Multivariable Model Predictive Control for a Gas Turbine Power Plant

HADI GHORBANI*  ALI GHAFFARI**  MEHDI RAHNAMA***
Msc. Student of Mechanical Engineering  Prof. of Mechanical Engineering  Msc. Student of Electrical Engineering

*  **  *** Department of Mechanical Engineering
K.N.Toosi University Of Technology, Tehran, Iran

**Islamic Azad University of Science & Research branch, Tehran Iran
Deputy of Operation Department of Montazer Ghaem CCPP

Abstract: In this brief, constrained multi variable model predictive control (MPC) strategy is investigated for a GE9001E gas turbine power plant. So the rotor speed and exhaust gas temperature are controlled manipulating the fuel command and compressor inlet guide vanes position. A nonlinear model is introduced using conventional mathematical models and ARX identification procedure as gas turbine plant model. Also a process control model is identified for future system outputs prediction. The investigated system is simulated under load demand disturbance. In comprehension with SpeedTronic control system, MPC controller can maintain the rotor speed more accurate using simultaneous exhaust gas temperature control.

Key-words: Gas turbine, Identification, ARX, Predictive control, Power plant, Modeling, Multivariable control

1. Introduction

Recently, gas turbines have found increasing service in the world because of their compactness, multiple fuel applications, fast start-stop sequence and etc. The Montazer Ghaem is one of the most effective plants in IRAN which consists of a series of General Electric MS9001E gas turbines with rated power 116.4 MW and SPEEDTRONIC MARK IV control system. As a brief survey in the history of gas turbine studies, a simplified mathematical model consists of a set of algebraic equations and related temperature, speed and acceleration controllers is provided by W.I.Rowen in 1983 [1]. Then it is modified by adding the influence of variable inlet guide vanes (VIGV) [2] and this frequency-domain model is validated by L.N.Hannet [3]. Physically based model to determine frequency dependency and a neural network simulator are another gas turbine models [4, 5]. The identification techniques have been concerned mainly about aircraft gas turbine engines e.g. [6]. A low order linear model using Box-Jenkins algorithm of a micro-turbine is presented in [7].

The application of Model Predictive Control (MPC) to control gas turbine is introduced by Vroemen and Essen in [8, 9]. Junxia presents an approximate model predictive control used to control shaft speed of a gas turbine engine in [10]. A nonlinear MPC based on Wiener model is developed to control the Alstom gasifier [11]. Moreover, a model based predictive control is applied on the gas turbine plant using Hammerstein model and GPC algorithm [12]. MPC is a control strategy which has developed considerably nowadays in a wide variety of application areas including power plants, chemical industries and etc. It uses a model of system to predict the response over a future interval called predicting horizon [13, 14]. The various MPC algorithms only differ among themselves in the model used to represent the process and the noise where cost function be minimized [15].

In this paper MPC controller is investigated for a MS9001E gas turbine (mounted in Montazer Ghaem power plant) in order to control speed and exhaust gas temperature by considering I/O constraints and using GPC algorithm. The plant model is identified using Rowen conventional model and ARX techniques. Also a model is identified as process model in order to predict future outputs. Disturbances and measurement noises are considered and a state observer is designed for estimating states which are not possible to measure them. Finally system is simulated under a load demand disturbance and results are presented in comprehension with SPEEDTRONIC software.
2. Gas Turbine System Description

Heavy-duty gas turbine consists of multi stages axial flow compressor with variable inlet guide vanes (VIGV), combustion chambers and multi stages expansion turbine, which drives an electric generator for electrical power supply. In order to recover wasted energy through the exhaust, the gas turbine is coupled with the steam cycle by means of the heat recovery steam generator (HRSG). Closing guide vanes at constant fuel flow ($W_f$), decreases cycle airflow ($W_a$), increase fuel-air ratio in the combustor and causes increasing exhaust temperature. The gas turbine overall model is shown in Figure 1 schematically.

Temperature of the gases entering the turbine ($T_1$) cannot exceed the limit imposed by the high temperature resistance of the materials. Nevertheless, if this temperature decreases too much, the plant (both gas turbine and HRSG) efficiency would become unacceptably low. Thus, it must be kept under safe limits [4]. Since in the Speed Tronic control, $T_f$ is not measured directly, it is controlled by means of exhaust gas temperature ($T_e$) and compressor pressure discharge (CPD) indirectly. $T_e$ is a function of fuel and air flow rate. In addition, $W_f$ and consequently CPD vary with ambient air temperature ($T_{amb}$), shaft speed ($\omega$) and IGV variations, considering constant site pressure. The related physical and thermodynamic relations are presented in [4, 16] in detail. Consequently, $G$ and $F$ are nonlinear functions, which express CPD and $T_e$ respectively by means of independent variables:

$$CPD = G(T_{amb}, \theta_{IGV}, \omega)$$

$$T_e = F(T_{amb}, \theta_{IGV}, \omega, W_f)$$

Turbine output torque is not appreciably affected by guide vane action and can be estimated by equation (3) [2, 3]:

$$T_{out} = \frac{1.16(W_f - 0.133)}{\omega}$$

Thus in a general form for nonisolated form the output power corresponds to:

$$P = f(W_f, \omega)$$

Instead of using fuel flow and mechanical power, it is possible to relate them with FSR (fuel stroke reference) and electrical power output signals respectively (see[4]). By using fuel command, the dynamic of stop-ratio and control valves is taken into account with combustion system. In addition, the electrical generator and rotor dynamics are considered with the power system.

3. Gas Turbine Plant Identification

In order to describe gas turbine system as close as possible to the real system, it is necessary to identify it based on I/O related signals. Thus exploiting Rowen conventional model, a nonlinear block diagram model is obtained which is illustrated in Figure 2.

Here the exhaust gas temperature, compressor pressure discharge and output electrical power blocks are estimated using the second order ARX identification techniques [17].

The loss function, FEP and fitness percent are determined in order to evaluate model. FPE is defined as Aikake's forward Prediction Error by equation 5:

$$FPE = V \times \frac{1 + d / N}{1 - d / N}$$

Figure 2- Gas Turbine plant model block diagram
Where $d$ is the number of estimated parameters and $N$ is number of estimation data. The loss function $V_N(\theta, Z^N)$ is defined as normalized sum of squared prediction errors. To fit models by regressors to data set it is pointed out the PEM (prediction-error identification method) procedure using a LSM algorithm. In order to validate the obtained model, Residual (prediction error) analysis tests are used, which consists of whiteness test and independence test. Each block transfer function are presented in Appendix A.

4. MPC controller design

According to the predictive controller strategy, future outputs are predicted at each time instant for a determined prediction horizon $H_p$ by using a process model. These predicted outputs at time $(t+k)$, $y(t+k|t)$ for $k = 1 \ldots H_p$, are depends on past I/O data and future control signals $u(t+k|t)$, $k = 0 \ldots H_p - 1$. These future control signals are calculated by optimizing a determined criterion to keep the process as close as possible to the reference trajectory $w(t+k)$. This criterion is takes from of the quadratic function of the errors between the predicted output signal and predicted reference.

The aim of control in this paper is keeping the shaft speed constant when the power demand rises. The manipulated control signals are fuel command (FSR) and the IGV position command considering the constraints on fuel and actuators. Here the exhaust gas temperature cannot exceed its allowed range during this process. Thus the power demand and ambient temperature oscillations are system measurable disturbances.

The MPC algorithm computes the control sequence minimizing following quadratic cost function:

$$J(H_{p1}, H_{p2}, H_c, \lambda) = \sum_{j=H_{p2}}^{H_{p1}} (w(k+j) - \tilde{y}(k+j))^2 + \lambda \sum_{j=0}^{H_c} \Delta u^2 (k+j-1) \quad (6)$$

Here $H_{p1}$ and $H_{p2}$ are minimum and maximum predicting horizons respectively. $H_c$ is the control horizon and $\lambda$ is the move suppression coefficient. The strategy used in order to control gas turbine system is presented in Figure 3.

The gas turbine control model (process model) is a model used for predict system future parameters. The model which is exploited in this paper is a linear time invariant system described by following equation:

Figure 3- MPC strategy used for gas turbine control

$$\begin{align*}
x(k+1) &= Ax(k) + Bu(k) + B_v v(k) + B_d d(k) \\
y_m(k) &= C_m x(k) + D_v v(k) + D_d d(k) \\
y_u(k) &= C_u x(k) + D_v u(k) + D_d d(k) + D_{uu} u(k)
\end{align*} \quad (7)$$

$x(k)$: $n_x$ dimensional models state vector
$u(k)$: $n_u$ dimensional manipulated variables vector
$v(k)$: $n_v$ dimensional measured disturbances vector
$d(k)$: $n_d$ dimensional unmeasured disturbances
$y_m(k)$: measured outputs
$y_u(k)$: unmeasured outputs

This process model is identified exploiting ARX identification method. The related loss function and FPE are calculated 0.000313534 and 0.000337166 respectively.

Since the model all states are not measurable, a state observer must be designed in order to estimate states.

Measurement Update Equation:

$$\begin{bmatrix}
\hat{x}(k|k) \\
\hat{x}_d(k|k) \\
\hat{x}_m(k|k)
\end{bmatrix}
= \begin{bmatrix}
\hat{x}(k|k-1) \\
\hat{x}_d(k|k-1) \\
\hat{x}_m(k|k-1)
\end{bmatrix}
+ M(y_m(k) - \hat{y}_m(k)) \quad (8)$$

Time Update Equation:

$$\begin{bmatrix}
\hat{x}(k+1|k) \\
\hat{x}_d(k+1|k) \\
\hat{x}_m(k+1|k)
\end{bmatrix}
= \begin{bmatrix}
A\hat{x}(k|k) + Bu(k) + B_v v(k) + B_d \tilde{C} \hat{x}(k|k) \\
\tilde{A}\hat{x}_d(k|k) \\
\tilde{A}\hat{x}_m(k|k)
\end{bmatrix} \quad (9)$$
Correction Equation:
\[
\hat{y}_m = C_m \hat{x}(k|k-1) + D_{vm} v(k) + D_{dm} \hat{C} x_q(k|k-1) + \hat{C} \hat{x}_m(k|k-1) + C_x x_m(k|k-1)
\]
(10)

Here gain \( M \) is the applied for minimizing estimation error covariance in Kalman filter because of measurement noises. Also \( x_d \) and \( x_m \) are disturbance model and measurement noise model states. The control model parameters are presented in Appendix B.

The constraints which are applied to this controller are expressed by following equations:

\[
u_{\text{min}} \leq u(k+j) \leq u_{\text{max}} \quad \text{for} \quad j = 1, \ldots, H_c \\
y_{\text{min}} \leq y(k+j) \leq y_{\text{max}} \quad \text{for} \quad j = 1, \ldots, H_p
\]
(11)

The input constraints are hard and the outputs are applied softer.

5. Results and Discussion

- Plant model identification:

Data sampling is done from full speeds no load to full load (81.6 MW base load) conditions with sampling interval 1.0 sec. During collecting data, the HRSG is started and consequently the related steam turbine is paralleled to the network. Due to the starting HRSG and gas turbine loading, the control module is on manual model; therefore, operator controls the guide vane manually. The site ambient temperature variations are measured about 28 to 32°C.

Recorded signals are air temperature \( T_{\text{amb}} \), shaft speed \( \omega \), IGV position \( \theta_{\text{IGV}} \) and FSR as input signals and exhaust temperature \( T_e \), compressor pressure discharge \( \text{CPD} \) and electrical power \( \text{Pe} \) as output signals. The identified model specifications are embossed in Table 1.

![Figure 4- simulation results under load increasing](image)

<table>
<thead>
<tr>
<th>Loss Fcn.</th>
<th>FPE</th>
<th>Fit%</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T_e )</td>
<td>0.0005085</td>
<td>0.0005641</td>
</tr>
<tr>
<td>( \text{CPD} )</td>
<td>0.0000828</td>
<td>0.00008951</td>
</tr>
</tbody>
</table>
Controller parameters
Considering the actuators working range and flame stability, the input constraints are applied as \[
\begin{bmatrix}
0.1935 \\
0.67
\end{bmatrix}
\leq
\begin{bmatrix}
\text{FSR} \\
\text{IGV}
\end{bmatrix}
\leq
\begin{bmatrix}
1 \\
1
\end{bmatrix}
\text{.}
\]
The turbine speed oscillations can cause defects on network frequency and \( T_x \) must be limited because of economical and physical considerations. So output constraints are taken into account: \[
\begin{bmatrix}
0.995 \\
270
\end{bmatrix}
\leq
\begin{bmatrix}
N \\
T_x
\end{bmatrix}
\leq
\begin{bmatrix}
1.005 \\
536
\end{bmatrix}
\text{.}
\]
Since the \( H_{p1} \) usually is equal to the model delay time, it is taken zero here. \( H_{p2} \) must be taken close to the rise time of the system. Nevertheless, choosing it too long requires much calculation time. Thus considering the sample time 0.01 sec, the \( H_{p2} \) is set around 3 (sampling period) by repeated test for best control performance. The control horizon \( H_c \) must be no longer than number of output lag terms avoiding increasing calculation time increasing. Consequently, \( H_c = 1 \) sampling period.
Manipulated control inputs are weighted as 0.1 and 0.12 for FSR and IGV respectively and their rising rate weights are chosen 0.1.
The gas generated control system is modeled dynamically with MATLAB SIMULINK. An electrical power increase is applied to the model when the ambient air temperature is varied during 14000 seconds. Consequently the constant frequency is obtained by manipulating the FSR and IGV parameters. Also the gas exhaust temperature remained in approved range. In comprehension with the SPEEDTRONIC, the rotor speed under these circumstances improved perfectly by means of fuel increasing. Since the IGV manipulates the gas exhaust temperature with low effect on output power, the speed control using guide vane position is not reasonable. Thus having constant speed needs much more fuel consumption and consequently increases exhaust temperature when the load demand increases.

6. Conclusion:
In this brief, a MPC controller is investigated for a MS9001E gas turbine (mounted in Montazer Ghaem power plant) in order to control speed and exhaust gas temperature. It is considered the I/O constraints and a GPC algorithm is used. The plant model is identified using Rowen conventional model and ARX techniques in order to simulate compressor pressure discharge, exhaust gas temperature and electrical power. Also a model is identified as process model in order to predict future outputs. Disturbances and measurement noises are considered and a state observer is designed for estimating states which are not possible to measure them. Finally system is simulated under a load demand disturbance and results are presented in comprehension with SPEEDTRONIC software. Results show that MPC control can give a constant speed when the system is subjected in a load demand disturbance simultaneous perfect temperature control.

7. Nomenclatures:
\begin{itemize}
\item \( \text{ARX} \) Auto Regressive with eXogenous inputs
\item \( \text{CPD} \) Compressor Pressure Discharge
\item \( \text{CPR} \) Compressor Pressure Ratio
\item \( \text{FPE} \) Akaike’s Forward Prediction Error
\item \( \text{FSR} \) Fuel Stroke Reference
\item \( \text{GPC} \) Generalized Predictive Control
\item \( H_p \) Prediction Horizon
\item \( \text{IGV} \) Inlet Guide Vanes
\item \( LSM \) Least Square Method
\item \( T_{\text{amb}} \) Ambient Air Temperature
\item \( T_f \) Firing Temperature
\item \( T_{\text{out}} \) Turbo Generator Torque
\item \( T_x \) Exhaust Gas Temperature
\item \( W_a \) Air Flow rate
\item \( W_f \) Fuel Flow rate
\item \( W_g \) Exhaust Gas Flow rate
\item \( \theta \) Unknown Parameters Vector
\item \( \varphi \) Regression vector
\item \( \eta \) Turbine Efficiency
\end{itemize}

References:
5. C. Boccaletti, G. Cerri, and B. Seyedan, "Neural Network Simulator of a Gas Turbine With a Waste
Appendix A

The plant model transfer functions for Figure 2 are presented as following based on Table 2 given I/O signals:

<table>
<thead>
<tr>
<th>Plant</th>
<th>Transfer Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_x(s)$</td>
<td>$\frac{9719s^2 + 344.5s + 372.3}{s^2 + 3.266s + 0.9384}$</td>
</tr>
<tr>
<td>$T_x(s)$</td>
<td>$\frac{21.98s^2 + 207.6s + 327.2}{s^2 + 3.266s + 0.9384}$</td>
</tr>
<tr>
<td>$\omega(s)$</td>
<td>$\frac{-119s^2 + 312.3s - 148.6}{s^2 + 3.266s + 0.9384}$</td>
</tr>
<tr>
<td>$T_x(s)$</td>
<td>$\frac{0.7975s^2 + 0.8849s - 1.42}{s^2 + 3.266s + 0.9384}$</td>
</tr>
</tbody>
</table>

Output power estimation system:

<table>
<thead>
<tr>
<th>Plant</th>
<th>Transfer Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_e(s)$</td>
<td>$\frac{0.3827s^2 + 0.8935s + 0.2562}{s^2 + 1.3331s + 0.2015}$</td>
</tr>
<tr>
<td>$P_e(s)$</td>
<td>$\frac{-0.212s^2 - 0.4496s - 0.05068}{s^2 + 1.3331s + 0.2015}$</td>
</tr>
</tbody>
</table>

Compressor system dynamics:

<table>
<thead>
<tr>
<th>Plant</th>
<th>Transfer Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega(s)$</td>
<td>$\frac{2.081s^2 + 5.078s + 1.833}{s^2 + 4.574s + 1.083}$</td>
</tr>
<tr>
<td>$\omega(s)$</td>
<td>$\frac{-0.4447s^2 - 0.4645s + 0.8496}{s^2 + 4.574s + 1.083}$</td>
</tr>
<tr>
<td>$\omega(s)$</td>
<td>$\frac{-0.06243s^2 + 0.1525s + 0.05521}{s^2 + 4.574s + 1.083}$</td>
</tr>
</tbody>
</table>
Appendix B

The process model can be described by a simplified denotation as below:

\[ x(k + 1) = Ax(k) + Bu(k) \]
\[ y(k) = Cx(k) + Du(k) \]

Where A, B, C and D coefficients are given as following:

\[
Ax(k) = \begin{bmatrix}
0.6897 & 7.421e-6 & 0.2019 & 1.386e-5 & 0.1036 & -1.406e-5 & -0.006072 & 0.007168 & -0.002625 & 4.694e-5 \\
-57.13 & 0.5061 & 161.1 & 0.1742 & -8.422 & 0.03467 & 70.6 & -214.2 & 86.35 & -0.4043
\end{bmatrix}
\]

\[
Bu(k) = \begin{bmatrix}
0.006706 & -0.01074 & 0.006172 & -3.786e-5 & 0.003951 & 0 \\
0.003951 & 273.9 & -142.7 & 0.7871 & 0.3314 & 4.481
\end{bmatrix}
\]

\[
Cx(k) = \begin{bmatrix}
0.6897 & 7.421e-6 & 0.2019 & 1.386e-5 & 0.1036 & -1.406e-5 & -0.006072 & 0.007168 & -0.002625 & 4.694e-5 \\
-57.13 & 0.5061 & 161.1 & 0.1742 & -8.422 & 0.03467 & 70.6 & -214.2 & 86.35 & -0.4043
\end{bmatrix}
\]

\[
Du(k) = \begin{bmatrix}
0.006706 & -0.01074 & 0.006172 & -3.786e-5 & 0.003951 & 0 \\
0.003951 & 273.9 & -142.7 & 0.7871 & 0.3314 & 4.481
\end{bmatrix}
\]