Performance Analysis and Comparison of Reduced Order Systems using Chebyshev polynomial, Improved Pole Clustering and Fuzzy C-means Clustering Techniques

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Abstract: A mixed method for model order reduction of a linear, single input-single output systems is presented. The denominator of the original system is reduced by using modified pole clustering techniques and fuzzy C-means clustering algorithm. The Chebyshev polynomial has been used for reducing the numerator of higher order transfer function. Then the result has been compared for both the reduction techniques.

Keywords: Model order reduction, Chebyshev polynomial, Modified Pole Clustering, Fuzzy C-means Clustering techniques, Integral square error

1. Introduction

Higher order models are very complicated to use in real-time systems. The higher order model is complex and difficult to handle because of computational problem. The reduced order model makes simpler for controlling the system, reduces the complexity and gives the best result[1-12]. Here, we take input-output relationship of the system in the form of transfer function.

The Proposed method is a mixed method of Fuzzy C-means Clustering and Chebyshev polynomial and other mixed methods are Modified Pole Clustering and Chebyshev polynomial. In literature [13], Chebyshev polynomial used with the pole clustering method in fourth order. It is a low order system. Now we are checking in higher order system’s example. We are also used to reduce denominator by Fuzzy C-Means Clustering method for checking performance with pole clustering method. In the first mixed method, Poles are clustered by fuzzy C-Means Clustering algorithm and numerator coefficient reduce by Chebyshev polynomial, and second, denominator reduces by Modified Pole Clustering and numerator reduce by Chebyshev polynomial.

2. Problem Formulation

Let the single-input single-output (SISO) higher order transfer function of the system:

\[ G(s) = \frac{M(s)}{D(s)} = \frac{a_2 + a_3 s + a_4 s^2 + \ldots + a_m s^{m-1}}{b_0 + b_1 s + b_2 s^2 + \ldots + b_n s^n} \]  

Where a and b are scalar constants.

Let the corresponding reduced \( r \)th order model is

\[ G_r(s) = \frac{\tilde{M}_r(s)}{\tilde{D}_r(s)} = \frac{d_2 + d_3 s + d_4 s^2 + \ldots + d_m s^{m-1}}{e_0 + e_1 s + e_2 s^2 + \ldots + e_n s^n} \]  

Where \( d \) and \( e \) are scalar constants.

3. Fuzzy C-Means Clustering

A large set of data are grouped into clusters of smaller sets of similar data is called Clustering of data. Fuzzy c-means (FCM) is a method of clustering of data where any one piece of data allows to belongs more than one cluster. FCM method was developed by Dunn in 1973 and it was improved by Bezdek in 1981. It is based on minimization of objective function:

\[ J = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2 \]  

(3)

Where \( j \) is number of cluster. \( j = 1, 2, 3, \ldots c \).

And \( i \) is the number of data set, \( i = 1, 2, 3, \ldots n \) and \( m \) is a weighting exponent, \( u_{ij} \) is a degree of membership.

\[ d_{ij}^2 = \left\| x_i - v_j \right\|^2_a \]  

(4)

d_{ij} is the Euclidean distance between data points \( x_i \) to cluster center \( v_j \) and \( A \) is a symmetrical positive definite matrix, which means \( A=I \) matrix.

Updating the membership grades by iteration method, FCM iteratively moves the cluster centers to the right location in a data set. The initial centers are more important. For a durable approach, using an algorithm to determine all the cluster centers. FCM run several times, each starting with different value of membership grades of data.

If \( k \) pairs of complex conjugate poles in the cluster, using a same FCM algorithm for both real and imaginary parts individual the cluster is obtained as

\[ [(\alpha_1 + i\beta_1), (\alpha_2 + i\beta_2), \ldots, (\alpha_k + i\beta_k)] = \alpha_i + i\beta_i \]  

(5)

Where \( \alpha_i \) and \( \beta_i \) are the cluster center of real and imaginary poles, respectively.

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4. Chebyshev Polynomials

The chebyshev polynomial[5] and [13].Of the first kind are denoted by \( T_n(y) \), where \( y \) of degree \( n \) which is defined as:

\[
T_n(y) = \cos(n \cos^{-1} y)
\]

\( y \in [-1, 1] \).

This polynomial is recursively expressed as:

\[
T_{n+1}(y) = 2yT_n(y) + T_{n-1}(y)
\]

(9)

Where \( T_0(y)=1 \) and \( T_1(y)=y \)

Expressing the Chebyshev polynomials as functions of \( y \) by equation 9 as:

\[
T_2(y) = 2y^2 - 1
\]

\[
T_3(y) = 4y^3 - 3y
\]

\[
T_4(y) = 8y^4 - 8y^2 + 1
\]

(10)

And also expression of reciprocal Chebyshev polynomial by equation 9 and 10.

\[
y^2 = \frac{1}{2}[T_0(y) + T_2(y)]
\]

\[
y^4 = \frac{1}{4}[3T_3(y) + T_1(y)]
\]

\[
y^4 = \frac{1}{8}[3T_5(y) + 4T_3(y) + T_1(y)]
\]

(11)

Procedure for Reduction

Step 1: The denominator polynomial(s) of the reduced order model is derived by Fuzzy C-means clustering technique.

Step 2: Then the denominator \( \hat{D}(s) \) is factories

\[
\hat{D}(s) = \prod_{i=1}^{n} (s - p_i)
\]

Where \( p_i \) is the reduce order poles.

Put \( s = j\omega \) then \( \hat{D}(j\omega) \) Complex conjugate of \( D(j\omega) \). So that we can find

\[
\hat{D}(\omega^2) = \prod_{i=1}^{n} \left( \omega^2 - \beta_i \right)
\]

(13)

Step 3: The function \( \hat{D}(\omega^2) \) is converted into chebyshev polynomial by equation 11.

\[
\hat{D}(T(\omega^2)) = \sum_{i=1}^{n} \beta_i T_{2i}(\omega^2)
\]

(14)

Step 4: Now The original \( n^{th} \) order system can be expressed as

\[
G(z) = \frac{\hat{N}(z)}{\hat{D}(z)} = \frac{\prod_{i=1}^{n} (z - z_i)}{\prod_{i=1}^{n} (z - p_i)}
\]

(15)

Where \( p_i \) and \( z_i \) are the poles and zeros of higher order system \( G(s) \), respectively and \( \zeta \) is constant.

Step 5: Same as, we derived:

\[
G(\omega^2) = G(j\omega) \hat{D}(j\omega)
\]

\[
G(\omega^2) = \zeta \prod_{i=1}^{n} (\omega^2 - \beta_i)
\]

(16)

Step 7: The function \( G(\omega^2) \) is expanded into power series around \( \omega^2 = 0 \) as

\[
G(\omega^2) = \sum_{i=0}^{\infty} C_i \omega^{2i}
\]

(17)

Step 8: The function \( G(\omega^2) \) is converted into Chebyshev polynomial as

\[
G(T(\omega^2)) = \sum_{i=0}^{\infty} c_i T_{2i}(\omega^2)
\]

(18)

Step 9: Then reduced order \( \hat{G}(\omega^2) \) can be expressed by the same method. After obtaining separate expansions in Chebyshev polynomial for numerator and denominator, the \( \hat{G}(\omega^2) \) can be written as:

\[
\hat{G}(T(\omega^2)) = \frac{\hat{N}(T(\omega^2))}{\hat{D}(T(\omega^2))} = \sum_{i=0}^{\infty} \alpha_i T_{2i}(\omega^2)
\]

(19)

Step 10: Then reducing order \( \hat{G}(\omega^2) \) can be obtained by the equation 11. Then polynomial \( \hat{N}(T(\omega^2)) \) is obtained by

\[
\hat{N}(T(\omega^2)) = \sum_{i=0}^{\infty} \alpha_i T_{2i}(\omega^2)
\]

(20)

Step 11: Then comparing the coefficient of \( T_2(\omega^2) \) then we get

\[
\alpha_0 = c_0 \beta_0 + \frac{1}{2} \sum_{i=1}^{n} c_i \beta_i
\]

and

\[
\alpha_i = c_i \beta_0 + \frac{1}{2} c_0 \beta_i + \frac{1}{2} \sum_{i=1}^{n} [c_{i-1} + c_{i+1}] \beta_i
\]

(21)

Using the equation 21, obtained the numerator parameter.

\[
\hat{N}(T(\omega^2)) = \sum_{i=1}^{n} \alpha_i T_{2i}(\omega^2)
\]

(22)

Step 12: The numerator parameter converts in model parameter by equation 9 and 10 as:

\[
\hat{N}(s) = \sum_{i=1}^{n} \epsilon_i s^i
\]

(23)

Step 13: now consider the gain adjustment factor

\[
\psi = \frac{\hat{D}(s)}{\hat{N}(s)} \bigg|_{s=0} = 1 / \hat{G}(s) \bigg|_{s=0}
\]

(24)

Finally, we obtain the transfer function of the reduced order model.

\[
\hat{G}(s) = \psi \hat{G}(z)
\]

(25)

5. Improved Pole Clustering

Sinha and Pal [3] used the inverse distance measure(IDM) criterion for solving the pole clusters from the poles of the original system. The poles of the higher order system may be

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all real, all imaginary or a combination of complex poles. It
solved individually as equation 8. Follow this step of
modified pole clustering techniques:

Step 1: first, solve pole centers

\[
P_t = \left( \sum_{i=1}^{n} \frac{-1}{|P_i|} \right) ^{-1}
\]

(26)

Step 2: Set c=c+1

Step 3: Find a modified cluster centre from

\[
P_c = \left( \frac{-1}{|P_c|} + \frac{-1}{|P_{c-1}|} \right) ^{-1}
\]

(27)

Step 4: Is k=c? if No, and then go to step 4, otherwise go to
step 5.

Step 5: Modified cluster centre of the k

\[p_k = p_c\]

Where k is the number of pole, p is value of pole and \(p_c\) is
pole cluster center. Pole is arrange in ascending order as

\[|p_1| <|p_2| <|p_3| < \ldots \ldots \mid p_k\]

6. Numerical Example

Consider a eighth order model [14].

\[
G(s) = s^8 + 514s^4 + 5988s^2 + 122664s^8 + 40320
\]

\[
N(s) = s^4 + 365s^3 + 4536s^2 + 22449s + 672845
\]

\[
118124s^4 + 109584s + 40320
\]

(28)

CHEBYSHEV AND FCM CLUSTERING:

It is reduced by Fuzzy C-Means clustering and Chebyshev
polynomial. Use the steps for obtaining reduced model. Follow us:

Step 1: Pole of the system G(s) is -1,-2,-3,-4,-5,-6,-7,-8. The
Denominator is reduce by fuzzy C-means clustering. Then pole
of reduce system is -2.3984, -6.6024.

\[
\Delta(s) = s^2 + 9s + 15.835
\]

(29)

Step 2:written in the form of complex conjugate.

\[
\Delta(\omega^2) = \omega^4 + 49.344 \omega^2 + 250.751
\]

(30)

Expanded denominator polynomial into Chebyshev
polynomial by equation 11 is

\[
\Delta(T(\omega^2)) = 0.125T_6(\omega^2) + 25.172T_5(\omega^2) + 275.8T_6(\omega^2)
\]

(31)

Step 3: The complex conjugate of the original net order
system can be expressed as an equation (16)

\[
G(\omega^2) = \frac{5.44e218\omega^8 + 1.192e420\omega^6 + 0.792e205\omega^4 + 0.987e10\omega^2 + 1.737e8\omega^4 + 1.02e9\omega^2 + 2.48e3\omega^2 + 1.62e9}{\omega^8 + 204\omega^4 + 10422\omega^2 + 67112\omega^2 + 1.474e7\omega^2 + 1.737e8\omega^4 + 1.02e9\omega^2 + 2.48e3\omega^2 + 1.62e9}
\]

(32)

6.35e207(\omega^2) + 5.72e207(\omega^2) + 1.59e97(\omega^2) + 1.768e127(\omega^2) + 8.589e427(\omega^2) + 1.515e1217(\omega^2) + 27197(\omega^2) + 1.22e-4T_4(\omega^2)
\]

\[
\Delta(s) = s^4 + 138.36s^2 + 3.088710T_4(\omega^2) + 1.788e010T_6(\omega^2) - 8.187e09T_4(\omega^2)
\]

(33)

Then comparing the coefficient of T_6(\omega^2) by equation (20)
and (21) then find numerator polynomial

\[
\hat{N}(T(\omega^2)) = 21.43e127T_5(\omega^2) + 52.94e127T_5(\omega^2)
\]

(35)

Translated into model parameter by equation 23 as

\[
\hat{N}(s) = 6.547e6s + 5.6138e6
\]

(36)

Now we are finding gain adjustment factor by equation (24)
and (25) obtain as:

\[
\Psi = 15.83525.6138e6 = 2.821e-6
\]

(37)

We got transfer function of the reduced order system

\[
\hat{G}(s) = \frac{18.4676s + 15.835}{s^5 + 9s + 15.835}
\]

(38)

CHEBYSHEV AND IMPROVED POLE CLUSTERING:

We consider same example and numerator reduce by
Chebyshev polynomial, and denominator reduces by pole
clustering method. Then pole of reduce system is

\[
P_1 = 1.0637
\]

\[
P_2 = 5.1327
\]

\[
|p_1| <|p_2| <|p_3| < \ldots \ldots |p_k|
\]

\[
\Delta(s) = s^3 + 6.1964s + 5.4597
\]

(39)

The denominator converts in Chebyshev for obtaining the
numerator by same above method:

\[
\Delta(T(\omega^2)) = 0.125T_4(\omega^2) + 14.238T_3(\omega^2) + 43.2T_0(\omega^2)
\]

(40)

By equation (15), expanded in Chebyshev polynomial as

\[
G(\omega^2) = 0.552T_6(\omega^2) - 0.085T_4(\omega^2) + 0.198T_2(\omega^2) - 0.004T_0(\omega^2) + \ldots \ldots
\]

(41)

Then comparing the coefficient of T_6(\omega^2) with equation(34)
by same above methods

\[
\hat{N}(T(\omega^2)) = 5.3767e127T_5(\omega^2) + 8.4316e127T_5(\omega^2)
\]

(42)

Translated into model parameter by equation 20 and 21 as

\[
\hat{G}(s) = \frac{10.241s + 5.4597}{s^5 + 6.1964s + 5.4597}
\]

(43)

We got transfer function of the reduced order system

\[
\hat{G}(s) = \frac{10.241s + 5.4597}{s^5 + 6.1964s + 5.4597}
\]

(44)
7. Comparison of Methods

The performance comparison of both the proposed algorithm is given in Table 1. The step responses of both reduce order models are compared with the original model shown in Figure 1. In the Table 1, comparing the integral square error of transient part of step response is in between original and reduced order models. The ISE is

\[ ISE = \int_0^\infty [y_o(t) - y_i(t)]^2 dt \]  

Where \( y_o \) and \( y_i \) are unit step response of original reduce order system respectively.

8. Conclusion

An algorithm which combined the advantage of two systems with Chebyshev polynomial, one is fuzzy C-means clustering and other is improved pole clustering. This method checked by an example, which reduced the numerator by Chebyshev polynomial and denominator reduced by Fuzzy c-means clustering. Now the second method apply on same example, which reduced the numerator by Chebyshev polynomial and denominator reduced by the improved pole clustering method. The Result of Step response and ISE error show in Figure 1 and Table 1 respectively. ISE of pole clustering method is minimum than fuzzy c-means clustering method. Reduced order model obtained is stable, mathematically simple, as well as in quality.

<table>
<thead>
<tr>
<th>Method of order reduction</th>
<th>Reduced model</th>
<th>ISE</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM clustering</td>
<td>( \hat{G}(s) = \frac{18.4676s + 15.835}{s^2 + 9 + 15.835} )</td>
<td>0.540</td>
</tr>
<tr>
<td>Improved Pole clustering</td>
<td>( \hat{G}(s) = \frac{10241s + 5.4597}{s^2 + 6.1964s + 5.4597} )</td>
<td>0.467</td>
</tr>
</tbody>
</table>

References


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