A Comparative Investigation of Modeling and Control Approaches for Gas Turbines: Fuzzy Logic, Neural Network, and ANFIS

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Abstract- This paper focuses on the identification and modeling of gas turbine dynamics, specifically those used in power generation plants. The approach utilizes experimental data and employs fuzzy reasoning systems. The resulting model serves the purpose of approximating nonlinear gas turbine systems and ensuring reliable system control. By incorporating uncertainties associated with human reasoning, such as fuzzy systems based on Takagi-Sugeno reasoning, it is possible to achieve highly reliable control systems. The primary goal of this paper is to increase the effective monitoring system by employing nonlinear identification techniques, namely fuzzy systems and neuro-fuzzy systems, based on real-time on-site experimental data. Additionally, the proposed identification approaches are evaluated through a comparative study, where the results obtained using the Nonlinear Autoregressive Exogenous Neural Networks (NARX-NN) modeling technique are compared with those obtained using the Adaptive Inference System combined with the techniques of Neuro-Fuzzy renowned ANFIS concept. The obtained investigation results further facilitate the comprehension and analysis of the nonlinearities present in these complex systems, ultimately aiding in the prediction of their dynamic behavior.

Keywords: Adaptive system, fuzzy modeling, gas turbine, ANFIS approach, combined Neuro-Fuzzy techniques, Takagi-Sugeno identification, variables estimation.

1. Introduction

The modeling of industrial systems, particularly in engineering applications, is crucial for representing their dynamic behavior using reliable mathematical models. These models are utilized in control systems. In practice, the modeling process involves gathering data from various sources such as experiments and theoretical analysis of the underlying physical phenomena. This knowledge enables the approximation of nonlinear systems by linear ones, which can then be used to develop effective monitoring systems and control strategies.

Several modeling strategies involve decomposing the overall nonlinear system into multiple linear sub-systems. This approach has been widely employed in various studies. For instance, Rabuška and Verbruggen [7-8] achieved the identification of composite linear models using fuzzy clustering, while Daouren et al. [14] developed an approach for parameter adaptation of nonlinear systems based on combined neural networks and fuzzy concepts. Other researchers, such as Babuska and Veen [6], Balazs Feil et al. [9], Do Won Kang and Tong Seop Kim [15], Houman Hanachi et al. [19], Abdollah Mehrpanahi et al. [2], and Benyounes et al. [1], have also contributed to the modeling of gas turbines through various techniques like clustering algorithms, fuzzy approaches, adaptive fuzzy neural networks, and control data adaptation.

Recent research efforts in the energy industry have focused on the modeling of gas turbine systems to optimize their design, manufacturing, monitoring strategies, and maintenance instructions. With the increase in the computational capabilities of modern computers has led to the integration of new approaches, in order to obtain better and more reliable results on the studied turbine variables identification. Indeed, in [45] Xianda Cheng et al. have realized an advanced real-time algorithm diagnostic applied to a turbine, while ensuring good accuracy of the proposed approach. Also, in [34] Mostafa A. Elhosseini et al. have proposed the estimation of the control parameters of a gas turbine via ANFIS and fuzzy controllers, to improve the efficiency of this turbine in the case of deviation of their output load. Furthermore, in [23] Keyu Jia et al. have optimized the models of a gas turbine with integration of hybrid renewable energy in order to ensure the storage of this energy produced. Although other works have been carried out recently, such as; Yuanzhe Zhang et al. in [47], Minghui Hu et al. in [29], Dušan Strušnik and Jurij Avsec in [16], Samira Pourhedayat et al. in [40], Yasser Chiker et al. in [46].

Previous literature has explored simplified representations of gas turbine systems [39], numerical approaches for evaluating reaction models [20], design modeling using analytical neural networks [24], parameter extraction based on dynamic studies using operational data [10], and model reduction for predictive control [44].

Practically, the modeling of gas turbine parameters can be classified into two categories; the first is based on the use of mathematical relations, which represent the various thermodynamic phenomena and energy balances. Hence, the second category is based on the techniques of linearization at the turns of the operating points, using advanced algorithms of artificial intelligence.

However, the modeling process of gas turbine systems remains an important and increasingly attractive topic for researchers in the energy industry. This paper adopts a fuzzy modeling approach for an industrial gas turbine, specifically the GE 5001P Gas turbine. The proposed model combines the Gastafson-Kessel (GK) fuzzy clustering algorithm and NARX-NN (Nonlinear Autoregressive with Exogenous Input) with the determination of the least squares regression, to minimizes the modeling errors. The main objective is to estimate and characterize the different instability sources of the system and unsteadiness while considering the system's characteristics. The learning task aims to gather maximum information on the interactions between different model variables of their physical behavior to create a reliable model capable of accurately predicting its real characteristics. The fuzzy models of nonlinear systems are treated as subsets of locally linear models at different operating points, and the GK algorithm is employed to ensure smooth transitions between the identified subsets, detect different geometric shapes of clusters in the data, generate local membership functions, and estimate consequence parameters using the least squares method.

The key advantage of this approach is the linearization around an operating point (usually a regular point) by decomposition of the complex large-scale system into linear simple sub-systems, allowing each sub-system to perform its designated function and detect any identification problems that may arise. Learning controllers can provide actual parameter values and account for deviations from theoretical values. This makes the proposed approach suitable and effective for modeling gas turbine systems.

The use of analytical models based on fuzzy reasoning enables the prediction and monitoring of machine behavior. The fuzzy approach offers the advantage of expressing data belonging to multiple classes, facilitating a better understanding of the system's reality. This can contribute to timely control state changes and improved performance, which are closely tied to functional states during the implementation of the modeling approach. The purpose of this approach is to improve real-time monitoring capability, with the use of modern identification algorithms, ensuring reliable with safe operation in power generation plants with economic recovery. The contribution of this work lies in incorporating fuzzy clustering and Takagi-Sugeno techniques to establish robust models that accurately represent the dynamic behavior of gas turbines based on actual and historical operational data.

2. Industrial Application

Monitoring industrial systems, especially those involving rotating machines, is crucial in various industries. It ensures the safe operation of these systems by mitigating basic instability phenomena and provides valuable information for their modeling and control. Several studies have addressed the dynamic behavior evaluation of rotating machines, such as the works of Achour El hamdaouy et al. [3], Ben Rahmoune Mohamed et al. [30-33], Jiandong Duan et al. [22], and Lazzaretto et al. [25].

In this paper, the dynamic behavior evaluation is conducted for a gas turbine used in an electrical power generating station located in M'SILA, Algeria. The station comprises 22 gas turbine units, and the specific gas turbine investigated is the GE 5001P engine, which consists of the following main elements; the turbine itself, the combustion chamber and the axial compressor. The combustion chamber receives a fuel supply, either in liquid or gaseous form, and mixes it with partially burned air provided by the compressor and turbine. The engine, illustrated in Figure 1, operates on a single shaft.

The operating principle of the gas turbine is straightforward. The air-gas mixture in the combustion chamber, pressurized through combustion, undergoes expansion in multiple stages to generate mechanical energy. This energy is used to drive the air compressor and produce usable shaft power collected by an alternator.

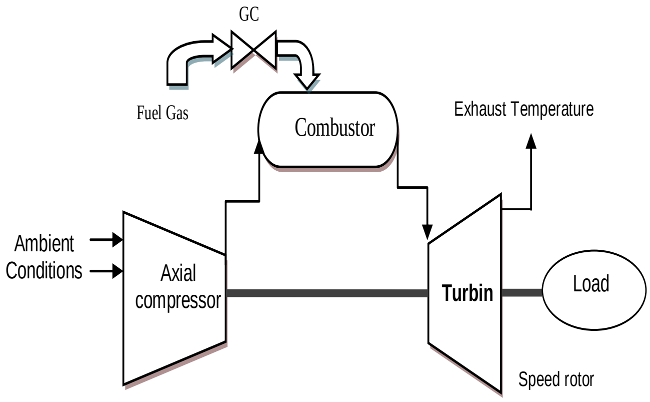

Fig. 1. GE 5001P Gas turbine representation [1]

To develop regulators to drive the studied turbine system MS 5001P, the strategy of estimating their model variables is used to automatically generate the inputs of the system, so as to obtain a desired behavior of the outputs of this machine. In effect, the MS 5001P turbine is employed in an electricity production station in M'Sila, Algeria, to supply power to the electricity network. Its specifications are listed in Table 1. As their nonlinear dynamic behavior is characterized and estimated through the use of fuzzy Takagi-Sugeno model, initially proposed in [43], combined with the linearization of fuzzy regions within the state space. The membership functions and their parameters are determined by minimizing an objective function based on fuzzy clustering techniques. To validate this approach, a comparative study is conducted between intelligent methods, namely the NARX-NN (Neural Networks in Nonlinear Autoregressive Exogenous form) modeling combined with the ANFIS technique, to the modeling the nonlinear behavior of this rotating machine.

Table 1. Studied turbine parameters

Quantity	Value
Compressor stages	16
Exhaust temperature (F°)	898
Heat rate (kJ/kW-h)	12,950
Air flow (103 Lb/hr)	928.5
Firing temperature (F°)	1,730
Output (kW)	24,700

Given the increasing complexity and severe operating conditions of the equipment, as well as the need for effective supervision strategies to prevent performance degradation, an integrated modeling and identification approach is proposed. This approach combines artificial intelligence tools, utilizing fuzzy concepts and the Gustafson Kessel algorithm, to enable the monitoring and synchronization control of different sensitive parts of the gas turbines.

3. Nonlinear Modeling System

In various industries, the development of robust mathematical models for system control is crucial. Artificial intelligence tools, particularly fuzzy systems, have gained significant attention in recent years for modeling nonlinear systems. These tools utilize available knowledge about the system's behavior, obtained through experiments or theoretical analysis of physical phenomena. Fuzzy logic has been extensively applied in industrial applications, including system control, modeling and diagnosis, process monitoring, speech and image processing, data classification, decision-making, and more. Notable research studies in these areas include the works of Hafaifa et al. [4], Ahmed Zohair Djeddi et al. [5], Bezdek et al. [11], Boon Chiang et al. [12], Choayb Djeddi et al. [13], Gustafson et al. [17], Hakim Bagua et al. [18], Jang et al. [21], Merouane Alaoui et al. [27-28], Nadji Hadroug et al. [35-36] and Sidali Aissat et al. [41-42]. The advantage of using fuzzy logic lies in its ability to incorporate human reasoning into analytical models.

3.1. Fuzzy modeling based on fuzzy C-means clustering

Formal modeling techniques that involve data processing and prior classification have recently gained popularity in various engineering domains. These models aim to effectively manage diverse models and consolidate knowledge to propose models that can be utilized in control and diagnosis systems. When expert knowledge is unavailable, system identification must rely on operational data to approximate the behavior of the nonlinear system. Numerous works have explored these approaches, such as those by Manjeevan Seera et al. [26], Paolo Giordani et al. [37], Pierpaolo et al. [38], and Takagi and Sugeno [43].

In this work, a fuzzy classification method is employed to determine models that accurately capture the turbine dynamics. This method partitions the data operating space of the turbine into multiple classes, where each class represents a fuzzy subset for locally linear models. By analyzing these fuzzy regions in the state space, dynamic representations of the turbine can be developed to establish a fuzzy knowledge model that describes the machine's nonlinear behavior. To obtain the membership functions required for the fuzzy clustering rules, the approach incorporates the Gustafson Kessel algorithm. This combined methodology effectively models of the turbine dynamics, with modeling data with sharp boundaries between classes.

The fuzzy data classification is carried out in a supervised way, those data are the measurements, resulting from turbine operating processes, each k^{th} observation constitutes a vector of N number of observations $z_k = [z_{1k}, \ldots, z_{nk}]^T$ given the measurements matrix:

$$Z = \begin{bmatrix} z_{11} & . & . & z_{1N} \\ . & . & . & . \\ . & . & . & . \\ z_{n1} & . & . & z_{nN} \end{bmatrix} \tag{1}$$

Each observation $z_k \in Z$ is linked to a vector representing the degrees of membership to various classes, which can be expressed as a membership matrix U or a fuzzy partition matrix, given by the following form:

$$U = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1j} & \cdots & \mu_{1N} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2j} & \cdots & \mu_{2N} \\ . & . & \cdots & & \cdots & . \\ \mu_{i1} & \mu_{i2} & \cdots & \mu_{ij} & \cdots & \mu_{iN} \\ . & . & \cdots & & \cdots & . \\ \mu_{c1} & \mu_{c2} & \cdots & \mu_{cj} & \cdots & \mu_{cN} \end{bmatrix} \tag{2}$$

The functional to be minimized by the algorithm (FCM) is expressed as follows [1]:

$$J_{FCM}(Z;U;V) = \sum_{i=1}^{c} \sum_{k=1}^{N} (\mu_{ik})^m D_{ikA}^2 \tag{3}$$

Where $U = [\mu_{ik}]$ represent the matrix of the partition, Z represent the measurements matrix, v_i represent the data center of the i^{th} data group, $V = [v_1, v_2, ... v_c]$ is the center vector of classified data measurements.

The application of the C-means fuzzy variant of the FCM algorithm is applied to the processing of studied turbine data, for the development of their model, with a number of data groups C of their operation. This is achieved after a series of iterative optimization by approximating the minima of an error function. While minimizing a cost criterion, given by:

$$J_{FCM}(u(.), v) = \sum_{j=1}^{N} \sum_{i=1}^{C} \mu_{ij}^m(x) \left\| x_j - v_i \right\|^2 \tag{4}$$

With $\sum_{i=1}^{C} U_{ij} = 1$, $1 \le j \le N$, $1 \le i \le C$.

The centres and degrees of membership are, for a m given value, calculated using the following formula:

$$V_i = \frac{\sum_{j=1}^{n} (U_{ij})^m x_j}{\sum_{j=1}^{n} (U_{ij})^m} \tag{5}$$

The final matrix $U = [\mu_{ik}]$ is obtained after a number of iterations which determines its stability of the distance between measurements; this is given by the following equations:

$$U_{ij} = \sum_{i=1}^{C} \left(\frac{\left\| x_j - v_i \right\|}{\left\| x_j - v_k \right\|} \right)^{\frac{-2}{m-1}} \tag{6}$$

With v_i is the classes center

To partition and judge the stability of the partition matrix, we must minimize the criterion of the sum of inter-class distance generalized to the fuzzy FCM algorithm. By the choose k initial means c_1, …, c_k and repeat the assignment of each point to its closest cluster, updating the mean of each cluster, by the following formula[1, 29]:

$$m_i^{(t+1)} = \frac{1}{\left| S_i^{(t)} \right|} \sum_{x_j} x_j \tag{7}$$

With S_i is the center of gravity of the class.

Assuming that the matrix A_i satisfies the condition:

$$\left| A_i \right| = \rho_i \tag{8}$$

The construction of the optimal matrix A_i leads to the use of the vector of the covariance given by the following expression:

$$F_i = \frac{\sum_{K=1}^{N} (\mu_{ik})^m (z_k - v_i)(z_k - v_i)^T}{\sum_{k=1}^{N} (\mu_{ik})^m} \tag{9}$$

The FCM is based on the updating of the membership function during the iteration of the algorithm, so the FCM thus changes the partition (matrix $U = [\mu_{ik}]$) by minimizing the objective function J_{FCM}.

The fuzzy clustering algorithm, using Gustafson Kessel learning [19] iteratively optimizes a classification criterion for knowledge extraction from fuzzy data fusion, with a priori knowledge of fuzzy aspect with consideration in the data classification process [29-30]. This algorithm relies on a specific analysis of the minimization problem with a performance criterion to prove models of the rotating machine converged to an acceptable modeling error. Where, each cluster corresponds theoretically to a uniform operation of a turbine operating area, which can be presented in the form of predictions with locally linear sub-models. With their data are drawn by cluster series. In the following, the algorithm for the execution is presented under the following steps:

- Beginning
- Determination of the data classes centers using :

$$v_i^1 = \frac{\sum_{K=1}^{N} (\mu_{ik}^{(1)})^m z_k}{\sum_{k=1}^{N} (\mu_{ik}^{(1)})^m}$$

- Determination of the covariance matrices and minimizing a cost criterion using :

$$J_{FCM}(u(.), v) = \sum_{j=1}^{N} \sum_{i=1}^{C} \mu_{ij}^m(x) \left\| x_j - v_i \right\|^2$$

Determination of the center of gravity of the class by:

$$m_i^{(t+1)} = \frac{1}{\left| S_i^{(t)} \right|} \sum_{x_j} x_j$$

- Partition matrix update using :

$$\mu_{ik}^{(1)} = \frac{1}{\sum_{j}^{c} 1 \left(\frac{D_{ikA}}{D_{jkA}} \right)^{\frac{2}{m-1}}}$$

- Improving of the partition matrix using :
- End

The use of the Gustafson-Kessel algorithm involves extracting classes of individuals with common characteristics in the Z data set, the number and the differential classes not being given a priori. A random initial partition of matrix U is taken and the calculations for $l = 0,1,....$ is repeated until the stopping criteria is verified. In this case, the parameter m has an important influence on the form of clusters in the system data, it is obvious when the factor m approaches a value of 1, the shape of the membership function changes for each cluster.

In Figure 2, the data set is partitioned into three classes of centers v_1, v_2 and v_3, represent the inputs variables in the turbine; The discharge pressure of the axial compressor, the temperature of the exhaust and the control valve position of gas fuel.

The matrix of the data partition gathers the degrees of belonging of the different classes of data points to the three classes. The data z_k is at a distance $d(z_k, v_1)$ from the first class and $d(z_k, v_2)$, $d(z_k, v_3)$ from the second and the third class.

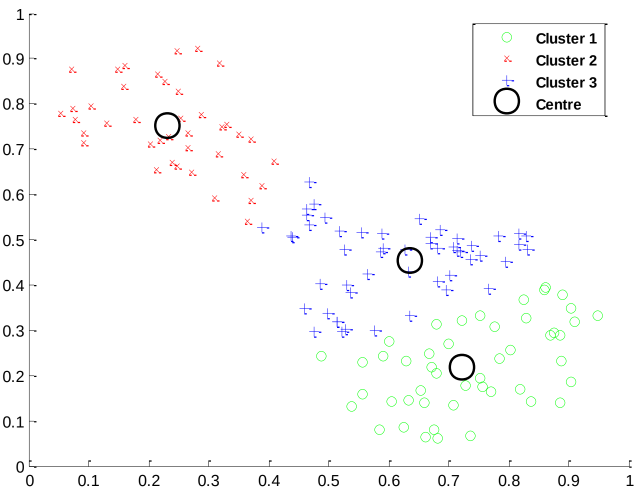

Fig. 2. Fuzzy classification by the FCM method

For the fuzzy model of type Takagi-Sugeno [35], a system can be described by its state representation as follows:

$$y_k = f_{NL}(x_k) \tag{10}$$

The main aim is to estimate the nonlinear function called f_{NL} presented in (10) via the use of Takagi Sugeno model given by the following form [1, 35]:

$$R_i: if\ x_1\ and\ ...\ and\ A_{ip}$$
$$Then:\ y_i = a_i x + d_i \tag{11}$$

With R_i is the i^{th} rule, x_i represent the observation vector, A_{in} is the fuzzy sets with $a_i^T = [a_1, a_1, .. a_{in}]$, d_i is the scalar and y_i is the output system.

The estimation f_{NL} can be ensured as a result; the first step starts by applying the Gustafson-Kessel clustering algorithm for the calculation of the fuzzy partition matrix U, the second step is dedicated for the estimation of the parameters a_i and d_i based on least squares techniques. It is well known that the defuzzification method used in Takagi Sugeno model is linear with respect to the parameters a_i and d_i.

3.2. NN-NARX Modeling

The NN-NARX modeling is used to estimate the behavior of highly nonlinear complex systems given by the following equation:

$$y(t) = F(y(k-1), y(t-2), ..., y(t-n_a)$$
$$u(k-1), u(t-2), ..., u(t-n_b)) \tag{12}$$

In this equation the output is $y(t)$ for n_a number of the output regressions and the input is $u(t)$ for n_b number input regressions with F the activation function, this function have different types; Polynomial form multilayer NNs, wavelet networks, and sigmoid networks. In polynomial form, the NARX models is given as follows [1, 11]:

$$y(t) = \alpha_0 + \sum_{i_1=1}^{n} \alpha_{i_1} x_{i_1}(t) + \sum_{i_1=1}^{n} \sum_{i_2=i_2}^{n} \alpha_{i_1,i_2} x_{i_1}(t) +.$$
$$....\sum_{i_1=1}^{n} .....\sum_{i_k=i_{k\_1}}^{n} \alpha_{i_1,......i_k} x_{i_1}(t).....x_{i_k}(t) \tag{13}$$

The Figure 3 presents the configuration system of the Nonlinear Autoregressive Exogenous Neural Networks (NARX-NN) model that which was used in the present work.

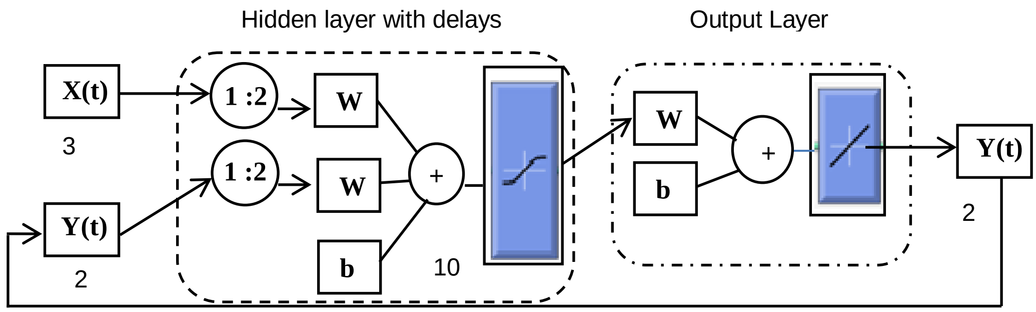

Fig. 3. Nonlinear Autoregressive Exogenous Neural Networks (NARX-NN) model [31, 35]

3.3. ANFIS Modeling

To overcome the shortcomings of conventional modeling approaches, the ANFIS concept by integrating a fuzzy TS type (Takagi-Sugeno configuration) will be the subject of this work. The Adaptive Inference System combined with Neuro-Fuzzy concept (ANFIS) is a hybrid approach that combines a fuzzy concept with an adaptive neural network. It utilizes a multilayer perceptron (MLP) neural network with five layers, where each layer corresponds to a step in the fuzzy inference concept, by the use of Takagi-Sugeno approach. ANFIS integrates the benefits of both fuzzy logic and neural networks to model complex system processes.

The ANFIS structure aims to improve the parameters model performances of the investigated rotating machine; witch using the adjustment of the five layers and the inference rules by means of the learning algorithm, as depicted in Figure 4. Each layer serves a specific purpose in the modeling process, such as fuzzifying the input variables, generating the fuzzy rule antecedents and consequents, aggregating the rule outputs, and defuzzifying the final output.

ANFIS has been widely used in various fields where nonlinear modeling and control are required. Its ability to integrate expert knowledge and adapt to data makes it a powerful tool for system modeling, approximation, and control tasks.

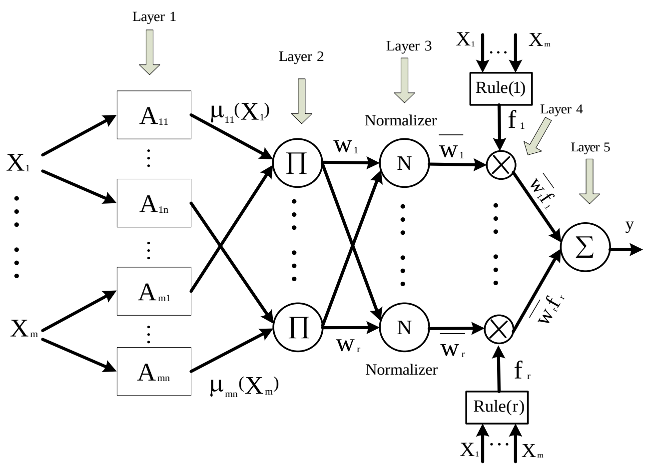

Fig. 4. A typical ANFIS model

Layer 1: Membership function characterization :

$$\mu_{A_{ij}}(x_j; c_{ij}; \sigma_{ij}) = e^{-\left(\frac{x_j - c_{ij}}{2\sigma_{ij}}\right)^2}$$
$$i = 1, \ldots\ldots NMF,\ j = 1, \ldots\ldots, m \tag{14}$$

With NMF represent the functions of membership, σ_{ij} is the variance, c_{ij} is the mean value, m is inputs number.

Given the different estimates are associated with the protocols of the ANFIS classification algorithm using the layers, each data point must belong in a data set to each cluster.

Layer 2: Their output produces the rule degree of the activation and is expressed as follows:

$$w_k = \prod_{i=1}^{m} \mu_{A_{ik}}(x_i) \tag{15}$$

Layer 3: Their outputs characterizes the degree normalized of the activation rule i, presented as follows:

$$\overline{w_k} = \frac{w_k}{\sum_{i=1}^{r} w_i} \tag{16}$$

Layer 4: Their output is determined based on the previous layer 3 output with a set of output parameters of the rule i, it is expressed as:

$$\overline{w_k} f_k = \overline{w_k}(p_{k0} + \sum_{j=1}^{m} p_{kj} x_j \tag{17}$$

Where f_k is the function of a consequent part of the rule k and P_{kj} represents the scalar coefficients.
Layer 5: Is represented by a single node at the level of which is effected the sum of signals from the layer 4, it can be presented as follows:

$$y = \sum_{i=1}^{r} \overline{w_i} f_i \tag{18}$$

The model variables predictions will be made through the use of data from their operation. In this application, a fuzzy model type Takagi Sugeno TS with zero order is used to establish the ANFIS turbine configuration and to ensure the partition of the input space. The ANFIS network is using the fuzzy clustering algorithm FCM and the back propagation learning algorithm in order to simplify the results.

4. Investigations Results

Practically, the governance of gas turbines plays a very important role, to improve their performance and efficiency in natural gas transportation stations or for other applications of electrical energy production. Indeed, this part of the paper proposes to make a comparison between three modern modeling techniques (Fuzzy, NARX, ANFIS), for a local linearization with optimal approximation of the GE 5001P Gas turbine model variable, followed by a comparison between these techniques based on a modeling error calculation. The different inputs and outputs of the modeling process are shown in Figure 5, where the choice of desired output variables will be the temperature of the exhaust and rotational speed of the turbine rotor. To improve the closed-loop behavior of the monitoring system, the inputs chosen are the discharge temperature of the axial compressor, the discharge pressure and the valve position of the aspiration gas.

However, the fuzzy approach implementation is performed to identify the model variables of GE 5001P turbine using real sensor data is will be presented. The focus is on processing incomplete data and restoring it to the system under consideration. To test the efficiency of the approximation techniques and ensure the improvement of the system performance.

The identification variables of examined turbine are conducted in a closed-loop system, specifically with an isochronous control type. The input/output data measurements are got from various sensors and need to be correlated to each other. These data are collected during a specified observation period under normal operating conditions.

Based on fuzzy modeling technique to this data, the system aims to capture the underlying dynamics and behavior of the gas turbine. The proposed model takes into account the instability phenomena affecting the turbine, as well as the operating conditions in the different regimes. Also, the uncertainties of the measurement data and the identification errors. With this model in place, it becomes possible to analyze and improve the overall system performance.

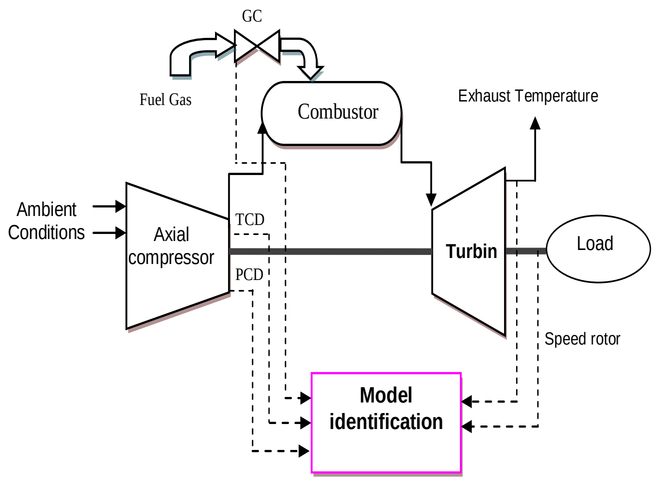

Fig. 5. Inputs and outputs used in the examined gas turbine modeling

To model the turbine dynamic representation using fuzzy clustering techniques, the system to be identified can be represented as a non-linear MIMO autoregressive system with three inputs, the discharge pressure of the axial compressor and exhaust temperature given by TCD and PCD, with the gas control valve position given by GCV. And two outputs, rotor speed (VR) and exhaust temperature (TE), the system model can be represented in two ways: either by a non-linear vector function f_{NL} or the system is decomposed into several subsystem of type Takagi-Sugeno model. The adopted fuzzy linearization structure for the turbine variables modeling is determined by using the following steps:

- Selection of the data and variables,
- Definition of membership functions and fuzzy clustering variables,
- Parameter estimation and model validation.

The proposed modeling approach utilized real data sets from the examined turbine. The application of the linearization method to simplify the representation of the input/output of these rotating machine variables makes it possible to have the results shown in Figures 1, 2 and 3. Where, Figure 1 show the fluctuation of the fuel gas flow rate, Figure 2 illustrates the changes in the discharge pressure within the combustion chamber, and Figure 3 showcases the variations in the discharge temperature. Additionally, Figure 4 demonstrates the changes in the gas turbine rotor speed, while Figure 5 displays the variation in gas turbine power.

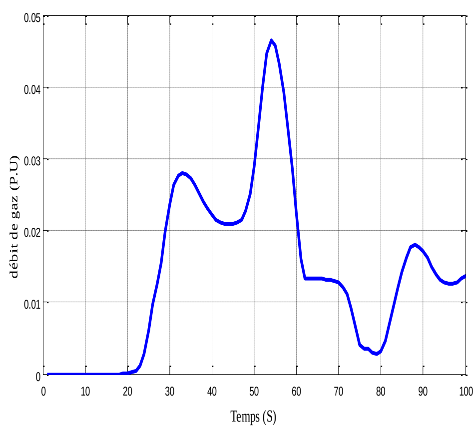

Fig. 6. Variation of fuel gas flow rate

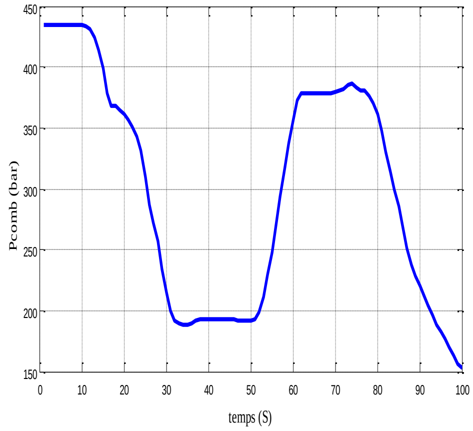

Fig. 7. Discharge pressure in the combustion chamber

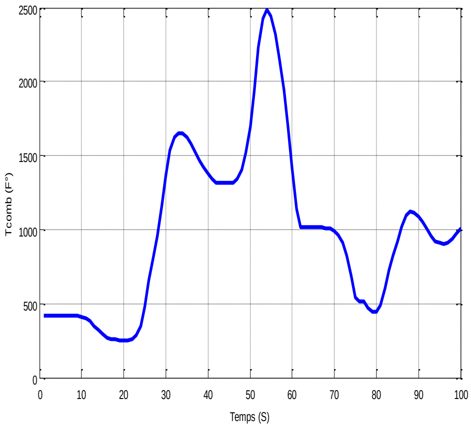

Fig. 8. Variation of discharge temperature

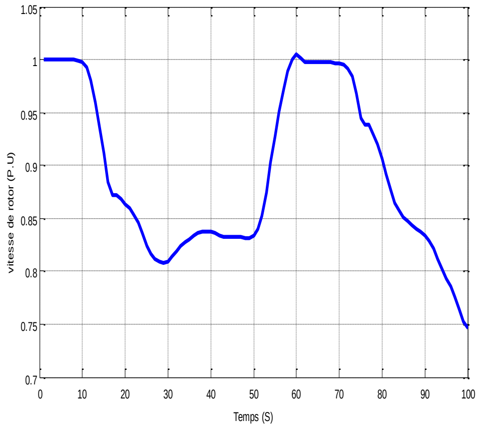

Fig. 9. Variation of gas turbine rotor speed

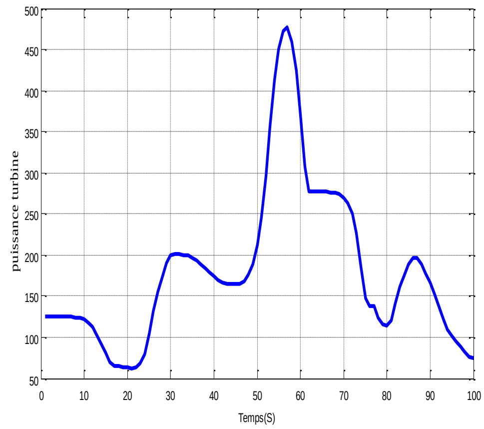

Fig. 10. Gas turbine power variation

Two data sets of N = 19000 equidistant point are generated in this application; the first 19000 points are the data for classification of the model parameters. Then, a validation data is used to test the efficiency of the fuzzy model. Figures 11 and 12 show the development and the observed real variables of the studied rotating machine respectively.

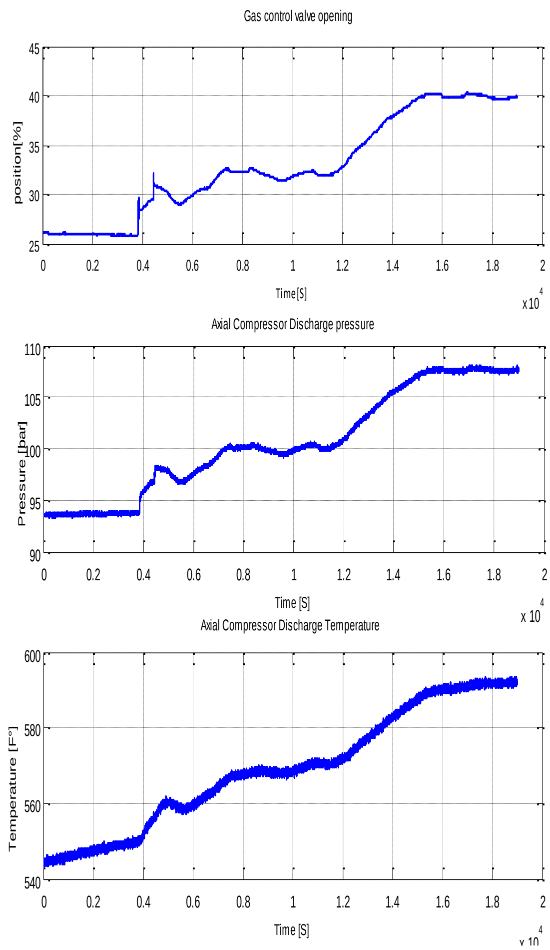

Fig. 11. Gas control valve position

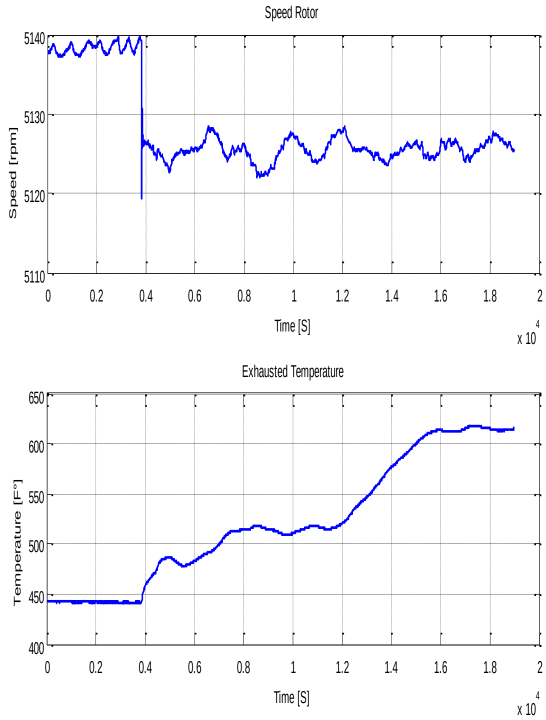

Fig. 12. Rotor speed variation and exhausted temperature

The obtained membership functions using fuzzy models by calculating the degrees of membership in the space directly, produces the input/output system variable of real data of the studied turbine, from the partition matrix U and by applying the mechanism of projection of these variables to facilitate the information interpretation of the obtained variables model. This concept is to project the rules of the fuzzy set step by step in the fuzzy partition matrix U via their input and output data which serve to identify the main variables of the identified model of the considered GE 5001P turbine. These used variables are the inputs for clustering, and the membership functions of the inputs and outputs of the fuzzy models are shown in Figures 13 and 14. These functions will be used to reproduce the fuzzy models inputs and outputs, with the used data for lift the complex regression problem of the examined turbine data in this paper.

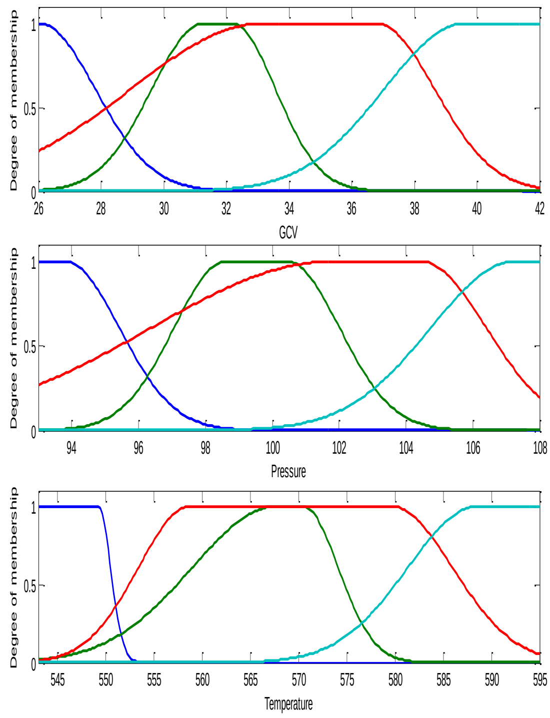

Fig. 13. Membership functions of inputs for fuzzy models

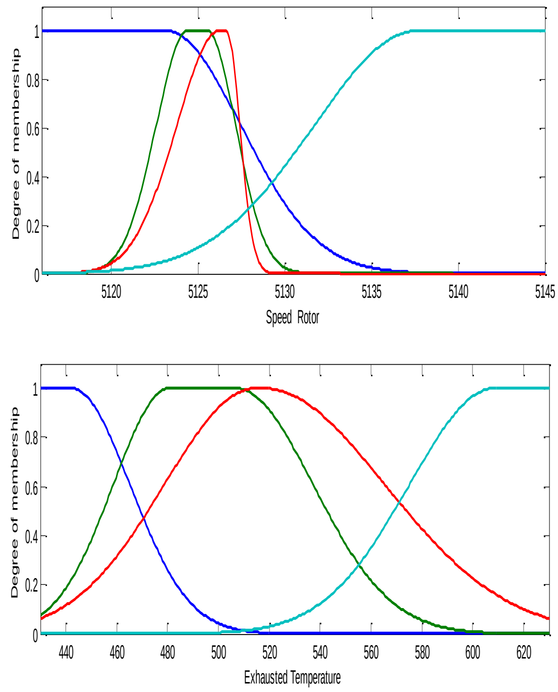

Fig. 14. Fuzzy models outputs membership functions

Validation tests of the approach carried out for the development of the obtained models are made, to solve the problem posed during the monitoring of the turbine, while the exhaust temperature increases and reaching up to 590 F° and the speed of rotation increases reaching up to 5100 rpm, as shown in figure 15. This figure shows the evolution of different used models; the fuzzy model, NARX model, and ANFIS model. Similarly, Figure 16 demonstrates the variation of the exhaust temperature, also comparing the fuzzy, NARX, and ANFIS models.

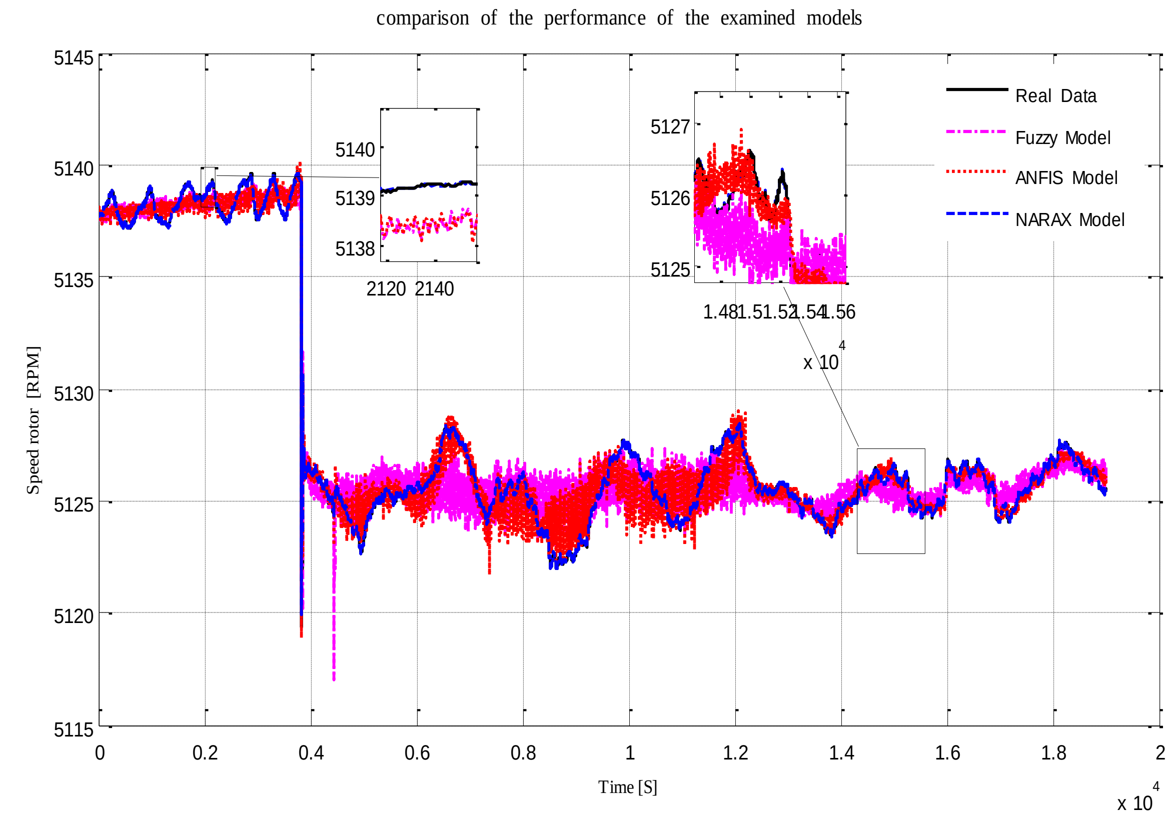

Fig. 15. Speed rotor variation with the validation model

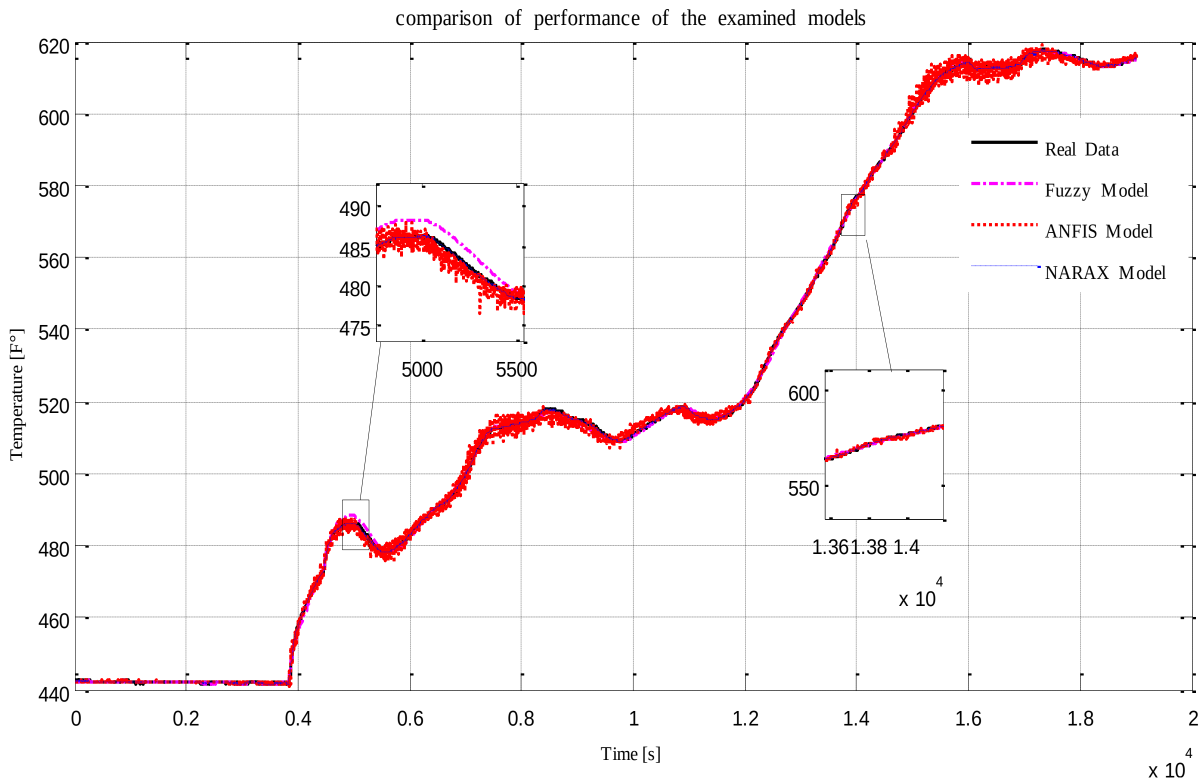

Fig. 16. Validation of the model of the exhaust temperature

To assess the quality of the approximation, the RMSE error criteria are used. The evaluation performance values was measured by RMSE, for the three models are presented in Table 2. The results indicate that all three models exhibit relatively small errors, highlighting their effectiveness in capturing the behavior of the gas turbine system.

Table 2. Results of RMSE error for the obtained models

	Gas turbine variables		
	Fuzzy model	NARX model	ANFIS model
Speed rotor	0,215	0,092	0,181
Exhaust temperature	0.064	0.0091	0.0073

The results obtained using the fuzzy modeling approach is deemed reasonable. The algorithm leverages fuzzy clustering techniques to determine the functions of the estimated parameters membership for the turbine variables model. The fuzzy clustering method, combined with the Gustafson Kessel algorithm, enables the automatic generation of data decomposition for the input-output system. The validity of the model is established through a comparative study involving the NARX-NN model and the ANFIS approach.

The determination and estimation of membership functions based on fuzzy clustering techniques, coupled with the minimization of an objective function, contribute to achieving improved results. The calculation of the RMSE error for each method further validates the quality of the fuzzy modeling approach.

5. Conclusion

In conclusion, this study conducted a comparative analysis of three different techniques for modeling a gas turbine: fuzzy logic with the Takagi-Sugeno model using the Gustafson-Kessel clustering algorithm, the NN-NARX Neural Networks in Nonlinear Autoregressive Exogenous form and the ANFIS Adaptive Inference System combined with neuro-fuzzy concept. The obtained results from these techniques demonstrate a good approximation of the turbine complex behavior.

The models generated through these approaches provide satisfactory representations of the turbine variables structure, enabling a deeper understanding with analysis of the underlying phenomena. Among the three techniques, the NN-NARX Neural Networks in Nonlinear Autoregressive Exogenous form combined with the ANFIS method exhibit superior performance in describing the turbine parameters compared to the fuzzy-based technique.

These models offer reliable representations of the investigated gas turbine system variables and have the potential to be utilized in gas turbine control and fault diagnosis applications. The findings of this study contribute to the development of robust mathematical models for industrial systems and pave the way for further advancements in gas turbine operation and optimization.

It is worth noting that further research and experimentation can be conducted to refine and enhance the proposed modeling techniques, considering different operating conditions and system configurations. Additionally, the application of these models in real-world scenarios and their integration into control and diagnostic systems can be explored for practical implementation.

Overall, the comparative study conducted in this work highlights the effectiveness of the Neural Networks in the Nonlinear Autoregressive Exogenous form (NN-NARX) approach combined with the adaptive inference system via neuro-fuzzy concept in modeling gas turbines, offering valuable insights for industrial applications.

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