect significantly the engine and ship performance prediction. Moreover, diagnostic applications of the simulation model are limited to high engine loads in this application.

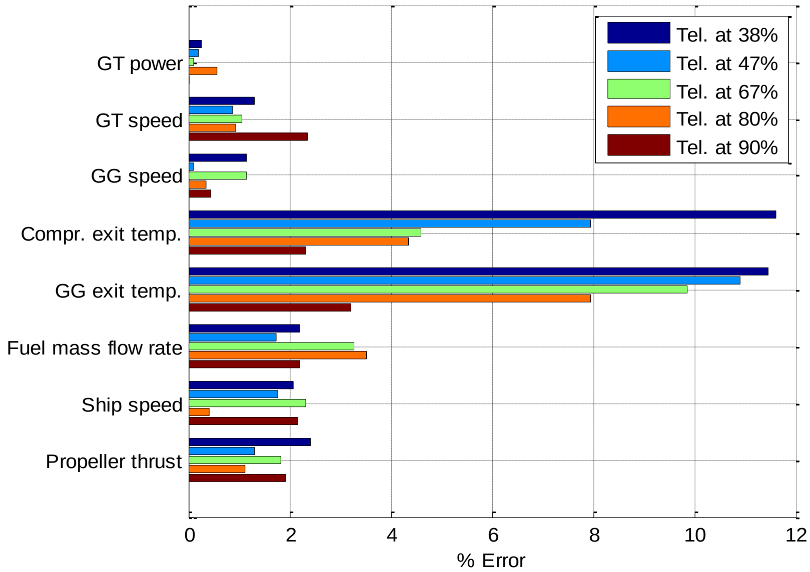

Fig. 4: Percentage errors between simulation model and sea trials experimental measures (absolute value)

3. Variables Selection

A variables selection analysis has been carried out in order to identify the minimum set of parameters which is able to provide the all the necessary information to define the status of the system. This target has been pursued through a design of experiments (DoE) analysis of the multivariate domain of the complete set of parameters. DoE techniques aim to extract as much information as possible from a limited number of experimental or computer experiments: the multivariate domain of the variables is filled with a number of points using pseudo-random techniques (Giunta *et al*, 2003). Some commonly used pseudo-random space filling techniques are: pseudo-Monte Carlo Sampling, Sobol sequence, Latin Hypercube Sampling, Central Voronoi Tessellation, Orthogonal Arrays. In this particular case a Sobol sequence algorithm has been used to fill the input variables domain: 16 input variables have been spanned, and 1500 experiment points (simulator runs) have been selected. The complete set of input parameters is reported in Table 2 together with the considered range for each variable.

Note that the telegraph lever position is imposed as constant for each set of experiments and 4 values have been considered (4, 8, 9, 10, the last corresponding to the maximum continuous rating), leading to 6000 experiments (simulator runs). The telegraph lever value sets the system operating point and has therefore a major (and obvious) influence on the remaining input variables; separate DoE dataset are needed for a given telegraph position. In addition, compressor fault coefficient *K_Ceta* is computed from *K_Cm* according to the following:

$$K_{Ceta} = 1 - 0.75(1 - K_{CM}) \quad (1)$$

Table 2: Input variables and their range

Variable name	**Description**	**Range**
T_C	[°C] air temperature	[-30 ; 40]
K_pin	Compressor inlet filter fault coefficient	[.95 ; 1]
K_Cm	Compressor mass flow rate coefficient	[.90 ; 1.05]
K_Thp	HP turbine fault coefficient	[.93 ; 1.05]
K_Tlp	LP turbine fault coefficient	[.93 ; 1.05]
K_dpout	GT outlet duct fault coefficient	[1E-6 ; 5E-6]
K_etam	Mechanical efficiency gear coefficient	[.9 ; 1]
K_FrShPort	Friction increase due to bearing fault (portside shaft)	[1 ; 2]
K_FrShStbd	Friction increase due to bearing fault (starboard shaft)	[1 ; 2]
K_Kt	Propeller thrust loss fault coefficient	[.908 ; 1]
K_Kq	Propeller torque increase fault coefficient	[1 ; 1.0928]
K_PortErr	Portside propeller pitch actuator error (°)	[-1 ; 1]
K_StbdErr	Starboard propeller pitch actuator error (°)	[-1 ; 1]
K_HullRes	Hull resistance coefficient increase	[2E-4 ; 1E-4]
Telegraph	Telegraph lever position	CONSTANT

Table 3: Output parameters after variable selection test

Variable name	**Description**
p_1	Compressor inlet pressure
p_2	Compressor outlet pressure
T_2r	Compressor outlet pressure
Eta_C	Compressor efficiency
n_gg	Gas generator shaft speed
M_f	Fuel mass flow rate
p_4	Low pressure turbine inlet pressure
T_5	Low pressure turbine inlet temperature
Pow_HPT	High pressure turbine power
Eta_LPT	High pressure turbine efficiency
p_6	LP turbine outlet pressure
T_6	LP turbine outlet temperature
M_1	Total mass flow rate
Q_GT	LP turbine torque
Eta_LPT	LP turbine efficiency
n_Prop	Propeller shaft speed (only for telegraph=10)
QPropPort	Propeller torque (portside)
Q_PropStbd	Propeller torque (starboard side)
TH_PropPort	Propeller thrust (portside)
TH_PropStbd	Propeller thrust (starboard side)
V_ship	Ship speed
NOX	NOX emissions
Eta0_PropPort	Open water propeller efficiency (portside)
Eta0_PropStbd	Open water propeller efficiency (starboard side)
BSFC	Brake specific fuel comsumption

A large number of output variables has been recorded for each of the 1500 simulations, in order to collect the maximum data useful for the variable selection process. This process has been pursued on the basis of a Student's t-test analysis. Student's t-test is commonly used to quantify the difference between two sets of data. In this particular case it provides an evaluation of the mutual influence between the input and output variables. According to the t-test results and to practical considerations (i.e. technological limits in measurement), a reduced number of effective output parameters has been obtained and listed in Table 3. For each telegraph lever position an exhaustive description of the system status is therefore provided by two sets of data: the input set, containing 1500 different pseudo-random generated working points, and the corresponding most effective output values.

4. Response Surface Development

The database obtained through the DoE provides an exhaustive description of the relationship between simulator's input and response parameters. Such relationship can be seen as the solution of two different problems:

- The direct problem, or simulation problem, consisting in the computation of the plant's performance parameters starting from the input parameters. This problem is tackled by the simulator by numerically solving the physical and thermodynamic differential equations that models the physical system. This approach has the intrinsic limitations of the numerical model and it is not particularly efficient for real-time analysis.
- The inverse problem, or diagnostic problem, calculates a subset of input parameters starting from the remaining parameters: the subset is composed by the diagnostic variables, or fault coefficients, which determine the health state of the system. The remaining parameters, called state variables, from which the diagnostic information stem, are measured data from the system. The solution of the diagnostic problem cannot be achieved using the simulation model whose input/output parameters cannot be easily inverted. This would require completely different governing equations not easily derivable form the actual set of governing equations.

A response surface method (RSM) is the most commonly used approach to model the relationship between a given set of input and output variables. RSM is usually associated to DoE analysis to explore the variables domain. In this work the artificial neural networks (ANN) have been used as RSM technique.

Artificial neural networks are mathematical models based on the human brain structure, which are useful to solve a large number of problems, for instance function fitting, clustering, classification, pattern recognition. The human brain is composed by a large number of elementary units (cells), which are called neurons interconnected one to another by synapses. A neuron is a sort of filter, which receives a number of signals and activates if the total signal is higher than a threshold, sending is own signal to the other neurons. The information speed is not very high, but the neurons are massively parallel-connected, so the result is a very fast processing unit. A neuron (Fig. 5) can be mathematically modeled as a weighted summation block and an activation block: the input signals are collected into the array $\boldsymbol{x} = (x_1, \ldots, x_n)$, while the vector $\boldsymbol{w} = (w_1, \ldots, w_n)$ contains the weights. The summation block simply computes the value of the scalar product $a = \boldsymbol{x} \cdot \boldsymbol{y}$, which is compared to the threshold value θ. The output value $y = f(a - \theta)$ is calculated through the activation function f. There are several types of activation functions, the most commonly used are hard limit, sign function, linear, sigmoid, hyperbolic tangent. The choice of the activation function depends on the structure of the problem.

In analogy to the human brain, an ANN is composed by a large number of interconnected neurons, organized into three or more layers. The number of input and output layer neurons corresponds to the number of input/output parameters of the problem, while the number of neurons in the hidden layer(s) can be chosen on the basis of many different criteria (Verbist *et al*, 2011). An example of a three layers ANN with three inputs and two outputs is shown in Fig. 6. The information flows from the input layer to the output layer, with no feedback. The advantage of using ANN is that there is no need to implement any description of the input/output relationship: the network 'learns' such relationship from data.

The learning process consists into the identification of the optimum weight values for each neuron, which can be done using many different algorithms, mainly based on optimization techniques. Usually the Feed forward back propagation algorithm is used: the algorithm consists in a forward step, in which the neuron outputs are computed at fixed weights, and a backward step, in which the neuron weights are updated back-propagating the error obtained comparing predicted and target outputs. Once the learning algorithm is implemented, it is possible to train an ANN to solve a problem on the basis of known data. Notice that once it is trained, an ANN is a black box that provides output values corresponding to any input pattern, so attention must be paid to ANN test and validation before trusting in network's results.

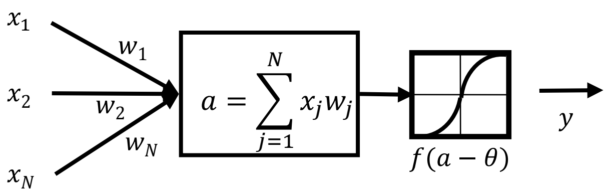

Fig. 5: Neuron model structure

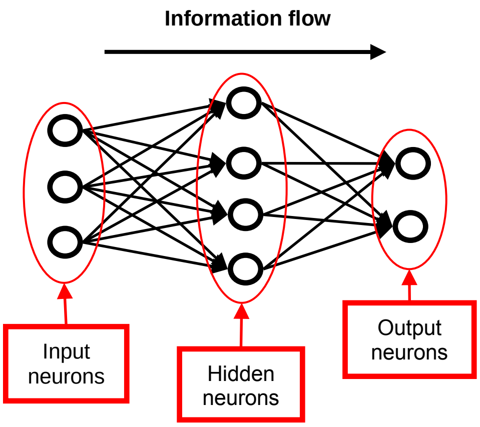

Fig. 6: 3 layers ANN structure

The performance of an ANN is usually evaluated through the mean square error (*MSE*) which expresses the difference between the predicted output vector $\boldsymbol{o}$ and target output vector $\boldsymbol{t}$. If the considered set is made by *N* patterns, the *MSE* is given by:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}|\boldsymbol{t}_i - \boldsymbol{o}_i|^2$$

MSE can be referred to training, test or and validation data: a low training data *MSE* is symptom of a good fitting (even over-fitting), while a low test and validation *MSE* (calculated on data which has not been used in the training phase) indicates a good generalization. In both the considered cases, 70% of data has been used for training, leaving the remaining 30% for test and validation.

4.1 Direct ANN – simulation problem

The direct ANN is trained to solve the simulation problem, so the input parameters of the network are the same as for the simulator. On the basis of physical considerations, propeller fault coefficients *K_Kt* and *K_Kq* have been merged into one factor called *F_prop*, with range [0 ; 1]. In addition, only a subset of the output variables selected by the previous analysis has been considered: redundant variables have been eliminated. Finally, each variable has been normalized to [0 ; 1] according to:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (3)$$

Table 4: I/O variables for the direct ANN

Input	Output
T_C	*p_1*
K_pin	*p_2*
K_Thp	*T_2r*
K_Cm	*n_gg*
K_Tlp	*p_4*
K_dpout	*T_5*
K_etam	*p_6*
K_FrShPort	*T_6*
K_FrShStbd	*M_1*
F_prop	*Q_GT*
K_PortErr	*n_Prop*
K_StbdErr	*Q_PropPort*
K_HullRes	*Q_PropStbd*
	TH_PropPort
	TH_PropStbd
	V_ship
	BSFC

Table 5: I/O variables for the inverse ANN

Input	Output
T_C	*K_pin*
p_1	*K_Cm*
p_2	*K_Thp*
T_2r	*K_Tlp*
n_gg	*K_HullRes*
M_f	*K_PortErr*
p_4	*K_StbdErr*
T_5	*F_prop*
p_6	*eta_tr*
T_6	
M_1	
Q_GT	
n_Prop	
Q_PropPort	
Q_PropStbd	
TH_PropPort	
TH_PropStbd	
V_ship	

The network output can be easily un-normalized by the inverted equation:

$$y = y_{norm}(y_{max} - y_{min}) + y_{min} \qquad (4)$$

The input/output variables are summarized in Table 4. The variable *n_Prop* is considered only for the maximum telegraph lever position. The ANN performance on validation data is shown in Fig. 7, in terms of *MSE*. The best performance is obtained at partial load (telegraph values 4 and 8), while at higher loads *MSE* increases: this effect is due to the strong non-linear effects introduced by the control system.

4.2 Inverse ANN – diagnostic problem

The inverse ANN is designed to compute the diagnostic parameters from a set of measured state parameters. A first approach is to simply invert direct ANN's input and output variables (except from the external temperature, which is measurable and does not provide information on the health status and is an input variable). However, there are some redundancies in diagnostic parameters definition: there are more than one parameter operating on the shaft line components. In order to overcome problems in training algorithm convergence, a more 'general' transmission fault coefficient has been defined. In particular:

$$eta_{tr} = \frac{Q_{PropPort} + Q_{PropStbd}}{Q_{GT} \cdot i} \qquad (5)$$

In Eq. (5), *i* is the gear ratio. In addition, the coefficient *K_dpout* has been found not significant, so this variable has been neglected.

The considered input/output variables are reported in Table 5.

The ANN performance on validation data is shown in Fig. 7, in terms of *MSE*. Note that the diagnostic networks perform better than the direct ones.

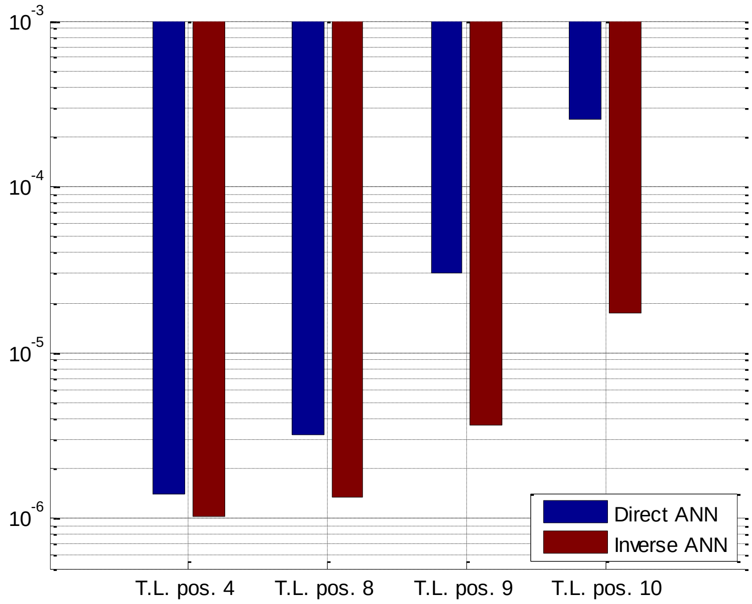

Fig. 7: Comparison between Direct/simulation and Inverse/diagnostic ANN performances (MSE) on validation data (logarithmic scale)

5. Applications

5.1 Propulsion system simulation using direct ANN

The direct ANN is an effective simulation tool when a low computational effort is needed, and transient conditions are overlooked: in fact, the direct network is trained on a set of points corresponding to different stationary working points of the plant, so it is designed to provide the steady state performance data corresponding to given input conditions. If transient data are required, for instance during engine acceleration, stopping and speed changes maneuvers, the use of the simulator is preferable but it requires a computational time of about 80 seconds on a standard laptop. The neural network is able to provide a simulation of a stationary condition in about 0.01 to 0.02 seconds on the same PC. A comparison between network and simulator results is presented for the following cases of component failure combinations:

Case 1: compressor degradation and pitch error on starboard propeller;
Case 2: hull and propeller degradation (for example due to fouling);
Case 3: partial degradation of GT main components (air filter, compressor, turbines).

The fault coefficient values relative to the different cases are summarized in Table 6. All results are presented in in Fig 8 in terms of percentage errors, and are referred to telegraph lever in position 8: notice that the accuracy obtained with the ANN based simulation is very high with respect to the values from the numerical simulator.

Table 6: Fault coefficients values in considered cases

	Case 1	**Case 2**	**Case 3**
T_C	25	25	25
K_pin	1	1	0.98
K_Cm	0.95	1	0.97
K_Thp	1	1	0.98
K_Tlp	1	1	0.98
K_dpout	1.00E-6	1.00E-6	1.00E-6
K_etam	1	1	1
K_FrShPort	1	1	1
K_FrShStbd	1	1	1
F_prop	1	0.6	1.00E-6
K_PortErr	1	0	0
K_StbdErr	0	0	0
K_HullRes	2.00E-4	3.00E-4	2.00E-4

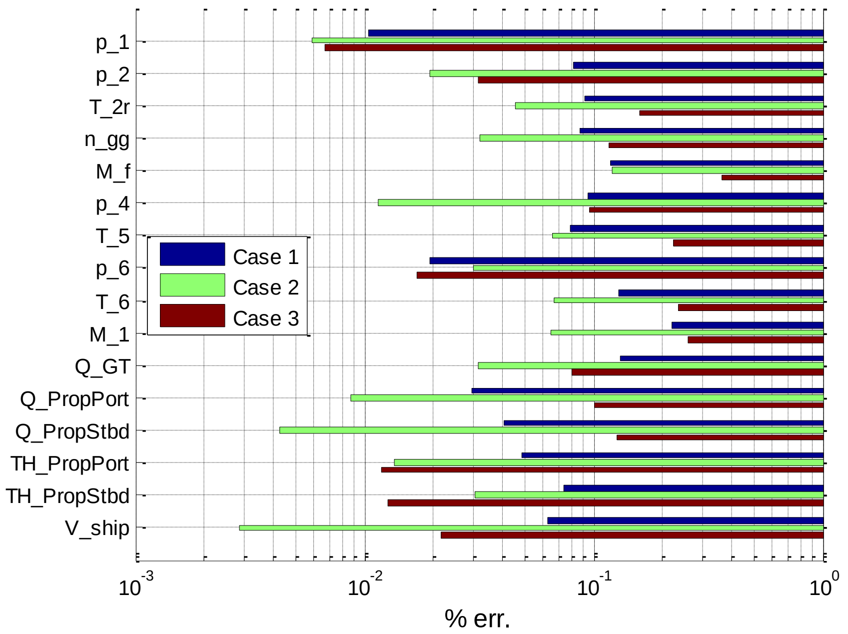

Fig. 8: Percentage errors (in absolute value) between SIMULINK simulation model and ANN outputs (logarithmic scale)

5.2 Propulsion system diagnostic using inverse ANN

Three applications for diagnostic purposes of the inverse network (with telegraph position fixed to 8) are presented. The same three faulty conditions considered in the case of direct ANN have been simulated, and a random noise has been added to the simulation outputs in order to check for the network robustness. In order to handle uncertainty in measured date, the approach suggested in Verbist *et. al*, (2011) has been used: the predicted coefficients have been evaluated as the arithmetic mean of 50 predictions based on error affected measures.

For each case a comparison between the measuring error-free output and the results obtained by introducing a population of measures affected by a random error is provided. The results obtained using an averaged value of the measures (affected by the same random error) over 50 samples have also been computed. The results are summarized in Figs. 9, 10, 11 in terms of percentage errors (except for the propeller pitch actuator error, where the absolute error is considered). The error-free prediction is accurate, as expected form the accuracy of the diagnostic ANN (Fig. 8). When the measuring errors are taken into account the accuracy is reduced and the use of the averaged value is preferred. The diagnostic network handles error affected measures with sufficient precision: in all the three cases the prediction on a single set of measures can be sufficient to make a plausible diagnosis. However, the evaluation of the fault coefficients is much more precise if the averaged value is considered (for instance, in case 2 the error on *K_HullRes* is reduced from about 30% to 6%). In some cases the error seems to increase using the averaged values (for instance in case 3 for *K_Cm* coefficient); this is due to the fact that a random error has been introduced into measures. If the *MSE* of all the predictions is computed (Fig. 12) a significantly better performance using averaged measured data is highlighted in two out of the three considered cases.

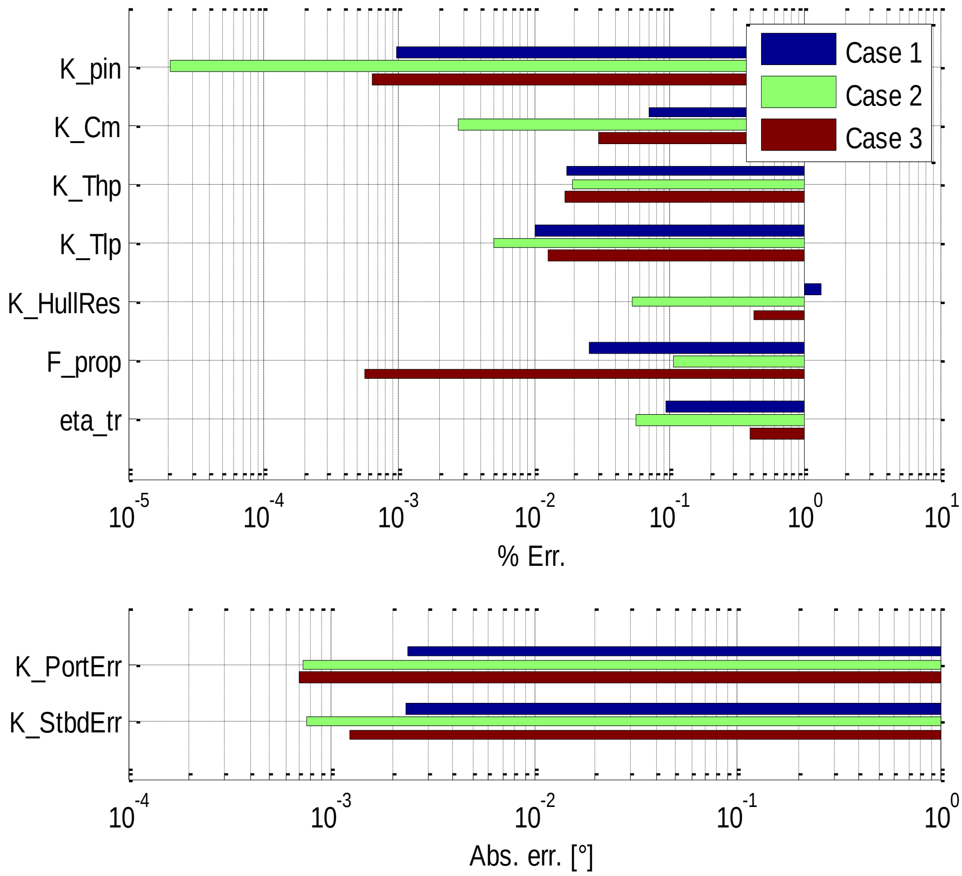

Fig. 9: Fault coefficients prediction errors using error – free input data (logarithmic scale)

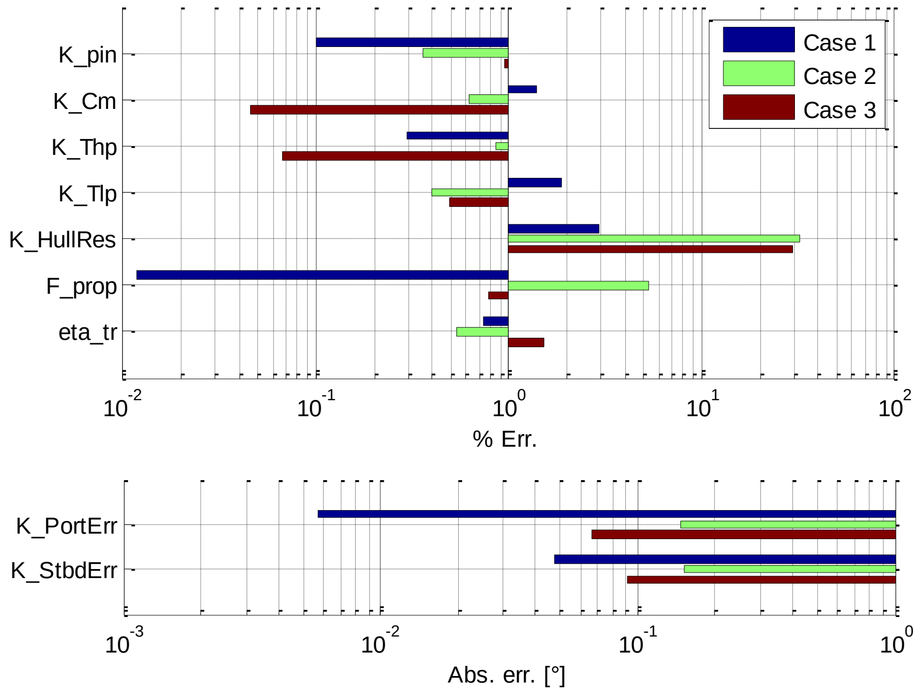

Fig. 10: Fault coefficient prediction errors using Gaussian error affected input data (logarithmic scale)

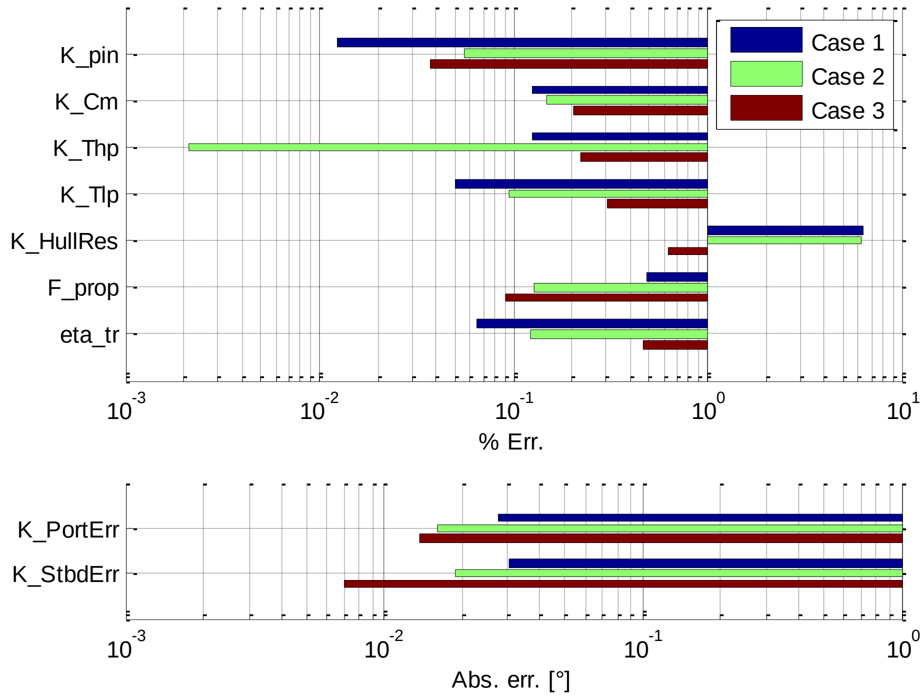

Fig. 11: Fault coefficient prediction errors using average value of 50 Gaussian error affected predictions (logarithmic scale)

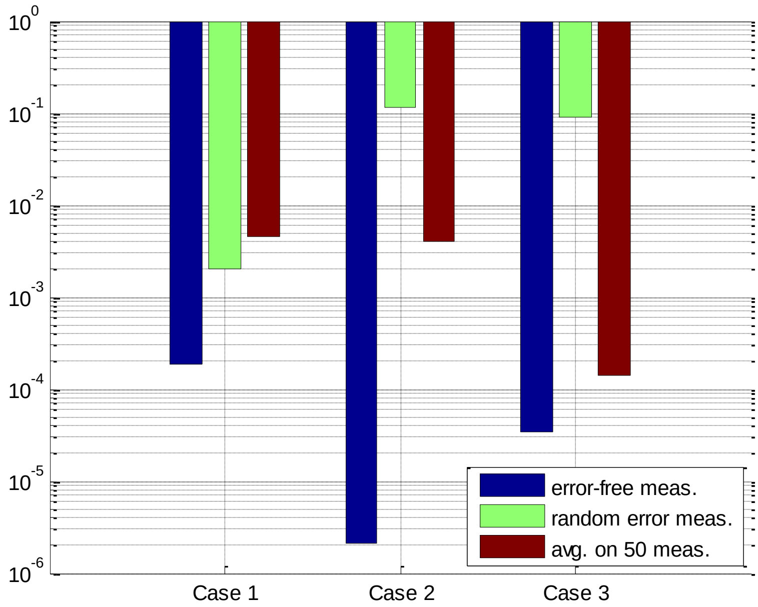

Fig. 12: ANN Performance (MSE) comparison in presence of measurement errors (logarithmic scale)

6. Conclusions

Artificial neural networks have been used for either simulation or diagnostic purposes. Starting from a DoE analysis of a marine gas turbine powered propulsion plant simulation model, the most significant variables of the problem have been selected. A simulation ANN has then been developed: the obtained network is able to provide information about stationary working points of the considered plant in terms of physical and performance parameters, corresponding to given fault conditions, with very short run times with respect to the numerical simulator. On the other hand the developed ANN is not able to simulate transient operating conditions, so it is not suitable for dynamic simulations (speed change, acceleration, etc.). The direct ANN has been verified to be sufficiently precise in reproducing the simulator’s behavior, in terms of *MSE*. A diagnostic ANN has been also developed, in order to get information on the fault conditions of the system through a set of diagnostic variables (fault coefficients), which are computed from a given set of measurable state parameters. The diagnostic network performance has been evaluated through *MSE* calculation. In addition, three sample fault cases have been simulated in order to test the diagnostic capability of the ANN when the effects of measurement errors are introduced. The diagnostic ANN has shown good diagnostic properties in case of noise-free input data, and a sufficient robustness against noise. Errors in fault coefficients prediction can be significantly reduced with the averaging of several predicted values from a set of error-affected computations. The presented approach is currently under development and research is oriented mainly to improve the diagnostic performances.

References

Altosole, M., Benvenuto, G., Campora, U., Figari, M. (2009): Real-Time Simulation of a COGAG Naval Ship Propulsion System, Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment,Vol. 223, No. 1, pp. 47-62. http://dx.doi.org/10.1243/14750902JEME121

Altosole M., Benvenuto G., Campora U. (2010): Numerical Modeling of the Engines Governors of a CODLAG Propulsion Plant, 20th BLACK-SEA International Congress, Varna, Bulgaria, 7-9 October.

Altosole, M., Campora, U., Figari, M.. Martelli, M. (2014): Performance Decay Analysis of a Marine Gas Turbine Propulsion System, Journal of Ship Research, Vol. 58, No 3, pp.1-13. http://dx.doi.org/10.5957/JOSR.58.3.130037

Benvenuto, G., Campora, U., Carrera, G., Figari, M. (2000): Simulation of Ship Propulsion Plant Dynamics in Rough Sea, 8th International Conference on Marine Engineering Systems (ICMES/SNAME 2000), New York, USA, May 22-23.

Benvenuto, G., Campora, U. (2005): A Gas Turbine Modular Model for Ship Propulsion Studies, HSMV, 7th Symposium on High Speed Marine Vehicles, Naples, Italy, 21 – 23 September.

Benvenuto G., Campora U. (2008): Simulation of a Governed Marine Gas Turbine in Faulty Conditions, HSMV 2008, 8th High Speed Marine Vehicles Conference, Naples, Italy, 22-23 May.

Campora, U., Figari, M. (2003): Numerical Simulation of Ship Propulsion Transients and Full Scale Validation, Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, Vol 217, No. 1, pp.41-52. http://dx.doi.org/10.1243/147509003321623130

Campora, U., Carretta, M., Cravero, C. (2011): Simulation of a Gas Turbine Engine with Performance Degradation Modeling, IMECE 2011, Proceeding of the ASME 2011 International Mechanical Engineering Congress and Exposition, Denver, Colorado, US, November 11-17. http://dx.doi.org/10.1115/IMECE2011-62532

Campora, U., Carretta, M., Cravero, C. (2013): Performance Decay Simulation of a Gas Turbine for Helicopter propulsion, Transaction on Control Mechanical Systems, Vol. 2, pp. 105-114.

Capelli, M. (2013): Un approccio per il monitoraggio e la diagnostica di impianti di propulsione navale basato su simulazione e metamodelli, Marine Engineer and Naval Architect Graduate Thesis, Genoa University, Engineering Faculty, Dipartimento di Ingegneria Navale, Elettrica, Elettronica e delle Telecomunicazioni (DITEN), Italy, March 16. in Italian.

Giunta, A., Wojktkiewicz Jr., S. F., Eldred, M. S. (2003): Overview of Modern Design of Experiment Methods for Computational Simulations, AIAA 2003 – 0649. http://dx.doi.org/10.2514/6.2003-649

Cohen, H., Rogers, G. F. C., and Saravanamuttoo, H. I. H. (1987): Gas Turbine Theory, (Third Edition), Longman Scientific and Technical, Harlow, Essex, England.

Cravero, C., Macelloni, P., Briasco, G. (2012) Three-Dimensional Design Optimization of Multi Stage Axial Flow Turbines Using a RSM Based Approach, ASME paper GT2012-68040, ASME Turbo Expo, Copenhagen (DK), June 11-5.

Cravero, C. (2013): Turbomachinery Design Optimization Based on Metamodels, 4th Inverse Problems Design and Optimization Symposium IPDO-2013, Albi (FR) June 26-28.

Palmé, T., Breuhaus, P., Assadi, M., Klein, A., Kim, M. (2011): New Alstom Monitoring Tools Leveraging Artificial Neural Network Technologies, ASME paper GT2011 – 45990.

Palmé, T., Breuhaus, P., Assadi, M., Klein, A., Kim, M. (2011): Early Warning of Gas Turbine Failure by Nonlinear Feature Extraction Using an Auto-Associative Neural Network Approach, ASME paper GT2011-45991.

NATO RTO, (2007): Performance Prediction and Simulation of Gas Turbine Engine Operation for Aircraft, Marine,Vehicular, and Power Generation, NATO RTO Technical Report TR-AVT-036.

Rigoni, E., Lovison, A. (2007): Automatic Sizing of Neural Networks for Function Approximation, Inter. Conference of Systems, Man and Cybernetics, ISIC, IEEE, pp. 2005-2010, Montreal, Canada. http://dx.doi.org/10.1109/ICSMC.2007.4413933

Tortarolo, F. (2000): Marine Gas Turbine Control System, Proceedings, The 33rd WEGEMENT School Fast Ship Propulsion Plants, 22 – 26 May, Genoa, Italy.

Verbist, M. L., Visser, W. P. J., van Buijtenen, J. P. (2011): Gas Path Analysis on KLM in-flight Engine Data, ASME paper GT2011-45625. http://dx.doi.org/10.1115/GT2011-45625