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## Control of the speed and exhaust gas temperature in gas turbine using adaptive neuro-fuzzy inference system



Journal of Automation  
& Systems Engineering

Nadji Hadroug \* , Ahmed Hafaifa \* , Abdellah Kouzou \* , Mouloud Guemana \*\* and Ahmed Chaibet \*\*\*

\* Applied Automation and Industrial Diagnostics Laboratory, Faculty of Science and Technology, University of Djelfa 17000 DZ, Algeria. Emails: [N.Hadroug@univ-djelfa.dz](mailto:N.Hadroug@univ-djelfa.dz), [hafaifa.ahmed.dz@ieee.org](mailto:hafaifa.ahmed.dz@ieee.org), [kouzouabdellah@ieee.org](mailto:kouzouabdellah@ieee.org)

\*\* Faculty of Science and Technology, University of Médéa, 26000, Algeria. Email: [Guemana\\_M@univ-medea.dz](mailto:Guemana_M@univ-medea.dz)

\*\*\* Aeronautical Aerospace Automotive Railway Engineering School, ESTACA Paris, France. Email: [Ahmed.CHAIBET@estaca.fr](mailto:Ahmed.CHAIBET@estaca.fr)

*Abstract-This work proposes the application of the hybrid approach using Adaptive Neuro-Fuzzy Inference System (ANFIS) to control the speed and exhaust gas temperature of a gas turbine. Create into various parts of the model of the examined gas turbine and given a comprehensive procedure to derive the parameters of the investigated gas turbine using the parameters of Rowen's model for dynamic studies, the parameters are estimated by use of available operational and performance data. This paper develops the studied single shaft heavy duty gas turbine model L7001B class 160-MW simple cycle for deriving the parameters of the model. The obtained results using the Adaptive Neuro-Fuzzy Inference System are validates by several robust tests.*

**Keywords:** Gas turbine; Adaptive Neuro-Fuzzy Inference System; ANFIS Controller; Mathematical model; Hybrid Learning .

### 1. INTRODUCTION

During the past several years, requests have been received for simplified mathematical models of general electric gas turbine generators to be used as input for comprehensive studies of gas turbine users' power systems. The intent of these studies has been the investigation of power system stability, the development of dispatching strategy and contingency planning for system upsets.

Gas turbines are one of the main sources for power generation in countries with natural gas resources and are installed in numerous places in the world due to their special characteristics. The needs of a power system analyst for a mathematical representation of gas turbines in dynamic studies lead to several publications in this area. One of the most commonly used simplified models was presented by Rowen taking into account the load-frequency and temperature control as well as the turbine's thermodynamic responses as a linear function and inlet guide vane effects in a separate work [2].

In this work, hybrid approach Adaptive Neuro-Fuzzy Inference System (ANFIS) can generate a high-quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods. The main objective of this study is to develop a tuning methodology of ANFIS controller parameters in controlling the exhaust temperature of a gas turbine system so that the closed-loop system is able to adapt to the

variation of ambient temperature, not only by reducing the error but also the values of rise time, settling time and maximum overshoot.

## 2. TYPICAL OF HEAVY DUTY GAS TURBINES

Heavy duty gas turbines (HDGT) are composed of three components: Multistage axial flow compressors, can-annular combustors and axial flow turbines shows in Figure 1. Air with atmospheric conditions is drawn to the compressor after passing air filters at the entrance. The multi stage compressor increases speed, pressure and temperature of the air before it reaches the combustor and inlet to the high pressure turbine parts [2].

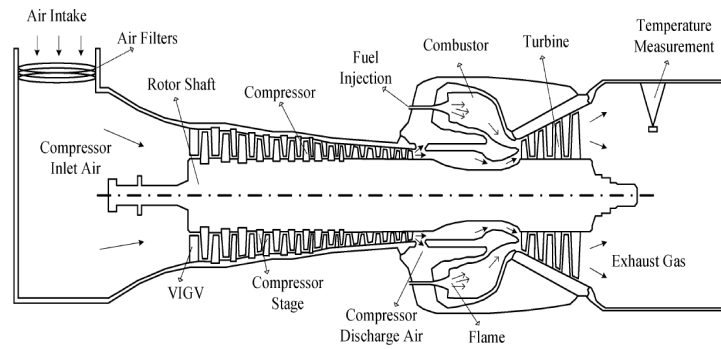


Fig 1. Schematic view of a typical Heavy duty gas turbine.

## 3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

**A. ANFIS Architecture** ; In this section we introduce the basic of ANFIS network architecture and its hybrid learning rule. Inspired by the idea of basing the fuzzy inference procedure on a feed forward network structure, Jang proposed a fuzzy neural network model (Adaptive Neural-based Fuzzy Inference System) whose architecture is shown in Fig. 1. He reported that the ANFIS architecture can be employed to model nonlinear functions, identify nonlinear components on-line in a control system, and predict a chaotic time series. It is a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference system.

The learning algorithm tunes the membership functions of a sugeno-type fuzzy inference system using the training input-output data. ANFIS consists of five layers; the adaptive nodes of the neural network are the nodes in Layers 1 and 4. The depicted model defines a controller with two inputs and one output. Each input has two membership functions [3]. We assume that the rule base contains two fuzzy if-then rules of a Takagi and Sugeno's type:

$$O_i^1 = \mu_{A_i}(x); i = 1,2 \quad (1)$$

Every node in Layer 2 is a fixed node labeled M, which multiplies the incoming signals:

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x); i = 1,2 \quad (2)$$

Every node in Layer 3 is fixed node labeled N for normalization. it calculates the ration of the i-th rule's firing strength to the sum of all rules firing strengths:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}; i = 1,2 \quad (3)$$

In Layer 4, every node is an adaptive node while the node function is:

$$O_i^4 = \bar{w}_i \times f_i = \bar{w}_i(p_i x + q_i y + r_i); i = 1,2 \quad (4)$$

The overall output of the network can be defined as [3]:

$$O_i^5 = f = \sum_i \bar{w}_i \times f_i \quad (5)$$

**B. Learning algorithm of the ANFIS;** Learning from a set of data for the identification of the parameters of the premises and of the consequences, the structure of the network being fixed. The learning algorithm begins by constructing an initial network, and then we apply a method of learning by retro propagation of the error. Jang has proposed to use a hybrid rule of learning which combines an algorithm of gradient descent with an estimate by least squares, it was then:

$$f = \bar{W}_1 f_1 + \bar{W}_2 f_2 \quad (6)$$

with

$$f_1 = p_1 x_1 + q_1 x_2 + r \text{ and } f_2 = p_2 x_1 + q_2 x_2 + r_2 \quad (7)$$

$$f = (\bar{W}_1 x_1).p_1 + (\bar{W}_1 x_2).q_1 + \bar{W}_1.r_1 + (\bar{W}_2 x_1).p_2 + (\bar{W}_2 x_2).q_2 + \bar{W}_2.r_2 \quad (8)$$

It is a linear combination of parameters consistent modifiable {p1, q1, r1, p2, q2 and r2 }. Note that in this algorithm, it optimizes both the parameters of the premise that those of consistent.

During the forward pass, the settings of the consistent are adapted so that the parameters of the premises are held constant, while during the past back, therefore, the roles are reversed (Fig. 2) ;

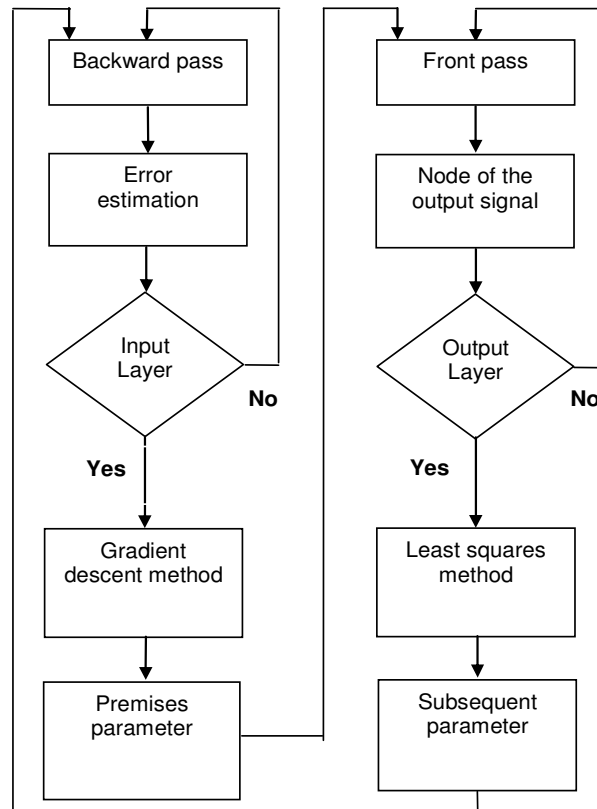


Fig 2. The learning Algorithm of ANFIS

The ANFIS used two types of passages for the modification of these parameters;

*Forward Pass:* For the transition toward the front (Fig 2), we can apply the least squares method for the identification of significant parameters (linear) [6]. For all of the parameters of premises (non linear), we can use the data for learning, so we do get a system of equation:

$$AX = B \tag{9}$$

With X is the matrix containing the unknown parameters in the parameter set consistent. It is a linear problem, the solution for X is reduced to a minimum  $\|AX - B\|^2$  :

$$X^* = (A^T A)^{-1} A^T B \tag{10}$$

- S1 is fixed and S2 is calculating sing the algorithm of least-square of the error (THE: least squares estimate). (S1: represents the parameters of a premise, S2: represents the parameters consistent).

*Backward Pass:* For the past in rear (Fig.2), the signals of errors propagate toward the rear. The parameters of the premises are adapted by the method of descent [7].

- S2 is fixed and S1 is calculate sing the back-propagation algorithm.

#### 4. THE MODELING OF GAS TURBINE

The typical model Rown of gas turbines in stability studies Consists of three control loops: Load – frequency control, Temperature control and Acceleration control.

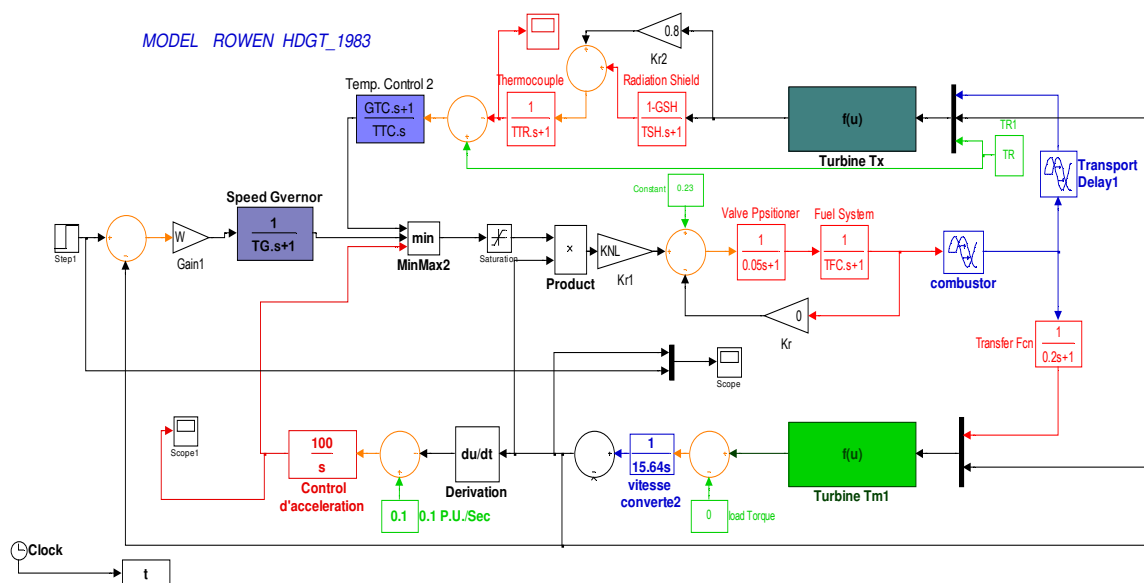


Fig 3. The Rowen's Model of HDGT for Dynamic Studies

For land based engines, performance data are frequently quoted at the single point ISO conditions . These data are given for our 60MW turbine in Table I.

Table 1. The data of heavy duty gas turbines

The metric Units	
Model	7001B
Turbine RPM	3600
Rating MW	160
Rated TR C°	510
Torque Kg.M	16.231
Inertia Kg.M2	7.834
Nominal frequency Hz	50

Fuel System: The lag time constant of the fuel system can be approximated if thermodynamic conditions of the fuel system.

Table 2. The estimated minimum fuel flow and no load consumption

No load fuel flow (kg/s)	~2.56
Min fuel flow to maintain combustor flame (kg/s)	~1.5

Table 3. The operational data for fuel system lag time estimation

Fuel	Gas
Fuel pressure	21 atm
Average temperature	320 k
Fuel piping approximate volume	0.26 m <sup>3</sup>

Table 4. The data of radiation shield for modeling purposes

Parameter	Symbol
Shield head diameter	DSH = 3.00 cm
Shield head length	LSH = 7.50 cm
Specific heat capacity per unit volume	Csp = 3.83 J/cm <sup>3</sup> K
Thermocouple tip length inside shield	Ltip = 16.0 mm
Convection heat transfer coefficient	h = 250 W/m <sup>2</sup> K
Shield head thickness	HSH = 0.08 mm

For a typical operating point are known. When operating with gas fuel, the following approximation of Methane thermodynamic properties is used to calculate density variations due to pressure changes[2]-[4];

$$T_v = \frac{P_0}{Q_0} V \left. \frac{\partial}{\partial P} \left( \frac{1}{v} \right) \right|_{T_0} \quad (11)$$

$$\left. \frac{\partial}{\partial P} \left( \frac{1}{v} \right) \right|_{T_0} = \left. \frac{(1/0.07) - (1/0.1)}{22 - 16.3} \right|_{320} = 0.78 \quad (12)$$

we will have

$$T_{FS} = \frac{21}{10.66} \times 0.26 \times 0.78 = 0.26s. \quad (13)$$

Note the nominal flow is used for the calculation, and temperature is also required to find the specific volume changes of Methane. There is also a lag time constant due to compressor discharge. Using the thermodynamic properties of air, (11) is used to approximate the lag time constant as follows;

$$\left. \frac{\partial}{\partial P} \left( \frac{1}{v} \right) \right|_{T_0} = \left. \frac{(1/0.14) - (1/0.2)}{22 - 14} \right|_{1050} = 0.36 \quad (14)$$

An average temperature is then enough to calculate the specific volume change due to pressure changes. Using the geometrical and operational data (see (11 ))

$$T_{CD} = \frac{17.7}{510} \times 16 \times 0.36 = 0.2s \tag{15}$$

The temperature at the thermocouple tip will then be approximated by

$$\frac{T_{meaure}}{T_{exhaust}} \approx \frac{A_2}{A_1} + \frac{1 - \frac{A_2}{A_1}}{\frac{C}{h.A_1} S + 1} \tag{16}$$

Where A1 is the total active area for convection heat transfer to the shield head, A2 is the area effective for convection heat transfer to the thermocouple tip, C (J/K) is the heat capacity of the shield head and h is the convection heat transfer coefficient.

The data in Table IV of the radiation shield can be utilized for modeling purposes. The heat capacity and convection transfer coefficient values are adopted form [2]-[5]. Let us assume convective heat transfer to the thermocouple tip to be a cylinder with a length of 2 times the length of thermocouple tip inside shield in each side, then from (14), the following values are estimated for radiation shield in Fig.4:

$$C_{SH} = \frac{A_2}{A_1} = \frac{\pi D_{SH} L_{tip}}{\pi D_{SH} L_{SH}} = \frac{4 \times 1.6}{7.5} = 0.85 \tag{17}$$

$$T_{SH} = \frac{C}{hA_1} = \frac{Csp \times \pi D_{SH} L_{SH} H_{SH}}{h \times \pi D_{SH} L_{SH}} = \frac{3.83 \times 0.08}{250 \times 10^{-4}} = 12.2s. \tag{18}$$

## 5. THE APPLICATION RESULTS

In this section, we present the obtained results for the application of ANFIS for controller system in Rowen model. The values of the applied variables and constants of model are expressed in Table VI .

Table 5. The dynamic Model Parameters

Parameter	value
Radiation shield parameter GSH	0.85
Radiation shield time constant TSh	12.2 s
Exhaust Temperature TR	510 °C
Fuel Demand signal Max Limit maxF	1.5
Fuel Demand signal Min Limit minF	-1
F1	$T_x = TR - 390 \times (1 - wf) + 306 \times (1 - N)$
F2	$Turb.torpue = 1.3(wf - 0.23) + 0.5 \times (1 - N)$
TI=	15.64



Application of ANFIS controller :the network of the ANFIS controller: who uses the two entries (Error Tx, Error N) to generate a single output . Each entry is fuzzifier by 3 fuzzy set of Gaussian types.

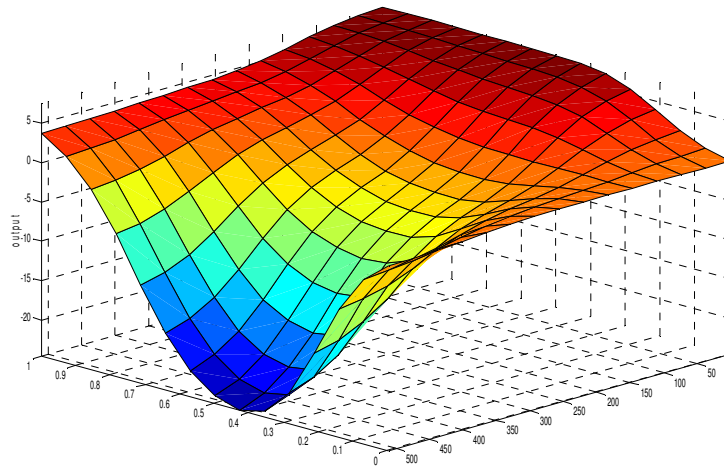


Fig 4. The control surface

The application results of gas turbine control system during start up using ANFIS are shown in Fig. 5 and Fig.6. Fig.7 shows the output speed of Rowen's model for Heavy duty gas turbines and the Fig.8 shows the exhaust temperature of the gas turbine which is measured by the thermocouple.

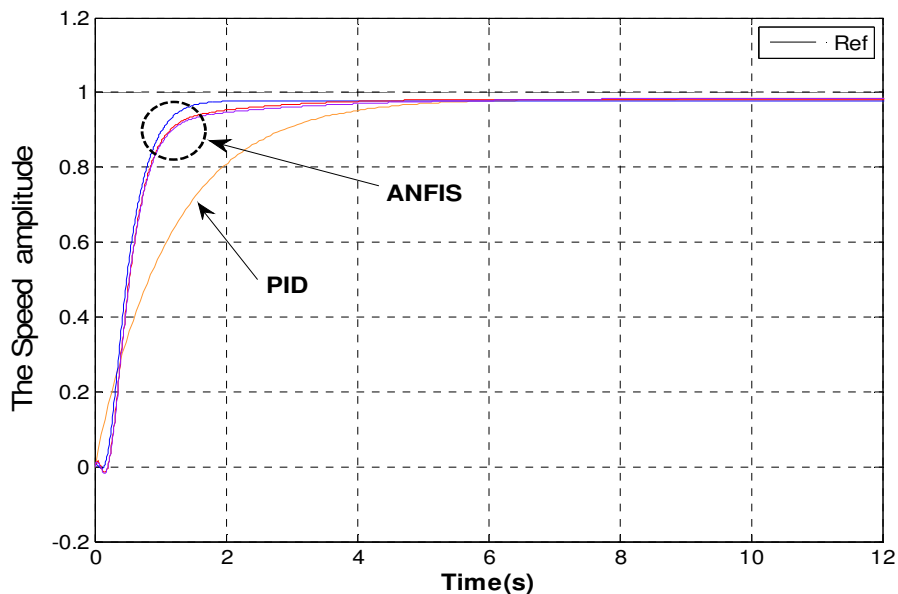


Fig 5. The output Turbine Speed of Rowen model.

It has been observed that the signals of " speed estimate and calculate " are very close to one another and give a good correlation with the curves determined by the calculation code.

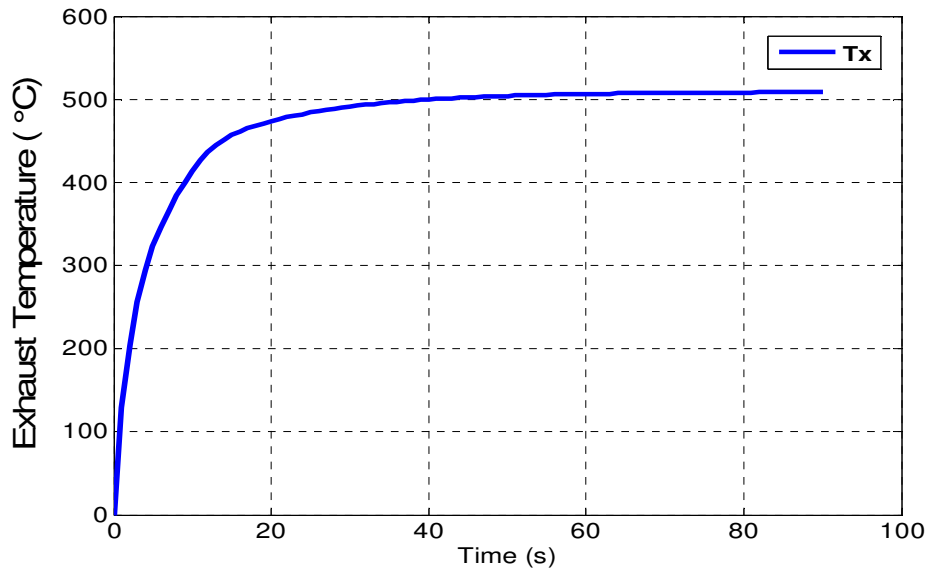


Fig 6. The exhaust temperature of Rowen model

The improvement of this response was obtained by imposing desired performances at 15% the overshoot value.

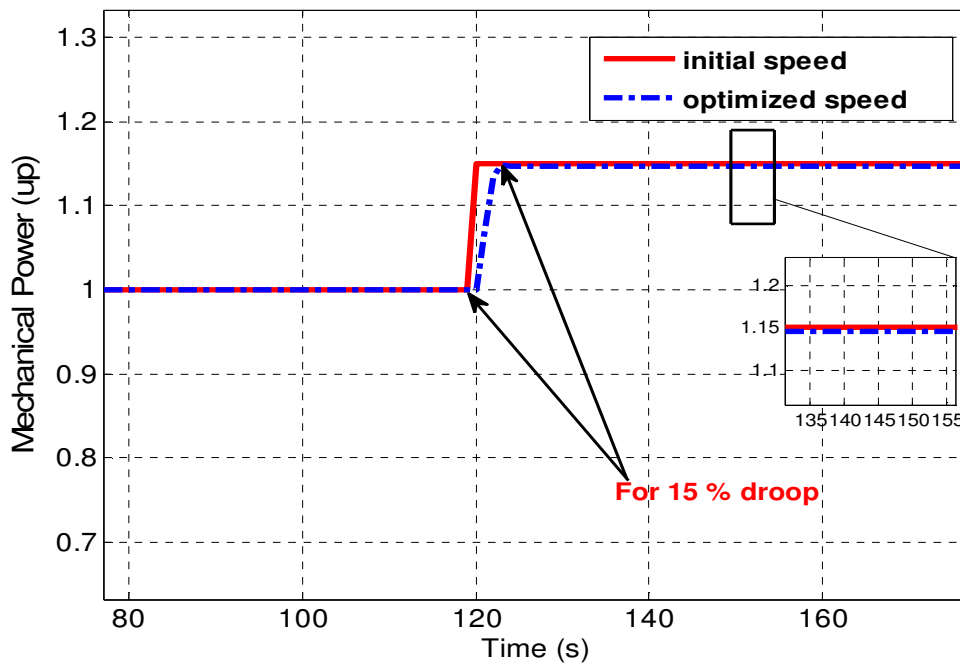


Fig 7. The turbine Speed output of Rowen model after speed step 15%.

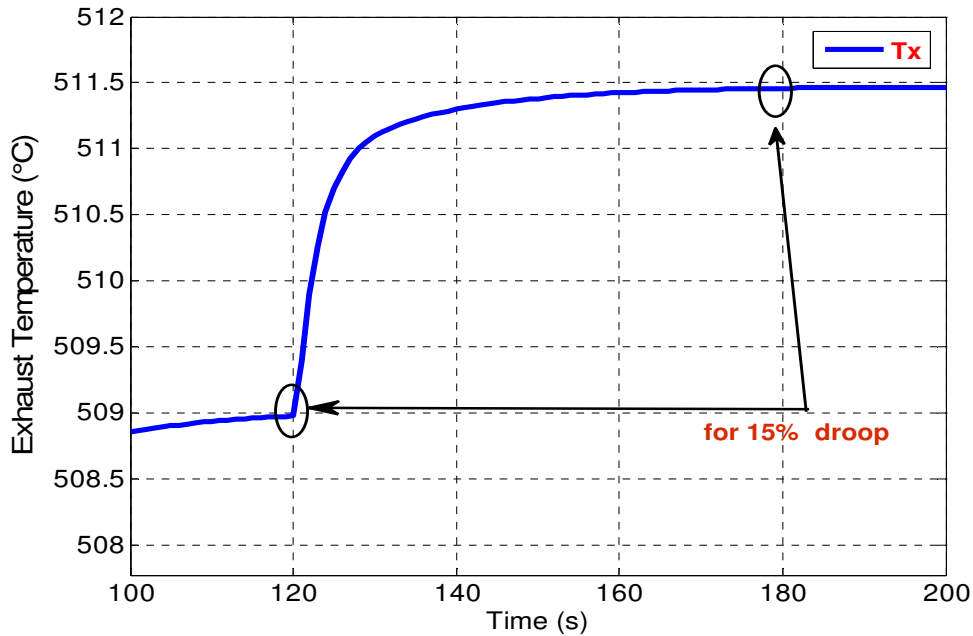


Fig.8. The exhaust temperature of Rowen model after speed step 15%.

## 6. CONCLUSION

This study has described the modelling of a 160 MW type of heavy duty industrial gas turbine (HDGT) and shown for estimating the parameters of Rowen's model in dynamic studies for educational purposes, we are show how used design of ANFIS controller for can generate a high-quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods.

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