ABSTRACT

The main purpose of this paper is to present a dynamic model for an old industrial gas turbine in the start-up and loading modes, using the performance information of the system and with the minimum access to the design and related technical datasheets. For the start-up mode in this model, the most fundamental variable which will determine the value of the other operational variables is the shaft speed and its rate of changes. For specifying the dynamic characteristics of the shaft movement during the system start-up, due to uncertainties and unspecified parameters, a lot of complexities will be encountered for modelling the system. Regarding the regional condition of the operating system, the most important environmental parameter affecting the system behavior, is the temperature in which the turbine is operated.

KEYWORDS: Dynamic model, Gas turbine, Linear regression, Start-up, Loading, Turbine exhaust temperature

INTRODUCTION

A dynamic model can be used to analyze system performance, to identify faults, to test and to design controllers, and plays an effective role in the whole process of performance and maintenance. Therefore, along with the simpler structure of turbines, correct utilization, timely detection of probable faults, providing proper scheduling for the maintenance process, and applying appropriate controllers with the help of a dynamic model and its based systems, can increase the positive properties of single shaft turbines.

In this paper, a dynamic model of an industrial single shaft gas turbine in start-up mode is presented. The service and back-up companies that carry out repair and maintenance work may face a lack of information on the system operation data. Furthermore, due to aging of the equipment and the necessity to revise and upgrade the system in different conditions, one of the operations that may be considered by the employer and the owners of gas turbines is the upgrading of the logic performance and the control system of the gas turbine. Therefore, in such situations, a reliable dynamic model can solve a significant part of the problems in this field. Different methods have been proposed for presenting a dynamic model. One of the main issues in the production of a dynamic model based on the physique of the system is the performance simulation of the gas turbine compressor. Therefore, in the production of a dynamic model for a gas turbine, compressor map is specified as a major distinctive factor. A considerable amount of studies has been carried out in the field of dynamic modelling of gas turbines. Among the first dynamic models presented in the field of gas turbine is the one suggested by Rowen which has been used in the analysis and design of controllers [1-2]. Along with these dynamic models, based on the combination of thermodynamic equations and turbine transformation functions, another model was presented by De Mello et al. in 1994 [3]. The advantage of this model is related to the use of thermodynamic equations with more details and accuracy. The results of this research have also been used in further research on dynamic modelling and controller design [4]. To compare these methods, Kee et al. presented an article which has examined the characteristics of each expressed methods [5].
In the following, other models, based on the compressor performance map, have been designed for dynamic modelling of the gas turbine. Except for numerical solution methods, the production methods of compressor map region have been presented based on the compressor map meshing [6-7], or by using adjustable equations [8-14] or by solving the thermodynamic equations of the map generator [15-19], and finally methods based on the convergence of thermodynamic equations [20-23]. Another suitable model in the field of the integration of black boxes and white boxes for two-shaft gas turbines is the study carried out by Corsa et al. which represents two modes, detailed and simplified mode [24].

In this paper, the modelling of the start-up and loading modes have been discussed. The most important variable in start-up mode is the shaft revolutions per minute (RPM) which other performance variables somehow depend on. Therefore, focus in start-up procedure is more on providing a precise and reliable model to achieve shaft speed. Then, considering the presented control structure in the dynamic model, we studied and calculated the appropriate functions to estimate turbine exhaust temperature (TET) and compressor pressure ratio (CPR). In the start-up mode, given the fact that there is a relatively defined and specific procedure for defining variables, especially power, we encounter less complexity and ambiguity in this section. One of the most important issues discussed in this study is to obtain the control variables functions of the TET and CPR, which have been discussed based on the functional logic of the system.

1. STUDIED GAS TURBINE

The most distinctive feature of this research, especially in providing a dynamic model for start-up mode of the system, is the use of online monitoring system data. The gas turbine which has been studied in this case is a 40 MW single shaft industrial gas turbine. The dynamic model of this turbine has been used based on the functional logic of the studied system in Rowen models [1-2]. The information and documentation for the dynamic modelling of this turbine is very limited and therefore the behaviour of this turbine based on the design information of this system is practically impossible. With regards to the fact that maintenance companies may encounter such problems, this research has been presented to provide a consistent dynamic model with the functional facts of the system.

2. MODELING

The modelling process in this research has been carried out in different methods and scenarios to provide the appropriate method. Start-up mode of the gas turbine is an open loop control mode which is performed based on a defined time process. During the start-up of the turbine, a significant number of variables are involved, and in order to reach the network frequency, there will be no linear relationship between shaft speed and fuel discharge. During the start-up, parameters such as bleed valve and Inlet Guide Vans (IGV), as well as the inertia of the shaft play an important role in the operator decision making in the process of increasing turbine speed in the intervals of fuel injection and turbine idle state. The trend for in Figure 1 illustrates this relationship and the role of indeterminacies in the production of the system's optimal output. It should be noted that the IGV starts to open at a certain RPM of the shaft (about 87%) and has an opening angle of 34 to 57 degrees.

![Figure 1. IGV Position, Shaft Speed and Fuel Flow Rate in Start-up Condition](image)

The amount and change rate of control parameters during the start-up mode depend on the turbine shaft speed and this parameter is the most important factor in determining them. The information available for the dynamic modelling of the gas turbine are the two input parameters, the fuel discharge rate, and the IGV position. According to the diagram presented for such a situation, there is a completely nonlinear relationship between the input and output parameters. In order to model the system in such situations, a solution is considered to be the combination of linear and nonlinear system inputs with dynamic delay transfer functions to achieve an acceptable accuracy. Several different scenarios in this field are considered for the production of outputs. In the first scenario, due to the privileged characteristics of the neural networks involved in generation, a nonlinear relationship has been considered between the variables. In the second scenario, the linear regression method has been used to estimate the inputs affect on the outputs. This process has been investigated in three different situations and according to the functional status of the IGV. The method used in the third scenario of the previous models has been used with some variations with respect to the indeterminacies. In this method, the fuel discharge and shaft dynamics transfer function are used as input to the shaft speed transfer function. Finally, in the fourth scenario, HW and NARX nonlinear detection methods for generating the I/O functions of the system have been used.

3-1. FIRST SCENARIO:

In the first scenario, the target was to extract a multivariate network to obtain the desired outputs. For this
purpose, at the data filtering phase, the minimum omission has been performed. There are 8 hidden tanh layers to generate the MLP network. Seventy percent of the data is also used to train the network and the remaining ones are used equally to validate and test the network. Figure 2 shows the model and its rate of correspondence with the data used for its production. In Figure 3, the result of testing a number of unused data for modelling is presented. Despite the complete nonlinearity of input and output data as shown in Figures 2 and 3, the accuracy of the obtained network is at an acceptable level. The network inputs were the fuel injection and the IGV opening rate. Some information in this section has been removed from the reference trending. Part of the omitted information returns to the time of operation, when fuel discharge has not been started, but the shaft has been moved by an electric motor. Another part of the data enters the end of this mode, in which the fuel injection rate is relatively decreased due to the shaft inertia effect and almost the system has tried to stabilize the speed of the shaft. The useful section of the required information is in the time range of 230 seconds to about 700 seconds.

In the second scenario, the I/O functions are extracted using linear regression. The functions obtained are calculated in three different operating modes of IGV, including closed, open, and opening IGV phases. For closed IGVs, there is a fairly proper number of points for providing functions that are compatible with increasing fuel discharge and shaft speed variations, and although they are somewhat nonlinear, but were with an acceptable accuracy. In the second part, the output shaft speed is a function of the fuel discharge and the opening of the IGV vanes, and a precise equation has been generated according to the almost linear state established between the inputs and the outputs. Finally, in the third section, due to the relatively high indeterminacies in system performance, only a few points at the beginning of this phase are used to extract the function associated with the IGV opening state. As previously explained, the information at the end of this mode and during the reach of the nominal shaft speed was influenced by the shaft's inertia, and this fact strongly influenced the accuracy of the functions. The extracted functions and their adaptation characteristics for producing outputs are presented in Table 1 and Figure 4:

<table>
<thead>
<tr>
<th>IGV Position</th>
<th>Correlation Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$IGV = 0$</td>
<td>$N = 9.202 \times 10^{-1} - 1.236 \times 10HR$</td>
</tr>
<tr>
<td></td>
<td>$+ 5.998 \times 10HR^2$</td>
</tr>
<tr>
<td>$1 \leq IGV \leq 0$</td>
<td>$N = -5.474 + 6.645 \times 10HR - 1.739 \times 10^3 HR^2$</td>
</tr>
<tr>
<td></td>
<td>$+ 6.897 \times 10^3 IGV + 3.022 \times 10^3 IGV^2$</td>
</tr>
<tr>
<td>$IGV = 1$</td>
<td>$N = -1.312 \times 10 + 1.417 \times 10^5 HR$</td>
</tr>
<tr>
<td></td>
<td>$- 3.576 \times 10^5 HR^2$</td>
</tr>
</tbody>
</table>

Figure 2. Conformity of Obtained Network and Input Data

Figure 3. Test of the Network Validation

3-2. SECOND SCENARIO:

Table 1 Correlation Functions of the Shaft Speed

1 The obtained functions associated the fuel heat rate to the turbine (as a general concept and instead of fuel flow rate) and IGV as the inputs to the model.
3-3. THIRD SCENARIO:

In this scenario, a similar function to the linear models presented in previous studies is defined between the fuel discharge and the turbine shaft speed. In this way, the fuel flow turns into a certain coefficient. As expected, such an interpretation should have a precise physical basis. It should be in a way that the coefficient between the shaft speed and the maximum amount of fuel injection in the start-up mode is about 5, while such a coefficient may not be true for other time segments of the turbine. The basic problem with using this method in start-up mode is the presence of open loop control in this mode. It is clear that under such conditions, this scenario will have two major weaknesses. First, the IGV effect has not been seen in the system performance, and second, there is merely a linear relationship between the fuel discharge and the shaft speed. Although, finally, there is a proper physical interpretation of this method, and it is possible to determine desired outputs by delay transfer functions, in any case, there is less precision in this case, the use of which may result in considerable reduction of the accuracy of the dynamic model.

In this scenario, detection methods for nonlinear systems are presented in two sections. The first part uses the NARX method and the second part uses the HW method. These methods have been used because of the possibility of using the time lag of these models. Therefore, they can be important and significant options in estimating nonlinear behavior along with system time lag.

3-4. FOURTH SCENARIO:

This method is one of the most common ways to identify nonlinear systems. The structure of this method in general is as follows:

\[ y = F(y(t-1), y(t-2), ..., y(t-n_y), u(t-1), u(t-2), ..., u(t-n_u)) \]  

In this equation, \( y, u \) are the I/O signals and \( n_y, n_u \) are the number of output and input regressors, respectively. The proposed function is essentially an estimator function that obtains outputs based on inputs. These structures are presented in the form of nonlinear blocks WN\(^1\), SN\(^2\), TPN\(^3\) and NN\(^4\) for the production of this function. The TPN method was used to compare the results of using these blocks. It should be noted that the number of regressors in each method is determined by the accuracy of the outputs of the system.

3-4-1. NARX METHOD:

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3-4-2. HAMMERSTEIN-WIENER:

The model is a block type model with a linear dynamic section and a static nonlinear section. Due to the definition of static nonlinear inputs of the system, which are the same inputs and outputs of the dynamic model, this nonlinear detection method is also included in gray box methods [25]. However, despite the high accuracy of the extracted dynamic models, the accuracy of the linearization in the production of the final linear model will be affected. Here, because of the
evolution to the higher ratio of the Hammerstein-Wiener method, this method has been used in identifying the system in relation to the other two methods (which are somehow underlined by this method). In the approximation of the NARX method, TPN has been used. Also, in determining the number of units of the HW method for inputs and outputs, the number of units are 4 and 10, respectively. Here, modelling non-linearity is calculated via the linear piecewise algorithm. The specifications and accuracy of the outputs obtained from these two methods are presented in Table 2.

Table 2. Specifications of NARX and HW Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>FED</th>
<th>MO</th>
</tr>
</thead>
<tbody>
<tr>
<td>NARX Method</td>
<td>99.85%</td>
<td>((n_1, n_2, n_3) = (2, [4, 2], [3, 1]))</td>
</tr>
<tr>
<td>HW Method</td>
<td>97.28%</td>
<td>((n_1, n_2) = ([1, 1], [1, 2], [1, 1]))</td>
</tr>
</tbody>
</table>

The final adaptation of the methods mentioned is shown in Figure 6. At first glance, it seems that apart from linear regression and neural network methods, the other cases are relatively spaced out with the expected curve and will not be able to fit well into the operational condition. The uncertainties affecting the system's outputs have affected the system's operational behaviour on the inputs, and a completely uncertain behaviour in high-expansion regimes, especially over a period of over 70%. This is due to the entry of IGV variable and the uncertainties caused by bleedings and inertia of the turbine shaft.

![Figure 6. Comparison of the Proposed Methods with Real Performance](image)

Although in NARX and HW methods, the time effect in generating nonlinear input and output variables has been used, the responses obtained with the reference curve did not match significantly. Therefore, the delay time functions in these methods are also presented to provide a better match. These functions are based on trial and error and have the highest consistency with respect to the configuration of its four constants. In other words, these functions are a lag compensator whose coefficients are obtained according to the correspondence value with the reference curve in each of the scenarios. In the following, based on the degree of compliance with the power plant’s trenches, the delay transfer functions are defined for each method (Table 3).

<table>
<thead>
<tr>
<th>Method</th>
<th>Compensator</th>
</tr>
</thead>
<tbody>
<tr>
<td>NARX</td>
<td>(70s + 5.189)</td>
</tr>
<tr>
<td></td>
<td>(1000s + 2.7)</td>
</tr>
<tr>
<td>HW</td>
<td>(300s + 1.085)</td>
</tr>
<tr>
<td></td>
<td>(1000s + 2.7)</td>
</tr>
<tr>
<td>NN</td>
<td>(50s + 1.031)</td>
</tr>
<tr>
<td>SD</td>
<td>(120.45s + 0.186)</td>
</tr>
<tr>
<td></td>
<td>(600s + 0.13)</td>
</tr>
<tr>
<td>LR</td>
<td>(-250s - 1.185)</td>
</tr>
<tr>
<td></td>
<td>(500s + 0.23)</td>
</tr>
<tr>
<td>IGV=0</td>
<td>(2010s + 0.9246)</td>
</tr>
<tr>
<td></td>
<td>(500s + 0.23)</td>
</tr>
</tbody>
</table>

Finally, after the transformation sequence is applied to the primary model output, the output behaviour of the system is modified according to the Figure 7. The maximum spacing between the trends provided with the operation line of the shaft speed is shown in the mentioned figure. By applying the delay transfer functions when somehow representing the overlap of the obtained functions with non-deterministic systems, the behaviour of the curves has been significantly modified. According to the obtained diagrams, all methods are in an acceptable range for modelling. The main logic is to select a more appropriate model for changes in the behaviour of outputs based on input changes.

![Figure 7. Compensator Effects on Proposed Methods](image)

The most important external disturbances in changing the behaviour of the system are the fuel heat rate (HR) degradation and environmental conditions. Changing the heat
rate value of a fuel due to the change in the type of fuel consumed or its sources is the most important turbulence affecting the behaviour of the system. The dynamical model obtained in addition to covering nonlinear behaviour of I/O variables should be able to provide maximum adaptation of the system behaviour in the presence of disturbances. In the following, the analysis of the effect of the variation of the heat rate on the system behaviour is discussed, in order to examine how to modify the model in the event of disturbances. In order to study the results of this method, its output have been investigated in terms of changes in fuel discharge variations. The criterion of the correctness of the functionality of the selected method is the amount of displacement of the trends while making these changes. In the scenarios presented, according to the logical conformance to the system conditions, neural network, NARX, shaft dynamics, linear regression and eventually HW method are preferred. Due to the proper distance from the operation line, the neural network method has been introduced as the preferred method. The reason for this choice is that, in addition to proper conformance with the reference state, during the change of conditions, the pattern of variations creates a trend for a linear correction. The linear regression method has a relatively good behaviour in the IGV closed duration, after IGV opening procedure, the behaviour of the system is divergent, and so if controller design is used for this model, the controller design for such changes will turn conservative. In the HW method, as well, considering that the model output is not sensitive to input changes, there is not a good performance. To improve the structure of the model for the indeterminacies of the fuel heat rate, the neural network method is preferred. In order to improve and adapt this method to performance outputs, it is necessary to determine the effect of fuel on the amount of distortion. That is, in other circumstances, it is possible to make a logical approximation of the change over the basis of the change in the fuel heat rate. The most suitable point for determining the best performance matching of the model with the system is the use of a performance trend that there is a roughly linear relationship between the fuel rate and the shaft speed. There are points in this situation in both IGV closed modes and IGV open. By filtering data, it is expected that, for every 10%, with the increase in fuel rate, shaft speed increases about 6%. In Figure 8, the boundaries close to the real change rate are presented.

So, given the distance from the modified performance line, the coefficient for the input fuel can be regained. In this way, the trend increases the round in three steps, including providing the neural network, applying a delay transfer function, and eventually using a correction factor for the higher and lower fuel heat rate. Finally, using a condition and applying coefficients of 94% and 107% for higher and lower fuel heat rates, respectively, the modified charts can be achieved.

![Figure 8. Determination of Fuel Heat Rate Effect on GT Shaft Speed in NN method](image)

One of the other control parameters is the TET. Although it does not close its limitations in the start-up mode, and does not have a high sensitivity to it in the control system, it is trying to get a function for this system, which simultaneously simplifies the high precision of this output in different situations. In this regard, to obtain the function associated with this parameter, the function of Table 4 is used. One of the most important requirements in this research is how data filters are used to reach the state that can meet the physical characteristics of the system based on the expected ones. In this section, the data filter is also used to generate this output. The Figure 9 is presented to compare how the model behaves in different conditions according to the variations of the two main parameters, namely, the shaft speed and fuel heat rate.

![Figure 9. Obtained TET Function Based on Fuel Heat Rate Variation](image)

<table>
<thead>
<tr>
<th>TET correlation Function</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( TET = 2.999 \times 10^1 + 5.178 \times HR - 3.770 \times N - 1.463 \times 10^1 \times IGV )</td>
<td>93.14%</td>
</tr>
</tbody>
</table>

![Table 4. TET Correlation Function](image)
As shown in Figure 10, the effect of fuel on the shaft speed with the higher pressure rise is more specified and the obtained function presents the turbine’s behavior differently in such a situation. In the low period, the effect of this difference is not recognizable due to the low level of the variables.

![Figure 10. Obtained CPD function variation based on fuel heat rate variation](image)

Table 5. CPD Correlation Function

<table>
<thead>
<tr>
<th>Correlation Function</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPD=(2.648 \times 10^{-1} \cdot 1.605 \times 10^{-10} )HR+6.547N+1.779IGV</td>
<td>99.87%</td>
</tr>
</tbody>
</table>

3.5. EFFECT OF ENVIRONMENTAL CONDITIONS:

In addition to the effect of the fuel heat rate, the influence of environmental parameters on the outputs of the system, whether in the start-up mode or in the loading modes, will be important. The ambient disturbance in this system involves merely ambient temperature due to the geographic location. Therefore, relation 7 is used to calculate the effect of temperature change on the shaft speed and the modified speed calculation. It should be noted that the modelling criteria is the performance trends at 308°K.

\[
\frac{n_{\text{new}}}{n_{\text{ref}}} = \sqrt{\frac{T_{\text{new}}}{T_{\text{ref}}}} \quad (7)
\]

The TET is also a function of the environmental conditions. In this context, relation 8, which is based on the empirical relationship between ambient temperature and the TET in ISO condition, is used to update the TET [26].

\[
TET_{\text{ref}} = TET_{\text{d}} + \left( \frac{T_{\text{amb}} - T_{\text{iso}}}{TET_{\text{d}}} \right) \quad (8)
\]

4. CONCLUSION

One of the main challenges to maintenance companies is the existence of performance data to check for corrections or sometimes to upgrade the system. Designing, testing, or upgrading the existing controllers require reliable dynamic models. Such a model is usually based on the design and operational information provided by the manufacturer, which may lead to problems in the process of repair and upgrading if there is no access to the documentation. The main purpose of this paper is to provide reliable dynamic modeling in different modes using monitoring system information. In this model, all of the disturbances and possible indeterminacies in drawing a final model have been investigated. The results in the start mode indicate the relative superiority of the NN method to generate a turbine output speed. In the loading and unloading modes, the functions obtained by LR are used to generate the dynamic model. For the parameters of the TET and CPR, the advantages and disadvantages of each of them were expressed in terms of simplicity, accuracy, and reliability. Most precision models are based on the information provided for system design or existing formulas. Although the dynamic model used to design or upgrade a controller does not require high accuracy, the purpose of this paper is to achieve results in terms of the results obtained from accurate models, which have been extracted from documents and based on design data. Ultimately, with such a plan, many restrictions on the lack of access to documents will be resolved.

References


