

Identification of Two-shaft Gas Turbine Variables Using a Decoupled Multi-model Approach With Genetic Algorithm

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Abstract

In industrial practice, the representation of the dynamics of nonlinear systems by models linking their different operating variables requires an identification procedure to characterize their behavior from experimental data. This article proposes the identification of the variables of a two-shafts gas turbine based on a decoupled multi-model approach with genetic algorithm. Hence the multi-model is determined in the form of a weighted combination of the decoupled linear local state space sub-models, with optimization of an objective cost function in different modes of operation of this machine. This makes it possible to have robust and reliable models using input / output data collected on the examined system, limiting the influence of errors and identification noises.

Keywords

genetic algorithm, multi-model approach, input data, output data, cost function, sub-models, non-linear systems, gas turbine

1 Introduction

Monitoring and understanding the behavior of gas turbines is an industrial challenge which has, in recent years, become increasingly important in most industrial sectors that use these rotating machines. Indeed, this industrial equipment are on a large scale and represent significant non-linearity's with uncertainties in their modeling. They are also subject to several specific faults which violate their observability. This can lead to premature aging of the components, or even unacceptable noise and vibration disturbances. This work is oriented in this direction to illustrate and show how, in a monitoring policy, the variables are measured, processed, monitored in the form of sub-models and are used for the development of a global model of a gas turbine. This work raises one of the major problems when looking for a reliable mathematical representation for this type of rotating machine.

However, several works have been carried out in this field to overcome the gas turbines modeling issues and their use in control and diagnosis [1–11]. In 2020, Evans et al. [12] carried out an identification of the dynamics of gas turbines using signal analysis techniques in the frequency domain for the purpose of turbine

control. Amirkhani et al. [13] proposed a nonlinear robust fault diagnosis approach for a gas turbine using an adaptive threshold approach based on Monte Carlo modeling. Also, in 2019, Rossi et al. [14] applied a hybrid system for the dynamic simulation of a gas turbine, and Colera et al. [15] proposed a numerical diagram for the thermodynamic analysis of gas turbines in order to improve the efficiency of this type of machine. Hadroug et al. [16] have linearized the dynamic of the two-shaft gas turbine model around the operating points using turbine input / output data. Other works such as Benrahmoune et al. [17] and Tahan et al. [18] carried out a system for detecting and modeling the vibrational behavior of a gas turbine based on the approach of dynamic neural networks in real time based on the performance of industrial gas turbines. Cuneo et al. [19] and Asgarshamsi et al. [20] proposed optimization approaches on gas turbine models in a hybrid system taking into account the degradation of their components.

The aim of this work is the identification of a nonlinear model of gas turbine under constraints, using genetic algorithms with the multi-models' approach (sub-models) in a

real operating environment using input / output databases of the operating history of the examined turbine, in order to ensure proper operation of this rotating machine.

2 Multi-model approach

In the industrial literature, several structures make it possible to group different sub-models, in order to generate the global output of the multi-models. These approaches can be distinguished according to their use and their form, with the aim of apprehending the nonlinear behavior of a system by a set of local models ($i = \overline{1, L}$), characterizing the functioning of the system in different operational zones [21–23]. Hence, each zone being characterized by a sub-model f_i , the multi-model approach aims to replace the search for a single model $F(\cdot)$ which is often difficult to obtain, by the search for a family of sub-models $f_i(t)$ and of weighting functions $\mu_i(\xi(k))$, that transition between these sub-models. Depending on the evolution area of the nonlinear system, the output of each sub-model contributes more or less to the approximation of the overall behavior of the nonlinear system, given by [22]:

$$F(\cdot) = \sum_{i=1}^L \mu_i(\xi(k)) f_i(\cdot). \quad (1)$$

With the $\mu_i(\xi(k))$ are the weighting functions which ensure the transition between the sub-models, they have the following properties [24, 25]:

$$\sum_{i=1}^L \mu_i(\xi(k)) = 1, \quad \forall k \quad (2)$$

$$0 \leq \mu_i(\xi(k)) \leq 1, \quad \forall i = 1 \dots L, \forall t,$$

where ξ is the index variable which depends on the measurable state variables of input or output of the system.

Multi-models have a very good capacity for representing complex dynamic behaviors in several industrial applications and appear to be quite suitable for modeling systems from real data from their operation [21, 26, 27]. Hence, the contribution of each sub-model is defined by the weighting functions, which is based on the decomposition of a complex model into a sub-model that is easier to solve, whose individual solutions lead to the resolution of the global problem. These multi-models constitute universal approximations, a nonlinear system can be approximated with an imposed precision by increasing the number of sub-models [24, 28, 29].

Analytically, three distinct methods can be used to obtain a multi-model, by identification if the inputs and outputs of nonlinear systems are available, by linearization around different operating points or by poly convex transformation of local models and functions of activation.

However, the sub-models can be presented in different ways, all giving rise to different classes of multi-models. Two large families of multi-models are given in scientific literature; multi-models coupled and multi-models decoupled. In this work, the multi-decoupled model approach will be used for the modeling of gas turbine variables, the state representation in this structure assumes that the process is composed of local decoupled models and admits independent state vectors.

2.1 Decoupled multi-model approach

The problem of non-linear identification of systems is reduced to the identification of subsystems defined by linear local models weighted by activation functions, as shown in Fig. 1. The form of a multi model resulting from the aggregation of the sub-models in the form of a decoupled state structure, given by the following state representation [22, 24, 25]:

$$\begin{aligned} \hat{x}_i(k+1) &= A_i(\theta) \hat{x}_i(k) + B_i(\theta) u(k) + D_i \\ \hat{y}_i(k) &= C_i(\theta) \hat{x}_i(k) \\ \hat{y}_i(k) &= \sum_{i=1}^L \mu_i(\xi(k)) \hat{y}_i(k) \end{aligned} \quad (3)$$

$$\text{with } \hat{y}_i(k) = \sum_{i=1}^L \mu_i(\xi(k)) = 1, \quad \forall k.$$

Where $x_i \in \mathfrak{R}^n$ is the state vector of the i^{th} sub-model, $u \in \mathfrak{R}^m$ is the control vector, $y_i \in \mathfrak{R}^n$ is the vector of measures, the matrices A_i , B_i , C_i and D_i are the state matrices of the sub-models, ξ is the index of the weighting functions μ_i and θ is the parameter vector.

The construction of a multi-model from inputs and outputs requires the definition of a multiple model structure with the definition of the weighting functions and the estimation of the parameters of the activation function of the local models. In particular, in this case the global output of the multi-model is given by the weighted sum of the local outputs and that each sub-model has its own state space and this varies as a function of the control signal independently [24, 25].

The transition from one sub-model to the other is ensured by on the weighting functions, shown in Fig. 2, corresponds to the case of piecewise linear models, in this work weighting functions are of the Gaussian type, given by [30, 31]:

$$\omega_i(\xi) = \exp\left(-\frac{(\xi - c_i)^2}{\sigma^2}\right), \quad (4)$$

where $\omega_i(\xi)$ is a function of the center c_i , σ is the dispersion common to all the weighting functions. The indexing variable ξ will be defined by the input signal, the fuel

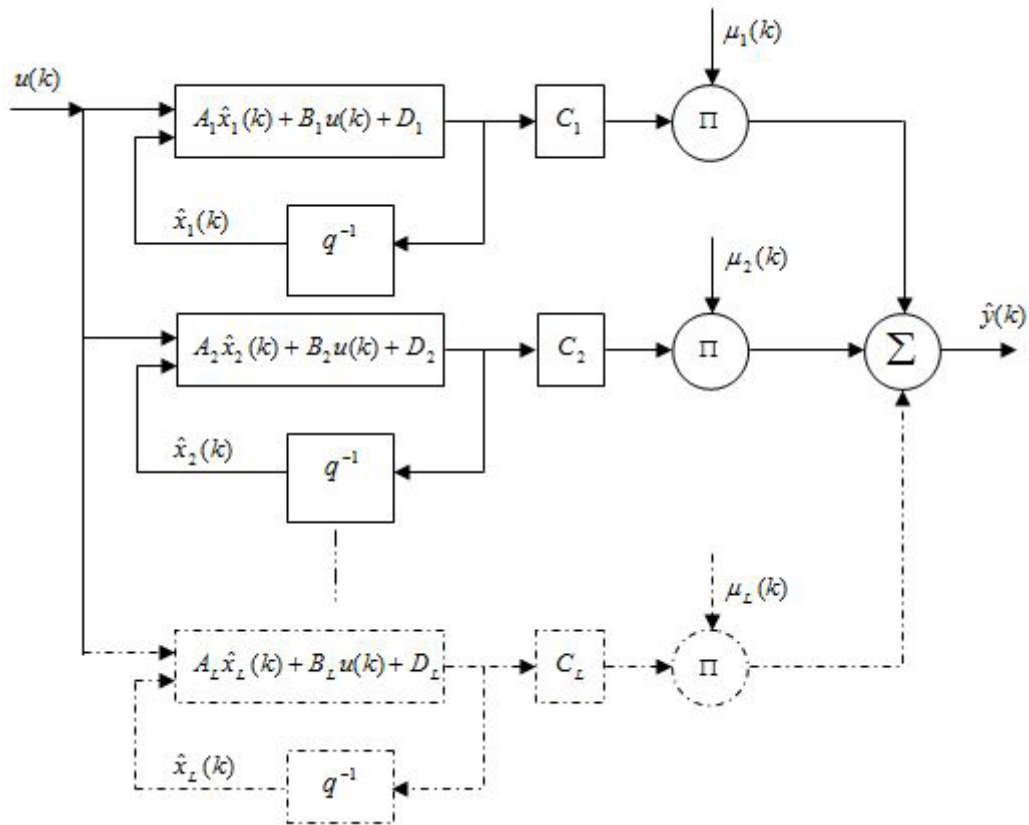


Fig. 1 Structure of a decoupled multi-model system

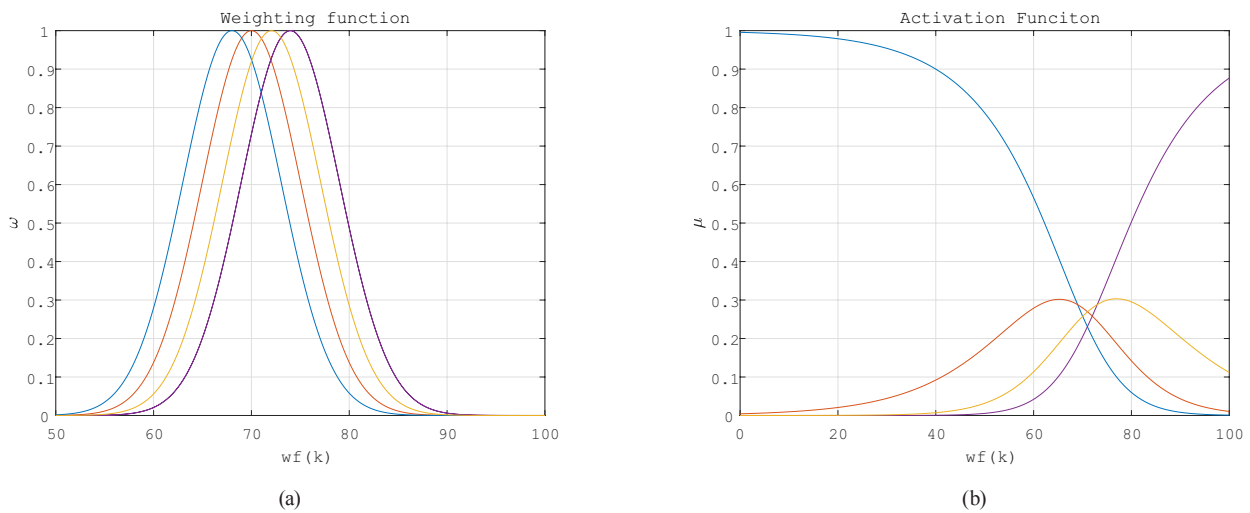


Fig. 2 Activation and weighting functions; (a) Weighting function; (b) Activation function

flow, with the condition given by Eq. (2) must be fulfilled. In order to respect the condition given by Eq. (5) the functions $\omega_i(\xi)$ are normalized and finally the activation functions are calculated by [21, 24]:

$$\mu_i(\xi) = \frac{\omega_i(\xi)}{\sum_{j=1}^L \omega_j(\xi)} \quad (5)$$

The activation function μ_i determines the degree of activation of the i th local model associates, according to the zone where the system evolves, this function indicates the more or less important contribution of the model.

The activation function μ_i determines the degree of activation of the i th local model associates, according to the zone where the system evolves, this function indicates the

more or less important contribution of the corresponding local model in the global model. Also, it ensures a gradual transition from this model to neighboring local models.

For the stability of multi models, it depends on the existence of a common, symmetric and definite positive matrix, which guarantees the stability of all local models. These stability conditions can be expressed using linear matrix inequalities, it is a question of looking for a symmetric and definite positive matrix and its associated Lyapunov function such that certain simple conditions guarantee the stability properties. However, the stability of a system represented by Eq. (3) can be verified if there is a symmetric matrix definite positive P and the following conditions are satisfied [24, 25]:

$$A_i^T P + P A_i < 0, \quad \forall i \in \{1, \dots, M\}. \quad (6)$$

The decoupled multi-model is stable if and only if all the sub-models are stable, i.e. the matrix A_i is a diagonal block matrix. Therefore, stability is ensured if is only if the eigenvalues λ_i of \tilde{A}_i are determined.

The construction of a multi-model from system inputs and outputs requires multi-objective optimization for defining the structure of multiple models, all the objectives are formulated under a set of constraints. Therefore, the global model determination can then be considered as a multi-objective optimization problem, namely to determine models with decoupled local states is to have completely independent sub-models. For this, the technique of genetic algorithm will be used later to solve this problem of multi-objective optimization.

3 Genetic algorithms

The genetic algorithm is a technique of optimization and research by imitation of the observed processes and based on the principles of genetics and natural selection. These algorithms develop a population of candidate solutions, each candidate is a solution, coded in the form of a binary chain called chromosome, or the cost of each chromosome is then evaluated using a cost function [32, 33]. After the chromosomes have been evaluated, selection rules are established so that the best candidate undergoes genetic operations such as crossing and mutation.

The cost of the newly produced chromosomes is lower than that of the previous generation, they will replace the weaker chromosomes. This process continues until the termination criteria are met. The cost is the difference between the desired output and the actual output, which is represented by the global criterion [32–35]:

$$J_j = \frac{1}{N} \sum_{k=1}^N (y_j(k) - \hat{y}_j(k, \theta)). \quad (7)$$

Where $\hat{y}_j(k, \theta)$ is the output of j^{th} the multi model, $y_j(k)$ is the j^{th} actual output of the gas turbine and N is the number of measurements.

This criterion of Eq. (7) favors a good characterization of the global behavior of the nonlinear system by the multiple models, from which $\hat{y}_j(k, \theta)$ is defined by Eq. (8) [36, 37]:

$$\left\{ \begin{array}{l} x_i(k+1) = A_i(\theta)x_i(k) + B(\theta)u(k) \\ \hat{y}_{i,j}(k, \theta) = C_{i,j}(\theta)x_i(k) + D_{i,j}(\theta)u(k) \\ \hat{y}_j(k, \theta) = \sum_{i=1}^L \mu_i(\xi(k)) \hat{y}_{i,j}(k) \end{array} \right\} \quad (8)$$

hence, $\theta = [\theta_1 \ \theta_2 \ \dots \ \theta_L]^T$ is defined as being the column vector of the parameters of the multi-model to be estimated, which is partitioned into L blocks.

The matrices of the multi model A_i , B , $C_{i,j}$ and $D_{i,j}$ are given by:

$$A_i = \begin{bmatrix} 0 & 1 \\ a_{i1} & a_{i2} \end{bmatrix}, \quad C_{i,j} = \begin{bmatrix} C_{i,1} \\ \vdots \\ C_{i,p} \end{bmatrix} = \begin{bmatrix} c_{i,j} & c'_{i,j} \\ \vdots & \vdots \\ c_{i,p} & c'_{i,p} \end{bmatrix}, \quad (9)$$

$$D_{i,j} = \begin{bmatrix} D_{i1} \\ \vdots \\ D_{ip} \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix},$$

where B is considered as a constant vector in all the sub-models, p is the number of outputs to be identified in the multi-model.

The outputs to be identified in the multi-model of gas turbine system are; the rotation speed of the high pressure turbine (HP) and the rotation speed of the low pressure turbine (LP), the exhaust temperature of the high pressure turbine (T7) and the exhaust temperature of the low pressure turbine (T5). Consequently, all the outputs share the same matrix A_i in all the sub-models since B is taken as constants. The large number of parameters to find in the parameter vector θ , increases the complexity of the multi-model, which can lead to a gap between the outputs of the multi-model and the real outputs, in this work we divide the vector of parameter into vector contains the matrix parameters $A_{i=1,L}$, given by

$$\theta_A = [a_{i1} \ a_{i2} \ \dots \ \dots \ a_{L1} \ a_{L2}]. \quad (10)$$

And vectors contain the parameters of $C_{i=1,L}$ and $D_{i=1,L}$ each output given by:

$$\theta_j = [C_{i,j} \ D_{i,j} \ \dots \ \dots \ C_{L,j} \ C_{L,j}]. \quad (11)$$

This vector division is not only to reduce the complexity of the multi-model but allows us to use limits for the parameters search area for each output, however these limits can be used for all parameters or can be used for each parameter by a simple loop.

4 Investigations and applications results

The aim of this section is to present the results obtained from the identification of gas turbine model variables examined, this identification is based on the use of multiple models of the turbine optimized by the genetic algorithm. The dynamic behavior of the turbine is identified using the fuel flow from the combustion chamber and the variation of the air Inlet Guide Vane (IGV), which is a function of the ambient pressure and temperature of compressor section input as model inputs and outputs consider the rotational speed of the high pressure turbine HP (NGP), the rotational speed of the low pressure turbine LP (NPT) and the temperatures of HP and LP turbine exhaust given by T5 and T7, as shown in Fig. 3. The identification method used is based on genetic algorithms with a mechanism of natural selection, it combines a strategy for monitoring variations in very strong turbine parameters with more information on the model structure. This algorithm is used for the identification of model parameters in the form of multi-model of the turbine in a reasonable calculation time depending on its application in real time control of this rotating machine.

To analyze the dynamic behavior of a gas turbine, a decomposition of the overall model of the turbine into three models (L2, L3, L4) is proposed, for the four variables of turbine output examined. For this, the generation of the genetic algorithm comprises three operations which are not more complicated than algebraic operations, with all the sub-models are indicated in Table 1.

Fig. 4 shows the variation of NGP cost function of the rotation speed of the high pressure turbine (HP) in the local turbine models and Fig. 5 shows the variation of NPT cost function of rotation speed the low pressure turbine (LP) in the local turbine models; These cost functions evaluate a set of admissible speeds can involve various factors, such as the amplitude of the noise and the duration of vibration of each speed. It is clear that the variation of the cost function decreases when the new generation appears, with a global search on 100 inhabitants for 1000 generations, we notice that the best solution obtained for the NGP speed is given by the local model $L = 3$, and for the speed NPT is given by the local model $L = 4$. Indeed, these

results obtained show that the difference between the two results is small, this is because of, because of the method only a global search.

A small difference in the number of parameters to search θ can be considered more or less costly than a large number to search θ , we can also identify the vectors θ_{NGP} and θ_{NPT} while the vector θ_A which contains the parameters A_i is taken as a zero vector using the Eq. (11).

The quality of the sub-models obtained suggests real possibilities for applying NSGA II multi-objective optimization for optimizing the operations of matrix parameters A_i in state vectors θ_A , which are a function of two cost functions NGP and NPT and determine the optimal sub-models of the examined turbine. This is shown in Fig. 6, which shows the optimal sub-model parameters based on the cost function of NGP versus the cost function of NPT for local turbine models. The multi-objective optimization carried out shows that for the local model $L = 2$ has the best solution for the cost functions of NPT and NGP is (4.613, 0.4776), for the local model $L = 3$ is (4.437, 0.6133) and for the local model $L = 4$ is (5.064, 0.5446). The determination of the optimal turbine sub-model fitness examined is carried out by separating the population into several groups according to the degree of domination of each individual, can be simply defined as the domain which seeks a balance between the sub-models, to improve the overall model quality of the turbine.

The performance of the sub-models obtained perfectly follows the dynamic behavior of the turbine and in particular improves the precision and speed of the genetic algorithm itself by a more refined choice of the initial parameters, by calculations during the evaluation of the objective functions of cost function and noise and vibration constraints of the machine for each individual, and by taking into account other constraints related to the interaction of variables of global turbine models. This is clearly shown in Figs. 7 and 8. Hence Fig. 7 shows the variation of the exhaust temperature cost function of the low-pressure turbine (T5) in the local turbine models and Fig. 8 shows the variation of the exhaust temperature cost function of the high-pressure turbine (T7) in the local turbine models. To optimize the local sub-models of the global turbine model, the genetic algorithm approach initially generates a population of solutions of the model parameters, after the global model is obtained for each initial solution with the calculation of the coefficients of the correlation between the turbine system input / output variables, these local sub-models obtained are more reliable and robust.

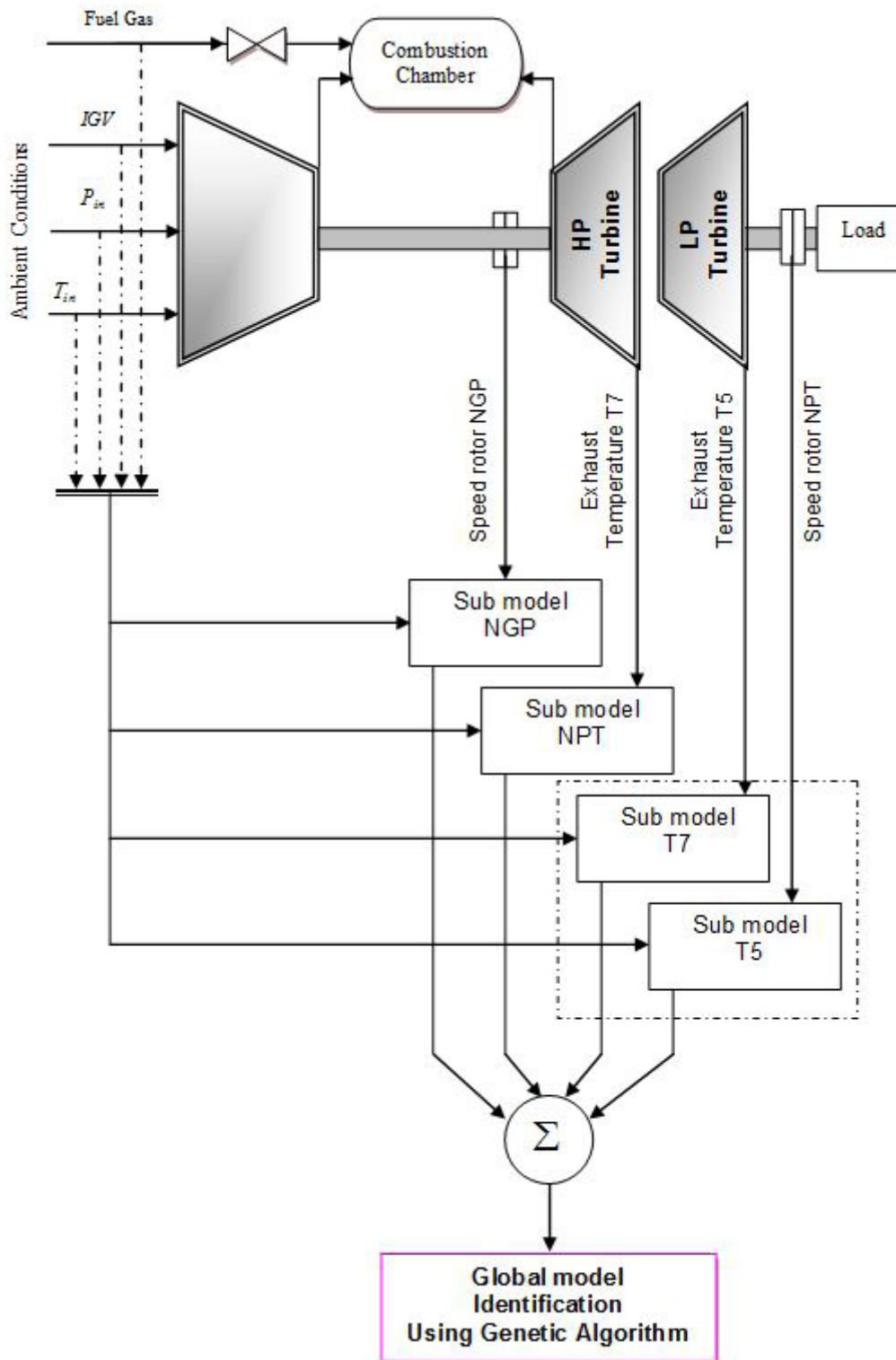
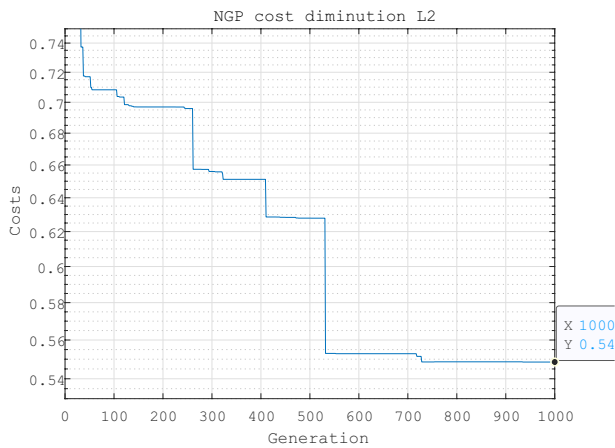


Fig. 3 Multi-model structure applied to the gas turbine

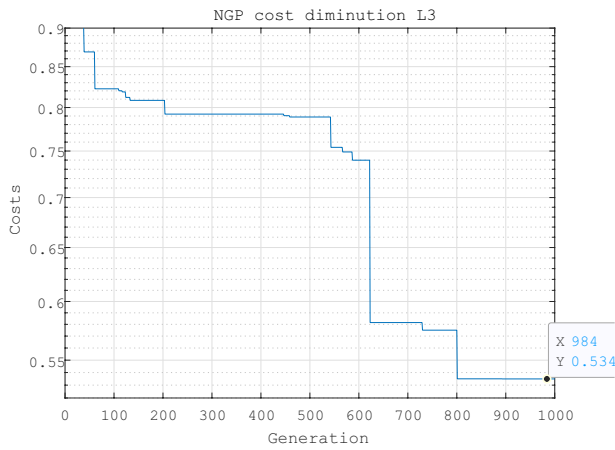
Table 1 Genetic algorithms parameters

Generations	1000
Population	100
Mutation rate	0.15
Selection rate	0.5

The results obtained are encouraging because the proposed genetic algorithm finds better solutions after 500 iterations of cost function optimization for the NGP, NPT, T5 and T7 given by the local model $L = 2$ and the genetic algorithm is capable of generate enough eligible



(a)



(b)

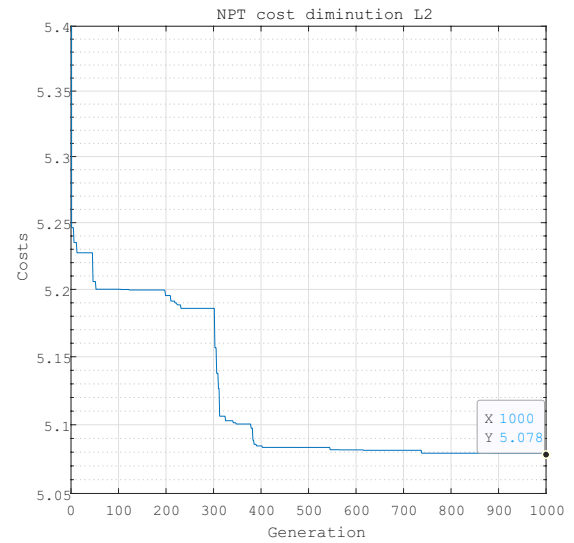


(c)

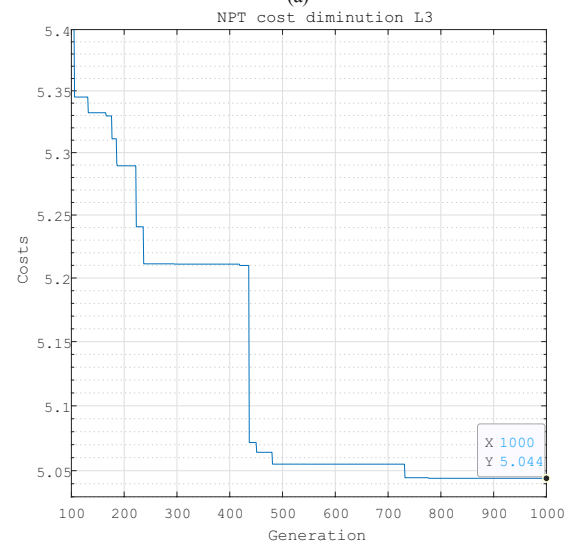
Fig. 4 Variation of NGP cost function in local turbine models;
 (a) Variation of NGP cost for L2; (b) Variation of NGP cost for L3;
 (c) Variation of NGP cost for L4

individuals to solve the problem of optimal global turbine model, which does not provide better results for the identification of turbine models.

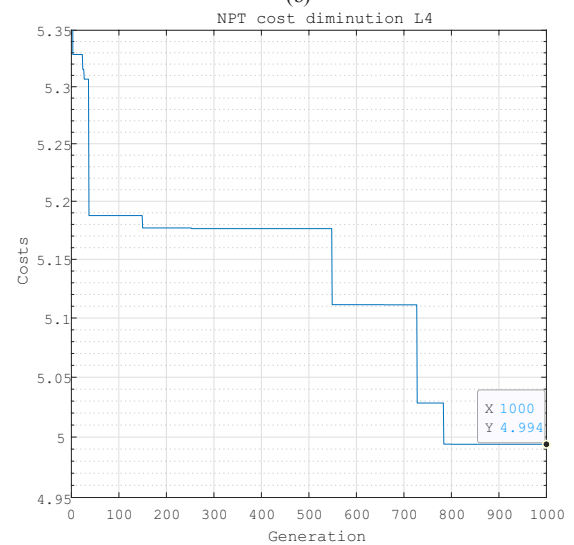
However, the variation of cost functions increases each time that the number of sub-models is increased, it is



(a)



(b)



(c)

Fig. 5 Variation of NPT cost function in local turbine models;
 (a) Variation of NPT cost for L2; (b) Variation of NPT cost for L3;
 (c) Variation of NGP cost for L4

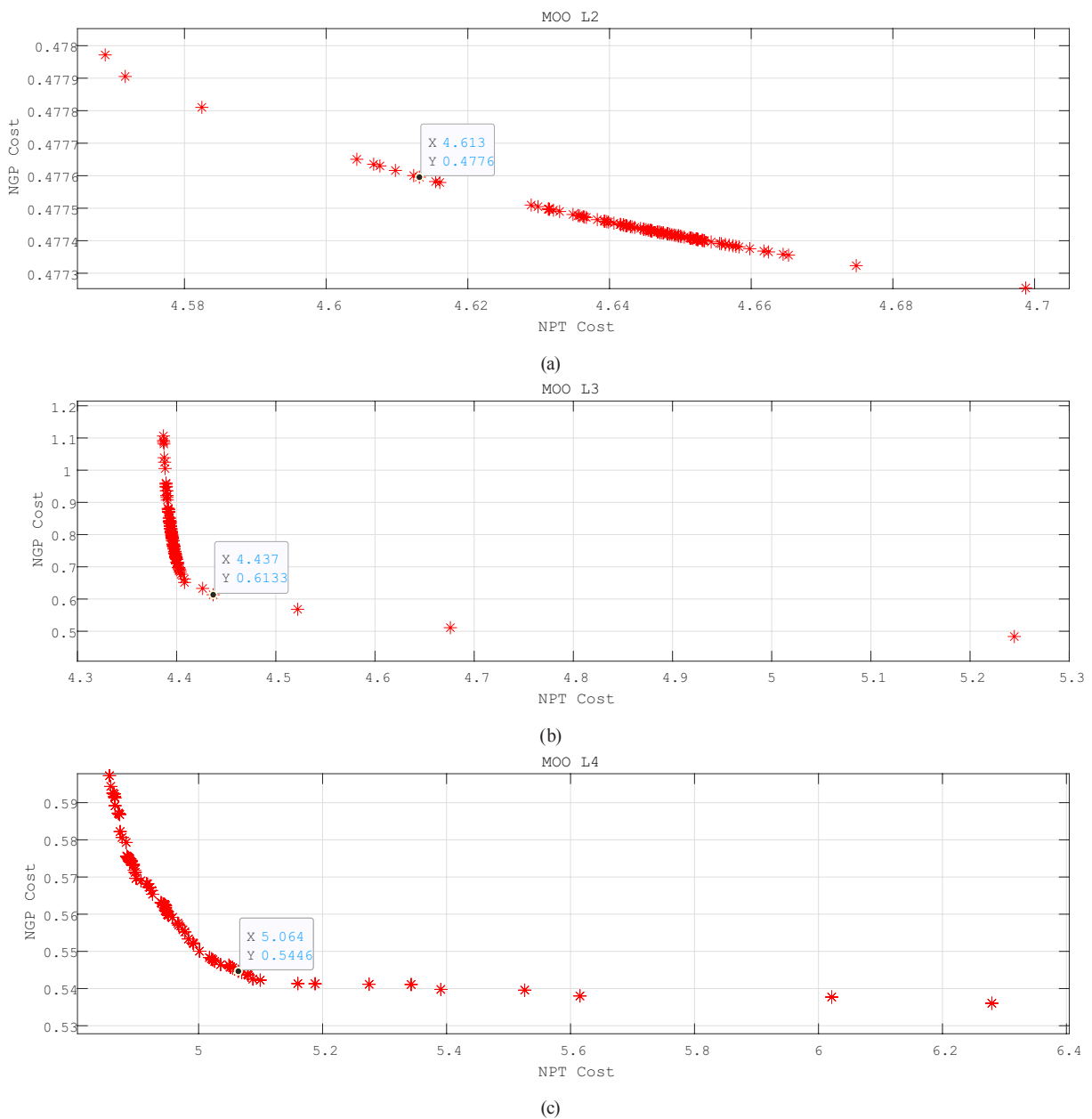


Fig. 6 Parameters of optimal sub-models based on the cost function of NGP as a function of the cost function of NPT for local turbine models; (a) Parameters of optimal sub-models for L2; (b) Parameters of optimal sub-models for L3; (c) Parameters of optimal sub-models for L4

because of the number of parameters to be optimized while the multi objective optimization to obtain is made with respect to NGP, NPT, T5 and T7. This is well shown on the results of comparison of multi-model outputs obtained with the actual outputs of the turbine in operation. Fig. 9 presents the results of comparison of variation of NGP sub-model obtained by the genetic algorithm and the actual output with the modeling error, we note that the model response obtained by the genetic algorithm is the same as the real answer and which have similar characteristics. This obtained sub-model is adapted to find the parameters corresponding to better performance of the overall gas turbine model. Hence,

Fig. 10 shows a comparison of the results obtained from variation of NPT sub-model by the genetic algorithm and the actual output with the modeling error, this sub-model is tested, in terms of normalized computation time (ratio of the overall calculation time to the calculation time of an analysis). The genetic algorithm converges to a local optimum model, while the genetic algorithm reaches an optimum of best value in terms of modeling error.

It can also be noted that the local models can be improved easily, without modifying the optimization algorithms. Fig. 11 shows that better results can be obtained using the T5 sub-model obtained by the genetic algorithm,

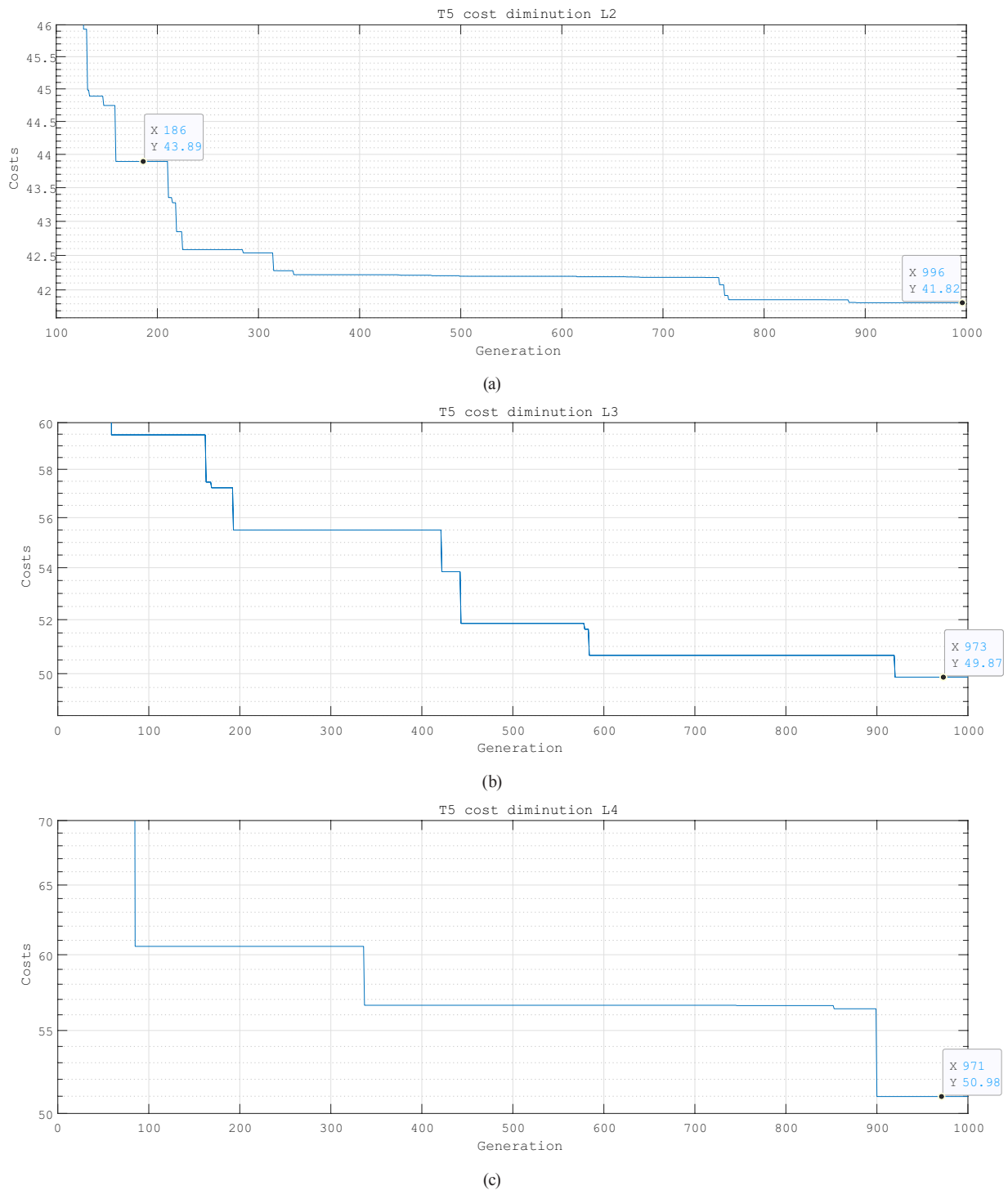


Fig. 7 Variation of cost function of T5 in local turbine models; (a) Variation of T5 cost for L2; (b) Variation of T5 cost for L3; (c) Variation of T5 cost for L4

validated by the comparison results of variation of and the actual output with the modeling error and Fig. 12 shows the comparison results of variation of sub-model T7 obtained by the genetic algorithm and the actual output with the modeling error. These tests have shown that this implemented model is able to converge very quickly

towards an optimal sub-model, by selecting the best generations of chromosomes encountered among the optimal populations. These chromosomes represent the optimal values for exhaust temperatures from the low-pressure turbine T5 and exhaust temperatures from the high-pressure turbine T7 for minimized cost functions.

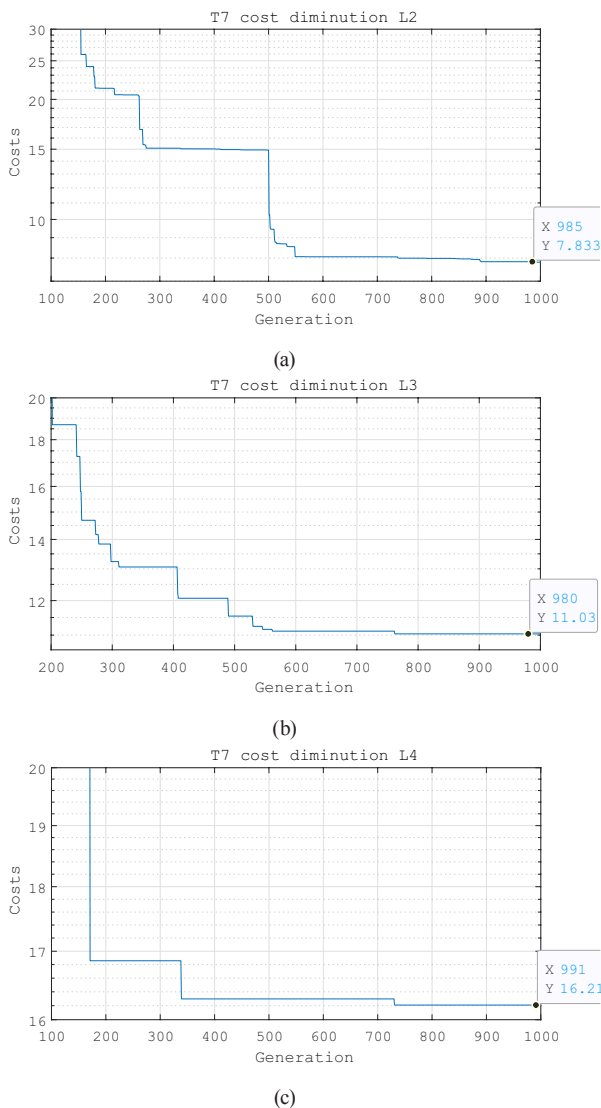


Fig. 8 Variation of cost function of T7 in local turbine models; (a) Variation of T7 cost for L2; (b) Variation of T7 cost for L3; (c) Variation of T7 cost for L4

4.1 Validation and comparison results

The multi-objective optimization method was used to determine the local sub-models of output variables from the gas turbine. In fact, Table 2 presents the identification result and validation cost functions for outputs of multi-model according to the number of sub-models ($L = 2, 3, 4$) of the gas turbine, as well as the different parameters, activation functions. It is obvious that there is a difference between the outputs for the different sub-models, for the NGP and the NPT the sub-model L3 had the minimum cost, with regard to the sub-model $L = 4$ had slightly minimum cost for NPT, but for temperature and turbine exhaust T5 and T7 the sub-model L2 had the minimum result, then the sub-model $L = 3$ and the last one is the

sub-model $L = 4$. This is because of the enormous surface research done even with the same limits, and for the turbine exhaust temperature.

The results showed a very good precision in particular for the NGP and NPT sub-models, as it is shown in Figs. 13 and 14. Hence, Fig. 13 presents the results of multi-objective optimization of function of cost of NGP for different local models (L2, L3, L4) and Fig. 14 presents the multi-objective optimization results of NPT cost function for the same local models. These results show the decrease in the cost functions for the different sub-models of the MMGA outputs, compared to the cost functions, it is clear that for the cost function of NPT the sub-model L2 were the fastest, but is not the lowest with a small difference compared to the L3 sub-model, for the cost function of NGP the L4 sub-model was the lowest, but nevertheless in the validation cost it has the highest cost, and this is due to a multi-objective optimization which is the same case with the NSGA II and for the exhaust temperatures T5 and T7 of the turbine the sub-model L2 is the highest with the least cost.

Other sub-models were then constructed by revising the choice of variables made during the sensitivity analyzes, Fig. 15 shows the results of multi-objective optimization of the cost function of T5 for the different local models (L2, L3, L4) and Fig. 16 presents the multi-objective optimization results of cost function of T7 for the same local models.

Through these results, the use of genetic algorithms could be more effective in identifying the turbine variables examined, when faced with large combinatorial problems of operating data from this rotating machine. This genetic algorithm has also made it possible to use partial decomposition in turbine sub-models, to improve overall model performance in the phase of developing the control strategy for this machine, using local sub-models of reduced size, on which they guarantee optimal solutions for control problems.

5 Conclusion

The practice of monitoring rotating machines requires reliable models that describe their dynamic behaviors for the development of different control strategies. These models, which correspond to representations comprising a set of operating parameters, make it possible to characterize and perfectly master the operation of the machine. However, the use of a linear model is desirable, since this type of

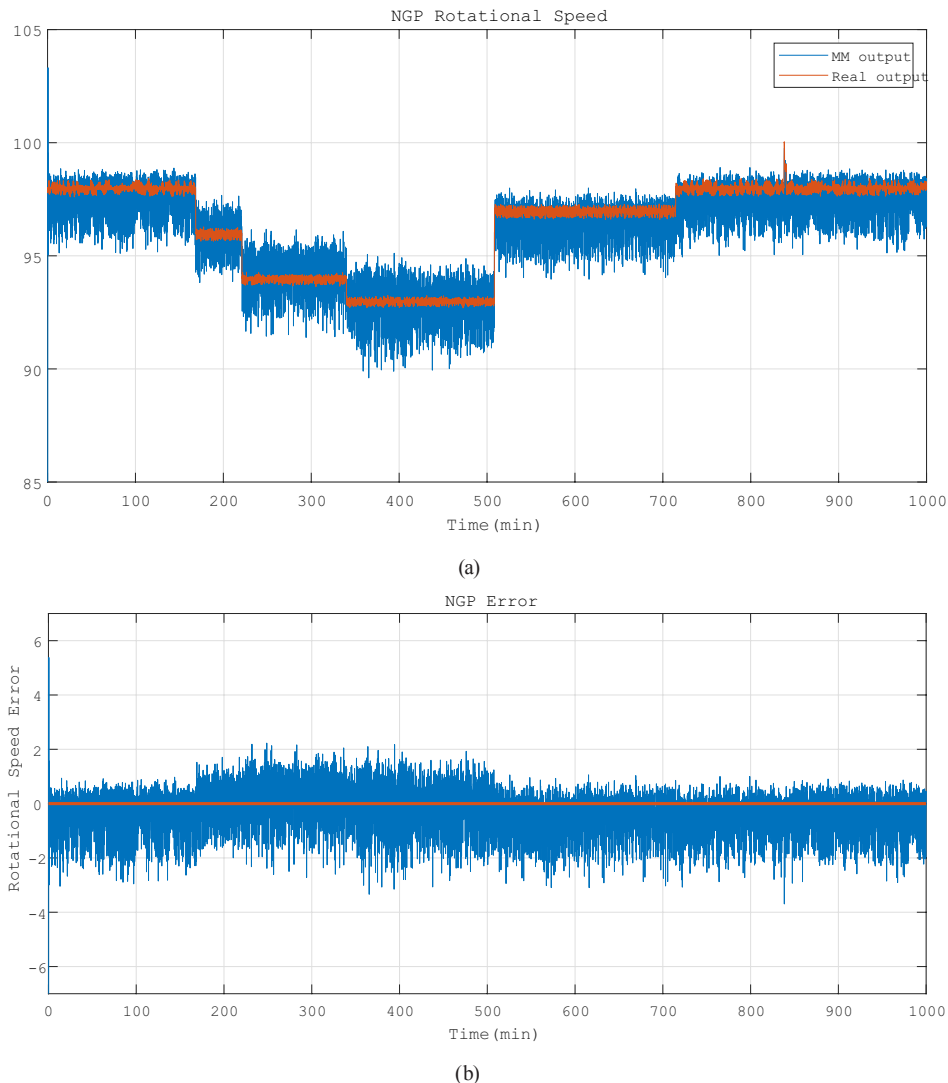


Fig. 9 Comparison of variation of NGP sub-model obtained by the genetic algorithm and the actual output with the modeling error; (a) Variation of NGP sub-model obtained by the genetic algorithm and the actual output; (b) Variation of the modeling error of the NGP sub-model

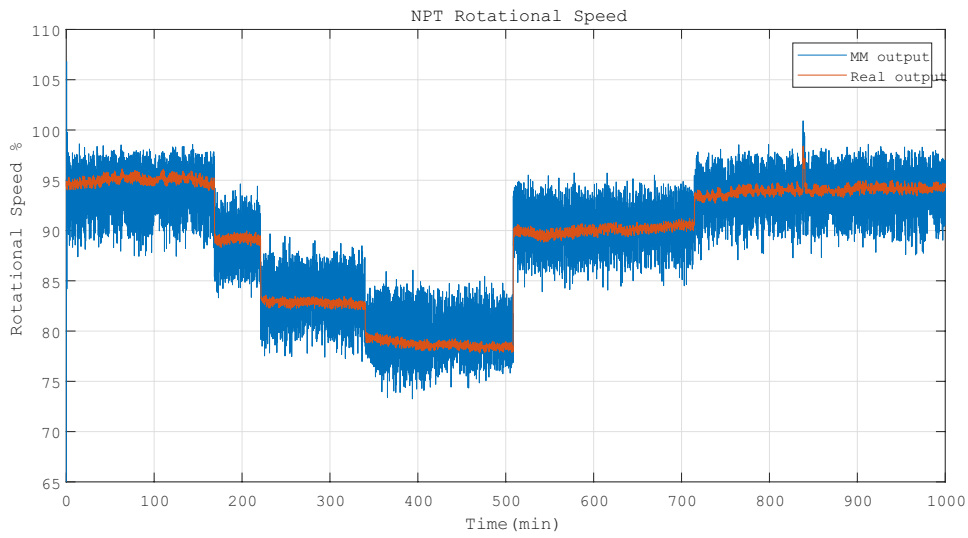
model has few parameters that are easy to determine, but the complexity of industrial gas turbine systems limits the use of linear models. For this, several approaches to modeling nonlinear systems have been developed to observe the nonlinearity behavior of this type of machine.

In this work, an approach of identification of a nonlinear model of a gas turbine under constraints was presented by using genetic algorithms with the approach multi-models (sub-models), and by exploiting the real data collected on the inputs / outputs of the examined turbine. The efficiency of the different sub-models was assessed based on fair comparison, between the behaviors modeled using the genetic algorithm method and the different real turbine outputs, using the mean square error as the evaluation criterion. Hence, the validation of the best sub-models obtained is considered using multi-objective cost function

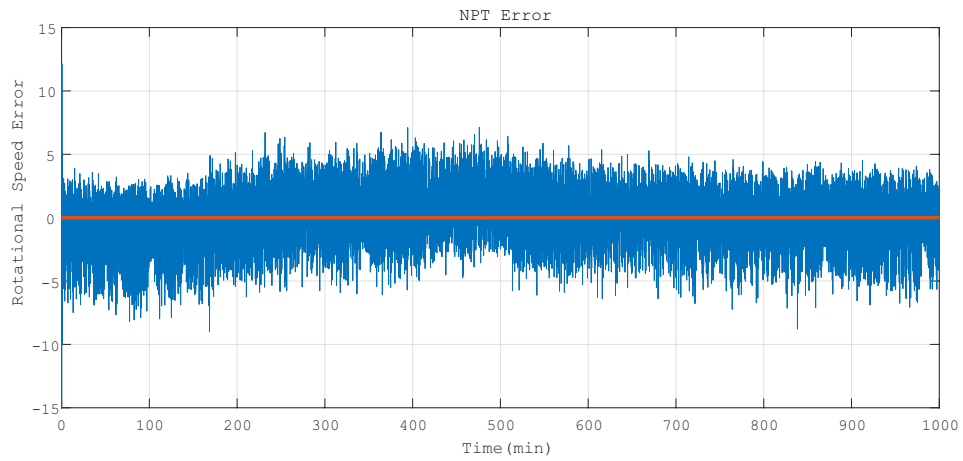
optimization for the different local models of the turbine system. These practical findings have confirmed the efficiency and robustness of the sub-models' identification method for the proposed turbine and offer good performance for the global model of this machine. Indeed, the determined sub-models characterize with acceptable precision and with reasonable complexity the behavior of the studied turbine and have great flexibility when synthesizing the regulators for the variables of this rotating machine.

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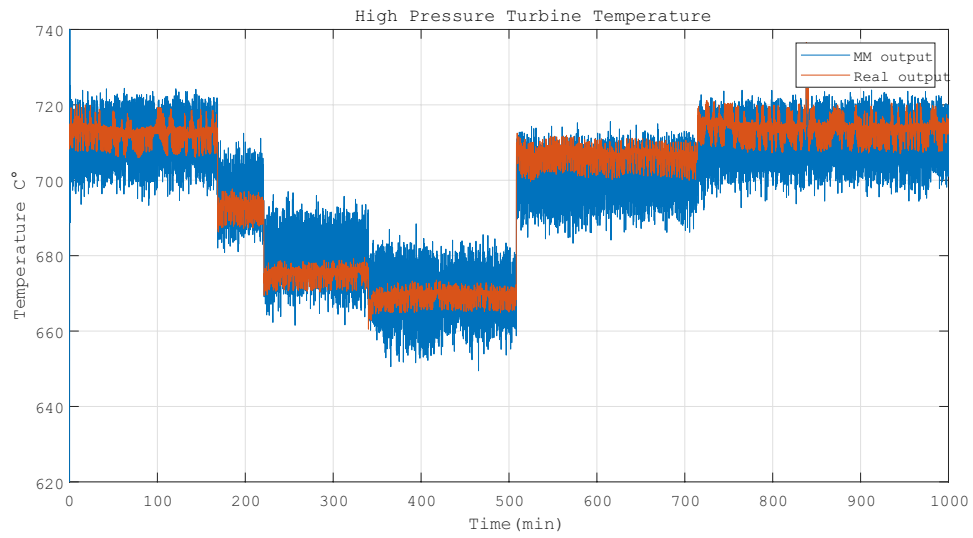


(a)

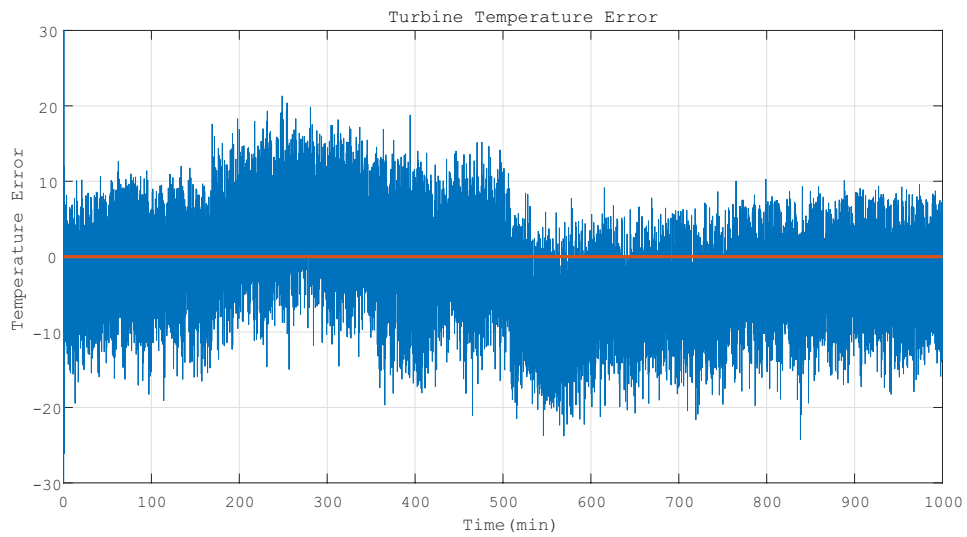


(b)

Fig. 10 Comparison of variation of NPT sub-model obtained by the genetic algorithm and the actual output with the modeling error; (a) Variation of NPT sub-model obtained by the genetic algorithm and the actual output; (b) Variation of the modeling error of the NPT sub-model



(a)



(b)

Fig. 11 Comparison of variation of T5 sub-model obtained by the genetic algorithm and the actual output with the modeling error; (a) Variation of T5 sub-model obtained by the genetic algorithm and the actual output; (b) Variation of the modeling error of the T5 sub-model

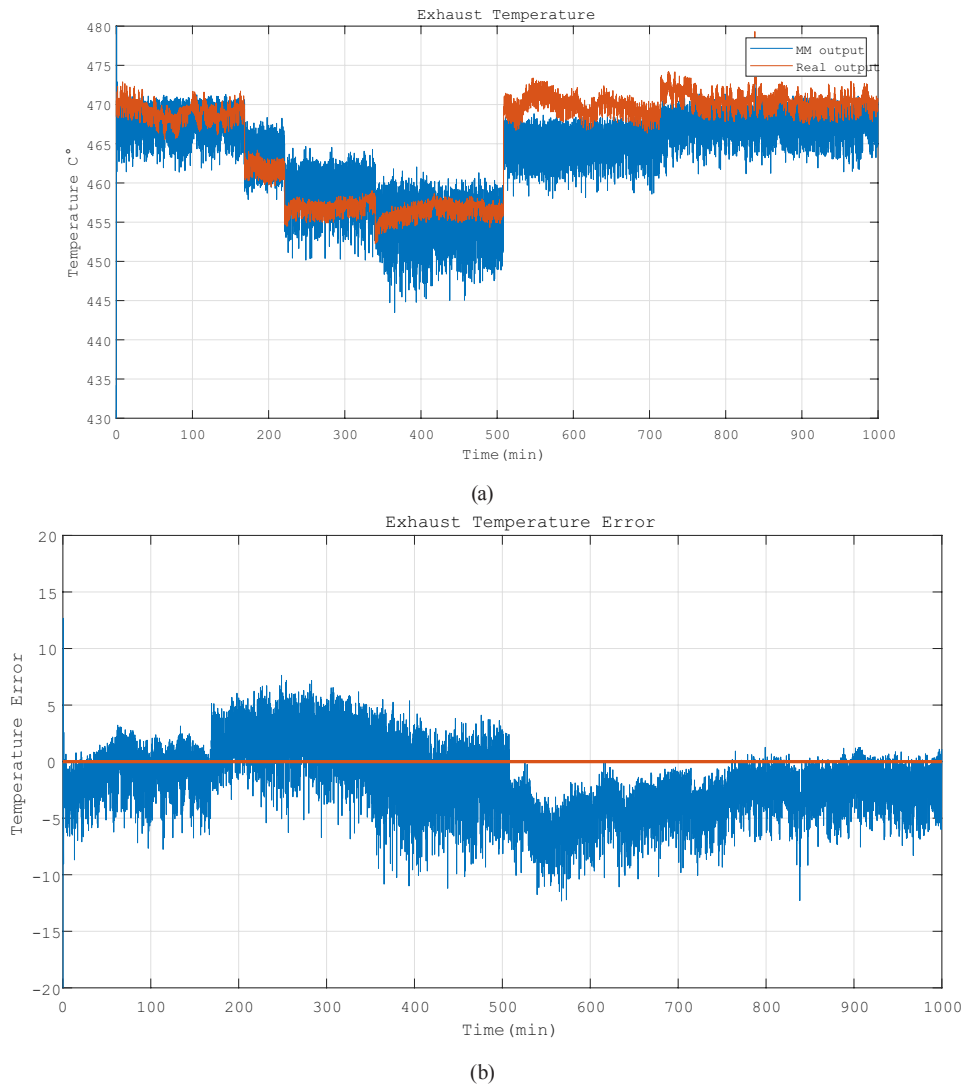


Fig. 12 Comparison of variation of T7 sub-model obtained by the genetic algorithm and the actual output with the modeling error; (a) Variation of T7 sub-model obtained by the genetic algorithm and the actual output; (b) Variation of the modeling error of the T7 sub-model

Table 2 Obtained results from different sub-models with activation functions

	Output	Identification Cost	NSGAI1	Validation Cost	σ	c_i
$L = 2$	NGP	0.5485	0.4776	0.3967	5.0144	[69.978, 73.914]
	NPT	5.0767	4.613	3.5112		
	T5	41.8155	-	42.1249		
	T7	7.812	-	9.2101		
$L = 3$	NGP	0.5329	0.6133	0.4907	4.9775	[69,949, 72.199, 73.965]
	NPT	5.044	4.437	3.7469		
	T5	49.8733	-	49.8141		
	T7	11.0348	-	14.9600		
$L = 4$	NGP	0.6670	0.5446	0.5695	5.0217	[68.016, 69.998, 72.053, 73.979]
	NPT	4.9940	5.064	4.4095		
	T5	51.5082	-	54.3880		
	T7	16.0361	-	13.3343		

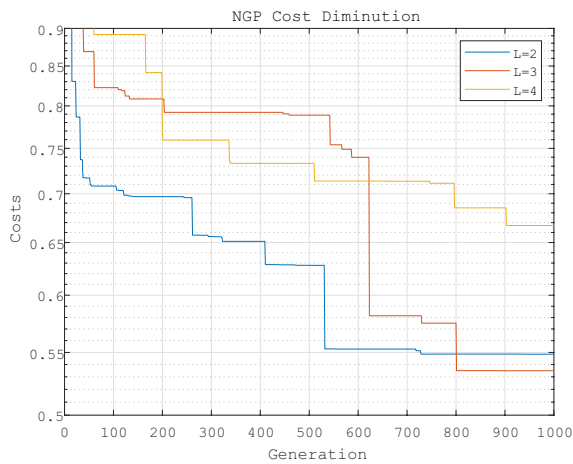


Fig. 13 Multi-objective optimization of NGP cost function for different local models

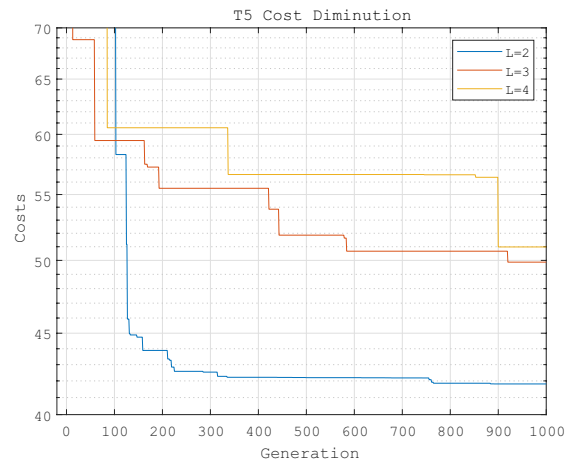


Fig. 15 Multi-objective optimization of cost function of T5 for different local models

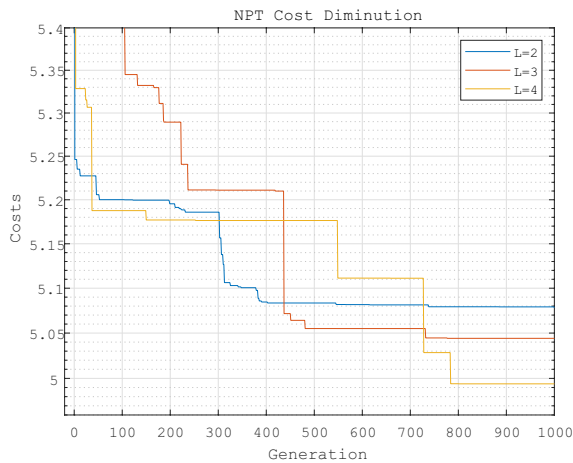


Fig. 14 Multi-objective optimization of NPT cost function for different local models

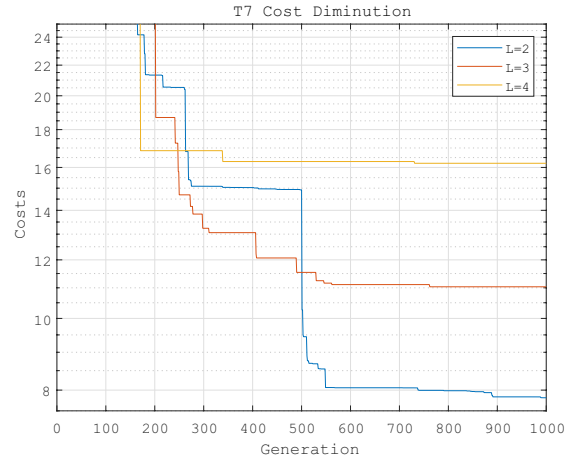


Fig. 16 Multi-objective optimization of cost function of T7 for different local models

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