An Adaptive Dynamic Matrix Control of a Boiler-Turbine System Using Fuzzy Inference

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Abstract—This paper proposes an adaptive Dynamic Matrix Control (DMC) using Fuzzy Inference and its application to boiler-turbine system. In a conventional DMC, object system is described as a Step Response Model (SRM). However, a nonlinear system is not effectively described as a single SRM. In this paper, nine SRMs at various operating points are represented as fuzzy inference rules. On-line fuzzy inference is performed at every sampling step to find the suitable SRM. Therefore, the proposed adaptive DMC can consider the nonlinearity of boiler-turbine system. The simulation results show satisfactory result with wide range operation of boiler-turbine system.

Index Terms—Power generation control, boiler-turbine control, dynamic matrix control, fuzzy inference, adaptive control.

I. INTRODUCTION

Model Predictive Control (MPC) refers to a class of control algorithms that compute a sequence of control inputs based on an explicit prediction of outputs within some future horizon [1],[2]. The important strengths of MPC is that it can consider the constraints of input and output variables which often exist in real industrial systems. Now, MPC has become a standard tool for process controls. One of the most well-known MPC algorithms for the process control is Dynamic Matrix Control (DMC), which assumes a step-response model (SRM) for the underlying system. The multivariable DMC controller has been discussed extensively in the past [2]-[4]. DMC has been successfully applied to numerous industrial processes, and many commercial software have been developed: DMC+®, SMC, RMPCT, HIECON, PFC, OPC, etc.

A Boiler-turbine system provides high pressure steam to drive the turbine in thermal electric power generation. This boiler-turbine system is usually modeled with a Multi-Input Multi-Output (MIMO) nonlinear system [5]. The severe nonlinearity and wide operation range of the boiler-turbine plant have resulted in many challenges to power system control engineers. Rovnak and Corlis discussed theoretical and practical aspects of DMC, and presented simulation results of a supercritical boiler [6]. Sanchez and others presented an application of DMC to steam temperature control of fossil power plants, and showed that the SISO (Single-Input Single-Output) DMC performs better than the PID control [7]. Kim and others presented the simulation results of DMC to boiler-turbine system [8]. In that paper, they presented simulation results that SRM from process test data is superior than SRM from linearization of mathematical model.

To overcome the nonlinearity of the boiler-turbine plant, many kinds of adaptive and artificial intelligence techniques have also been applied. Hogg and Ei-Rabaie presented an application of adaptive control, that is, the self-tuning Generalized Predictive Control (GPC) to a boiler system [9]. Prasad, Swidenbank and Hogg proposed a predictive control based on a neural network model [10]. Dimeo and Lee used genetic algorithm to enhance the wide range performance of PI controller or Linear Quadratic Regulator (LQR) [11]. Alturki and Abdennour applied a neural-fuzzy control to a boiler-turbine system [12]. They trained neuro-fuzzy system with the data from five LQRs which are designed for each operating point. Cheung and Wang presented a comparison of fuzzy and PI controller for drum-boiler system [13], and concluded that the fuzzy control system has better performance than PID control system especially in setpoint tracking.

In this paper, we proposed an adaptive DMC using fuzzy inference, and its application to a drum-type boiler-turbine system in a fossil power plant. In a conventional DMC, a single SRM describes the dynamics of entire operation range. Therefore, the control performance with single SRM has a limitation for nonlinear boiler-turbine system. The basic idea of this paper is the interpolation of SRMs. When SRM is updated on-line to consider the present plant condition, the SRM can effectively describe the dynamics of nonlinear boiler-turbine system.

At first, nine SRMs are prepared at typical nine operating points without loss of generality. Then, SRM of each operating point is represented as a fuzzy inference rule. Fuzzy inference with nine fuzzy rules is performed at every sampling step to find the suitable SRM. Therefore, the proposed adaptive DMC can consider the nonlinearity of boiler-turbine system. The simulation results show satisfactory result with wide range set point tracking.

II. BOILER-TURBINE SYSTEM

The model of Bell and Åström [5] is assumed as a real plant among various nonlinear models for the boiler-turbine
system. The model represents a 160 MW oil fired drum-type boiler-turbine-generator for overall wide-range simulations and is described by a third order MIMO nonlinear state equation as follows [5]:

\[
\begin{align*}
\dot{x}_1 &= -0.0018u_3 x_4^{9/2} + 0.9u_1 - 0.15u_3 \\
\dot{x}_2 &= (0.73u_2 - 0.16)x_4^{9/2} - x_2)/10 \\
\dot{x}_3 &= [14u_1 - (1.1u_2 - 0.19)x_1]/85 \\
y_1 &= x_1 \\
y_2 &= x_2 \\
y_3 &= 0.05(0.13073x_3 + 100a_{cs} + q_c)/9 - 67.975
\end{align*}
\]  

where,

\[
\alpha_{cs} = \frac{(1 - 0.0001538x_3)(0.8x_1 - 25.6)}{x_3[1.0394 - 0.00012304x_1]}
\]  

\[
q_c = (0.854u_2 - 0.147)x_1 + 45.59u_1 - 2.514u_3 - 2.096
\]

The three state variables \(x_1, x_2\) and \(x_3\) are drum steam pressure (\(P\) in kg/cm²), electric power (\(E\) in MW) and steam-water fluid density in the drum (\(\rho\) in kg/m³), respectively. The three outputs \(y_1\), \(y_2\) and \(y_3\) are drum steam pressure (\(x_1\)), electric power (\(x_2\)) and drum water level deviation (\(L\) in m), respectively. The \(y_3\), drum water level \(L\), is calculated using two algebraic calculations \(\alpha_{cs}\) and \(q_c\), which are the steam quality (mass ratio) and the evaporation rate (kg/sec), respectively.

The three inputs \(u_1, u_2\) and \(u_3\) are normalized positions of valve actuators that control the mass flow rates of fuel, steam to the turbine, and feed water to the drum, respectively. Positions of valve actuators are constrained to [0,1], and their rates of change per second are limited to:

\[
\begin{align*}
-0.007 &\leq \frac{du_1}{dt} \leq 0.007 \\
-2.0 &\leq \frac{du_2}{dt} \leq 0.02 \\
-0.05 &\leq \frac{du_3}{dt} \leq 0.05
\end{align*}
\]

### III. ADAPTIVE DMC WITH FUZZY INFERENCE

#### A. DMC Algorithm

For a Single-Input Single-Output (SISO) system, the prediction equation is in the following form:

\[
Y_{k+1|k} = Y_{k+1|k-1} + S\Delta U_k + Y^d_{k+1|k}
\]

where, \(Y_{k+1|k}\) is a \(p\times1\) vector representing a prediction of future output trajectory, \([y_{k+1|k},...,y_{k+p|k}]^T\) at \(t=k\), and \(p\) is the prediction horizon; \(Y_{k+1|k-1}\) is a \(p\times1\) vector representing the unforced output trajectory \([y_{k+1|k-1},...,y_{k+p|k-1}]^T\), which means the open-loop prediction while the input \(u\) remains constant at the previous value \(u_{k-1}\); \(\Delta U_k\) is an \(m\times1\) input adjustments vector \([\Delta u_{k-1},...\Delta u_{k+m-1}]^T\) and \(m\) is the control horizon; \(Y^d_{k+1|k}\) is a \(p\times1\) vector representing an estimate of unmeasured disturbance on the future output; and, \(S\) is a \(p\times m\) dynamic matrix containing the step-response coefficients as follows:

\[
S = \begin{bmatrix} s_1 & 0 & \cdots & 0 \\ s_2 & s_1 & \cdots & \vdots \\ \vdots & \vdots & \ddots & s_1 \\ s_p & s_{p-1} & \cdots & s_{p-m+1} \end{bmatrix}
\]  

where \(s_i\) is the amplitude of step response at the \(i\)-th sampling step.

To compute the inputs, the following on-line optimization is performed at every sampling time:

\[
\min_{\Delta U_k} \left\| E_{k+1|k} \right\|_\Lambda + \left\| U_{k} \right\|_\Gamma.
\]

where, \(E_{k+1|k} = Y_{k+1|k} - R_{k+1|k} = [e_{k+1|1},...,e_{k+p}]^T\) is a \(p\times1\) error vector, \(R_{k+1|k} = [r_{k+1|1},...,r_{k+p}]^T\) is a \(p\times1\) vector containing the desired trajectory of the future output, \(\Lambda\) and \(\Gamma\) are the weights for the weighted Euclidean norm of the corresponding vectors.

To the above, the following additional constraints are added:

\[
\begin{align*}
Y_{\min} &\leq Y_{k+1|k} \leq Y_{\max} \\
U_{\min} &\leq U_k \leq U_{\max} \\
\Delta U_{\min} &\leq \Delta U_k \leq \Delta U_{\max}
\end{align*}
\]

where \(U_k\) is an \(m\times1\) input vector, \([u_{k-1},...,u_{k+m-1}]^T\).

The resulting problem is a Quadratic Programming (QP) problem with the inequality constraints (15)-(17). Once the optimal inputs \([\Delta u_{k-1},...\Delta u_{k+m-1}]\) are computed, only the first input \(\Delta u_k\) is implemented and the rest is discarded. The procedure is repeated at the next sampling time.

In this study, the boiler-turbine system is a Multi-Input Multi-Output (MIMO) system which has three inputs and three outputs. Therefore, the vectors \(Y_{k+1|k}, Y_{k+1|k-1}, Y^d_{k+1|k}, R_{k+1|k}\) and \(E_{k+1|k}\) are extended to \(3p\times1\) vectors and \(\Delta U_k\) is a \(3m\times1\) vector in (12)-(17). The prediction equation of the boiler-turbine system is then in the following form:

\[
\bar{Y}_{k+1|k} = \bar{Y}_{k+1|k-1} + S\Delta U_{k} + \bar{Y}^d_{k+1|k}
\]

where,

\[
\bar{Y}_{k+1|k} = \bar{Y}_{k+1|k-1} \quad \bar{Y}_{k+2|k} \quad \cdots \quad \bar{Y}_{k+p|k}
\]
the three outputs and three inputs, and the subscripts 1, 2 and 3 in (20) and (22) are the indices for where, every matrix element $\bar{s}_i$ is a $3 \times 3$ vector containing nine amplitudes of the step response at the $i$-th sampling step.

The optimization problem (12) is also extended as follows:

$$\min_{\Delta U_k} \left\| \bar{E}_{k+1|k} \right\|_2 + \left\| \Delta U_k \right\|_2.$$  \hspace{1cm} (24)\]

where, $\bar{E}_{k+1|k} = \bar{Y}_{k+1|k} - \bar{R}_{k+1|k}$. The constraints vectors in (15)-(17) are extended to $3p \times 1$ and $3m \times 1$ vectors respectively, and considered in optimization (24).

**TABLE 1. NINE OPERATING POINTS**

<table>
<thead>
<tr>
<th>Operating points</th>
<th>$[y_1, y_2, y_3, u_1, u_2, u_3, x_3]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>OP1</td>
<td>[100, 50, 0, 0.271, 0.604, 0.336, 449.5]</td>
</tr>
<tr>
<td>OP2</td>
<td>[100, 85, 0, 0.402, 0.874, 0.547, 417.5]</td>
</tr>
<tr>
<td>OP3</td>
<td>[100, 120, 0, 0.533, 1.144, 0.757, 383.7]</td>
</tr>
<tr>
<td>OP4</td>
<td>[115, 50, 0, 0.284, 0.548, 0.337, 437.9]</td>
</tr>
<tr>
<td>OP5</td>
<td>[115, 85, 0, 0.415, 0.779, 0.544, 402.8]</td>
</tr>
<tr>
<td>OP6</td>
<td>[115, 120, 0, 0.545, 1.009, 0.750, 363.8]</td>
</tr>
<tr>
<td>OP7</td>
<td>[130, 50, 0, 0.298, 0.506, 0.338, 423.2]</td>
</tr>
<tr>
<td>OP8</td>
<td>[130, 85, 0, 0.428, 0.707, 0.541, 382.5]</td>
</tr>
<tr>
<td>OP9</td>
<td>[130, 120, 0, 0.558, 0.907, 0.745, 331.6]</td>
</tr>
</tbody>
</table>

**B. Nine Step-Response Models with Process Test**

In a conventional DMC, a single Step Response Model (SRM) describes the dynamics of entire range. The SRM plays a key role to the control performance of DMC. However, the boiler-turbine system (1)-(8) shows severe nonlinearity. Therefore, the control performance with single SRM has a limitation.

The basic idea of this paper is the interpolation of SRMs. When SRM is updated on-line to consider the present plant condition, the SRM can effectively describe the dynamics of nonlinear boiler-turbine system. Without loss of generality, several operating points are selected as base cases in this paper. The 100, 115 and 130 [kg/cm²] are selected for typical values of drum steam pressure ($y_1$). For electric power ($y_2$), 50, 85 and 120 [MW] are selected for typical values, while drum water level ($y_3$) is zero [m]. Therefore, nine operating points are selected as base cases. Using (1)-(8), the steady state values of inputs and states can be calculated with given output, $y_1$, $y_2$ and $y_3$. Table 1 shows selected 9 operating points.

Fig. 1. Nine step-response models at operating points of Table 1.

**C. Fuzzy Inference for On-Line Step Response Model**

After the concept of fuzzy set was introduced by Zadeh [14], the fuzzy theory has been widely applied in power
where, SRM\textsubscript{i} represents the corresponding step-response model in Fig. 1.

In these rules, “IF” part of each rule represents the operating point in Table 1, while “THEN” part of each rule represents the corresponding SRM in Fig. 1. Because the fuzzy rule is numbered with the order of operating points in Table 1, the index of rule can be interpreted as the index of operating point in Table 1.

In the fuzzy inference, the plant outputs \( y_{1(i)} \) and \( y_{2(i)} \) at \( k \)-th sampling point are applied into 9 rules (25)-(33). Then, the each rule calculates the “truth value” or “firing strength” as follows [16],[17]:

\[
\omega_i = \min \left[ \mu_{A_i}(y_{1(i)}), \mu_{B_i}(y_{2(i)}) \right], \quad \text{for } i\text{-th rule} \quad (34)
\]

where, \( A_i \) and \( B_i \) are linguistic fuzzy set of \( i \)-th rule. The truth value \( \omega_i \) is interpreted as “degree of match” between “IF” part of \( i \)-th rule and present outputs \( (y_{1(i)}, y_{2(i)}) \).

The output of fuzzy inference at \( k \)-th sampling time, \( \text{SRM}_{(k)} \), is calculated as weighted average of each SRM as follows:

\[
\text{SRM}_{(k)} = \frac{\sum_{i=1}^{9} \omega_i \text{SRM}_i}{\sum_{i=1}^{9} \omega_i} \quad \text{at } k\text{-th step} \quad (35)
\]

Therefore, the \( \text{SRM}_{(k)} \) can cope with the plant nonlinearity based on given nine SRMs. Fig. 3 shows the overall configuration of proposed control system.

System configuration of proposed control system.

According to the 9 operating points in Table 1, \( y_1 \) and \( y_2 \) are partitioned with linguistic values. Fig. 2 shows the membership functions of linguistic values \( A_1, A_2, A_3 \) of \( y_1 \) and \( B_1, B_2, B_3 \) of \( y_2 \). Then, the fuzzy inference rules are as follows:

\[
R_1: \text{If } y_1 \text{ is } A_1 \text{ and } y_2 \text{ is } B_1, \text{ Then SRM is } \text{SRM}_1. \quad (25)
\]

\[
R_2: \text{If } y_1 \text{ is } A_1 \text{ and } y_2 \text{ is } B_2, \text{ Then SRM is } \text{SRM}_2. \quad (26)
\]

\[
R_3: \text{If } y_1 \text{ is } A_1 \text{ and } y_2 \text{ is } B_3, \text{ Then SRM is } \text{SRM}_3. \quad (27)
\]

\[
R_4: \text{If } y_1 \text{ is } A_2 \text{ and } y_2 \text{ is } B_1, \text{ Then SRM is } \text{SRM}_4. \quad (28)
\]

\[
R_5: \text{If } y_1 \text{ is } A_2 \text{ and } y_2 \text{ is } B_2, \text{ Then SRM is } \text{SRM}_5. \quad (29)
\]

\[
R_6: \text{If } y_1 \text{ is } A_2 \text{ and } y_2 \text{ is } B_3, \text{ Then SRM is } \text{SRM}_6. \quad (30)
\]

\[
R_7: \text{If } y_1 \text{ is } A_3 \text{ and } y_2 \text{ is } B_1, \text{ Then SRM is } \text{SRM}_7. \quad (31)
\]

\[
R_8: \text{If } y_1 \text{ is } A_3 \text{ and } y_2 \text{ is } B_2, \text{ Then SRM is } \text{SRM}_8. \quad (32)
\]

\[
R_9: \text{If } y_1 \text{ is } A_3 \text{ and } y_2 \text{ is } B_3, \text{ Then SRM is } \text{SRM}_9. \quad (33)
\]

where, \( \text{SRM}_i \) represents the corresponding step-response model in Fig. 1.

IV. SIMULATION RESULTS

The control system and process model were developed with Matlab in a personal computer environment. The sampling time is determined as 5 [sec]. The prediction \( p \) is 600 [sec] and control horizons \( m \) is 100 [sec], and \( \bar{R}_{k+1|k} \) is fixed with three constant setpoint values. In (24), error and input change are weighted for the three outputs and three inputs as follows:

\[
\begin{bmatrix}
\bar{e}_{k+1|k} \\
\| \Delta \bar{n}_k \|
\end{bmatrix} = \begin{bmatrix}
\begin{bmatrix}
\bar{e}_{1(k+1)} \\
\bar{e}_{2(k+1)} \\
\bar{e}_{3(k+1)}
\end{bmatrix}^T & 1 & 0 & 0 & \bar{e}_{1(k+1)} \\
0 & 1 & 0 & \bar{e}_{2(k+1)} \\
0 & 0 & 100 & \bar{e}_{3(k+1)}
\end{bmatrix}
\end{bmatrix} \quad (36)
\]

\[
\| \Delta \bar{n}_k \| = \begin{bmatrix}
\Delta u_{1(k)} & \Delta u_{2(k)} & \Delta u_{3(k)}
\end{bmatrix}^T \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix} \begin{bmatrix}
\Delta u_{1(k)} \\
\Delta u_{2(k)} \\
\Delta u_{3(k)}
\end{bmatrix} \quad (37)
\]

In (36), the weight of the third output error is 100 while other output weights are ones, this is because the nominal value of \( y_1 \) and \( y_2 \) are about 100 times than that of \( y_3 \). The three control actions are equally weighted as ones. More extensive analysis to tuning the DMC is discussed in [4].

\( Y_{k+1|k} \) in (18) is taken as a constant bias of difference between the actual measurement and the open-loop model output. Output constraint (15) is not considered in this study and input constraints (9)–(11) are implemented in the form of (16), and three inputs are constrained in \([0, 1]\) in (17).

The system is assumed initially to be steady state with operating point 1 in Table 1, \( \bar{y} = (100, 50, 0) \), \( \bar{v} = (0.271, 0.604, 0.336) \). The reference is successively changed to demonstrate the wide range tracking ability of proposed adaptive DMC as follows:

\[
\bar{y} = \begin{cases}
(130, 120, 0), & \text{for } 0 < t < 400 \\
(100, 50, 0), & \text{for } 400 \leq t < 800 \\
(115, 80, 0), & \text{for } 800 \leq t \leq 1200
\end{cases} \quad (38)
\]

That is, the setpoints of pressure and electric load are increased to \((130, 120)\) at \( t=0 \), \((100, 50)\) at \( t=400 \), and \((115, 80)\) at \( t=800 \) successively, while the drum water level is kept to zero. The first step change represents abrupt increment of reference from operating point 1 to 9 in Table 1, second step
change represents abrupt decrement of reference from operating point 9 to 1, and the third reference is around the operating point 5.

Fig. 4 shows the three outputs of the simulation. In the figure, the horizontal axis is time [sec], and the vertical axis is [kg/cm²] for \( y_1 \), [MW] for \( y_2 \) and [cm] for \( y_3 \). The \( y_1 \) and \( y_2 \) track the references within 100 seconds, and \( y_3 \) tracks the reference within 150 seconds in every change. The drum water level is increased to 22 when the electric power is abruptly decreased, while within 15 in the other changes. Fig. 4 shows that the proposed adaptive DMC algorithm can successfully applied to the wide range operation of boiler-turbine system. Fig. 5 shows the three inputs of the simulation. The horizontal axis is time [sec] and units for input variables are normalized positions of valve actuators for the three inputs \( u_1 \), \( u_2 \) and \( u_3 \).

Fig. 6 and Fig. 7 show the internal process of proposed controller. Fig. 6 represents the dominant operating point which means the rule with maximum truth value in (34) as follows;

\[
i = \arg \max_{i=1,\ldots,9} (\omega_i). \tag{39}
\]

The horizontal axis is time [sec], and the vertical axis is the rule number or operating point in Fig. 6. At \( t = 0 \), the operating point is 1, because the simulation is started at operating point 1. As outputs are increased, the dominant operating point is moved to operating points 2, 3, 6 and 9 successively. From \( t = 400 \), the dominant operating point moved to 7, 4, 1 and it moves to operating points 2 and 5 from \( t = 800 \) successively.

Fig. 7 shows the truth value of dominant rule in Fig. 6 as follows;

\[
\omega = \max_{i=1,\ldots,9} (\omega_i). \tag{40}
\]

In Fig. 7, the dominant truth value is about 1 for 100-400 seconds. This means the plant outputs \( y_1 \) and \( y_2 \) match well with operating point 9 from Fig. 6. For 500-800 seconds, the dominant truth value is about 1 because the plant outputs match well with operating point 1. However, for 850-1200 seconds, the dominant truth value is about 0.86 and the dominant operating point is 5 from Fig. 6. This is interpreted that the nearest operating point is 5 and the degree of matching is about 0.86 in this time.

V. CONCLUSION

This paper proposes an adaptive Dynamic Matrix Control (DMC) using Fuzzy Inference and its application to boiler-turbine system. In this paper, nine SRMs are prepared at various operating points without loss of generality. On-line fuzzy inference with nine SRMs is performed at every sampling time to find the suitable SRM. The simulation shows satisfactory result with wide range operation of boiler-turbine system. Therefore, the proposed adaptive DMC can effectively consider the nonlinearity of boiler-turbine system. In case the operating points are selected properly, the proposed adaptive
DMC algorithm can be widely applied to various nonlinear plant control problem.

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REFERENCES


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