DEVELOPMENT OF PREDICTIVE CONTROL STRATEGY USING SELF-IDENTIFICATION MATRIX TECHNIQUE (SMT)

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Abstract

This article describes an easy to use predictive control strategy using self-identification matrix technique (SMT). A description for the condition number effect for suitable tracking behaviour has been analyzed. Simple rules based on the step response of the process are applied for the proposed matrix $\mathbf{W}_{\text{SMT}}$. A new formula is produced for the main controller tuning parameter $\lambda_p$. In the novel formula, $\lambda_p$ is mainly extracted by regression analysis of first order plus dead time processes. Several plants are used to compare the proposed controller as function of the tuning parameters and tuning strategy. The effectiveness of the proposed strategy in wide ranging plants parameters has been compared with other techniques. Simulation results show that the use of the proposed strategy results in superior performance compared to previous techniques. Even though the tuning is based on approximation of actual processes with a first order plus dead time model. However, this strategy would not be suitable for systems with strong nonlinearities.

Keywords: Model predictive control, Dynamic matrix control, Regression technique.

1. Introduction

Model predictive control (MPC) algorithm, a type of advanced process control algorithm. MPC has been widely used in the petroleum, chemical, metallurgical and pulp and paper industries over the past years. In recent years, interest in the subject of model predictive controllers (MPCs) performance assessment has increased steadily [1]. The common characteristic of all these controllers is the principle to determine an optimum value for the actuating variable by using
### Nomenclatures

- **A**: Dynamic matrix
- **G**: Open loop step response data
- **K_p**: The system’s DC-gain
- **M**: Control horizon
- **P**: Prediction horizon
- **R_i**: Parameters of weights for EPC, i=1,2
- **Si**: The processes statistical data i=1,2,...,30
- **T_s**: Sampling time
- **t_d**: FOPDT’s dead time
- **u_i**: The input sampled values, i = 1,2,..., n
- **W**: The weight matrix
- **W_EPC**: The weights matrix of EPC
- **W_SMT**: The proposed weight matrix
- **y_i**: The output sampled values, i = 1,2,..., n

### Greek Symbols

- **λ**: The move suppression coefficient.
- **λ_μ**: The proposed formula for move suppression coefficient
- **λ_tu**: The optimal tuning of move suppression coefficient
- **τ_r**: FOPDT’s time constant
- **ω_1**: First adjustable parameter of the proposed matrix
- **ω_2**: Second adjustable parameter of the proposed matrix
- **Δu**: The vector of manipulated variable moves

### Abbreviations

- **CN**: Condition Number
- **DMC**: Dynamic matrix control
- **EPC**: Extended Predictive Control
- **FOPDT**: First order plus dead time
- **MPC**: Model predictive control
- **SMT**: Self-identification Matrix Technique
- **SOPDT**: Second Order Plus Dead Time

Model of the system to be controlled and by minimizing a cost function. Main advantages of these controllers are system constraints can be handled systematically and can be considered in the model, and automatic identification of model parameters is possible. Besides the cost function, ability to calculate the future behaviour is one of the crucial points of an MPC scheme [2].

In the early eighties developed a novel MPC algorithm, which named as Dynamic Matrix Control (DMC). Calculated using the step response model, which can write predicted future output changes as a linear combination of future input moves. They presented their papers at the Automatic Control Conference in 1980 with their experimentally tuned DMC parameters [3, 4]. In a companion paper in 1983 [5] presented MPC based on discrete convolution models. The used controller parameters are N, P, M, and the sampling interval, T_s. Two weighting
matrices $Q$ and $R$ assuming that $Q = I$ and choose $R = \lambda I$. The parameter $\lambda$, serves as a convenient tuning factor for the MPC scheme [5]. An analytical expression for move suppression coefficient was derived by Shridhar and Cooper [6]. The derivation is based on assumption of the condition number to be around 500 and the control parameters obtained based on FOPDT approximation of the process. It is a tuning strategy to calculate the control parameters but still needs to estimate the sampling time “$T_s/\tau_r = 0.05$ or 0.15” in the second order and higher order systems [6]. This means the expression still needs more steps to design the controller for second and higher order systems.

A research group in University of South Florida presented a new method to calculate “$\lambda$” using “Analysis of variance-ANOVA”. The collection of statistical models used to analyze the differences between group means and their associated procedures. These models are more suitable with first order systems but are not accurate for higher orders for most systems [7]. Abu-Ayyad and Dubay [8, 9] represented another tuning strategy of MPC by reformulating the MPC law with another matrix and a method called Extended Predictive Control EPC. The formulation of the EPC control strategy begins by introducing a weighting move suppression matrix, $W_{EPC}$. The structure of $W_{EPC}$ matrix is designed to have three parameters of weights, $R_1, R_2$, and $\lambda$, for any value of the control horizon $M \geq 3$. It is difficult to calculate the proposed matrix parameters where $[R_1, R_2, M, \lambda]$ are calculated by estimation and investigation.

The layout of this paper is organized as follows: (1) Derivation and definition of DMC transfer function form and establishment of a gain-scaled move suppression coefficient. (2) A new proposed formula derived from the move suppression matrix $W_{STM}$. The formula is simple, valuable and can be implemented directly and easily in the MPC formulation algorithm. (3) Comparison of determinant matrix via the move suppression coefficient with other methods based on condition number, and formulation of an overall DMC tuning strategy. (4) Calculation of a new move suppression coefficient formula using multi-regression fitting techniques. (5) Discussion on the new tuning strategy with guidelines for selection of the sample time and prediction horizon, control horizon, move suppression coefficient, as well as comparison with some results of previous studies which had been done in predictive control mode.

2. Formulation of Model Predictive Control

The general predictive control law was based on the solution of a cost function with most of the algorithms, using a least-squares problem with weighting factors on the manipulated variable moves, as follows:

$$\min_{\Delta u} J = [e - A \Delta u]^T[e - A \Delta u] + \Delta u^T \mathcal{W} \Delta u$$

(1)

where $e$ is the vector of tracking difference between the reference trajectory and the prediction of the process, $A$ is the dynamic matrix, and $\mathcal{W}$ is the weighting matrix, and $\Delta u$ is the vector of manipulated variable moves. The form of the control law is given by:

$$\Delta u = (A^T A + \mathcal{W})^{-1} A^T e$$

(2)
2.1. Problem formulation

For simplicity, first order plus dead time (FOPDT) model formulation could be obtained

\[ G_p = \frac{K_pe^{-ts}}{\tau_r \tau_s + 1} \]  \hspace{1cm} (3)

where \( K_p \) is the system’s DC-gain, \( t_d \) is the dead time, \( \tau_r \) is the FOPDT’s time constant.

The system’s dynamic matrix \( A \) was made up of the control horizon \( M \) columns of the system’s step response appropriately, shifted down in order.

\[
A = \begin{bmatrix}
g_1 & 0 & \ldots & \ldots & \ldots & 0 \\
g_2 & g_1 & \ldots & \ldots & \ldots & 0 \\
\vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\
g_M & g_{M-1} & \ldots & \ldots & g_1 & 0 \\
\vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\
g_P & g_{P-1} & \ldots & \ldots & g_{P-M+1} & \end{bmatrix} \]  \hspace{1cm} (4)

The system matrix \( A^T \) was then written in the final approximate form of the matrix as [1, 2]:

\[
A^T = K_p^2 \begin{bmatrix}
\Phi_{11} & \Phi_{12} & \ldots & \Phi_{1M} \\
\Phi_{12} & \Phi_{22} & \ldots & \Phi_{2M} \\
\vdots & \vdots & \ddots & \ddots \\
\Phi_{M1} & \Phi_{M2} & \ldots & \Phi_{MM}
\end{bmatrix} \]  \hspace{1cm} (5)

Let \( \Phi_{ij} = P - k - \frac{i}{2} \frac{T_S}{\tau_p} + 3 - \frac{1}{2} (i + j) \) \( i, j = 1, 2, \ldots, M \)

The parameter \( k \) is the discrete dead time calculated as \( k = \tau_r / T_s + 1 \), and \( T_s \) is the sampling time, and \( \tau_r \) is the time constant. Note that the approximate \( A^T \) matrix has a Hankel matrix form with the added feature that the elements of every row were successively decreased by 0.5 from left to right. The observation made by [5] that the \( A^T \) matrix becomes increasingly singular for large values of the prediction horizon, \( P \), and control horizon, \( M \). Therefore, it was assumed that as the prediction horizon \( P \), \( \Phi_{11} \cong \Phi_{12} \cong \Phi_{13} \cong \ldots \cong \Phi_{MM} \) [8].

An analytical expression for move suppression coefficient \( \lambda \) was derived by [6] based on the assumption that the condition number was 500, which was the upper limit of ill conditioning in the system matrix.

Reformulating MPC with another matrix called Extended Predictive Control EPC presented in [8, 9]. The formulation of the EPC strategy begins by introducing a weighting move suppression matrix \( W_EPC \). The structure of \( W_EPC \) is designed to have three parameters of weights, \( R_1, R_2 \), and \( \lambda \), for any value of the control horizon \( M \geq 3 \).

In this research, the proposed strategy could affect different type of models of first, second, and high order systems, and give more quality responses compared to the previous studies. Especially for enhance the signal performance in terms of decrease the rise time and eliminate the overshoot. The proposed method depends on the transient response output data with respect to the sampling data as shown in Fig. 1. The block diagram of the proposed method is shown in Fig. 2. The prediction horizon \( P \) was set to a value of 20% higher than the settling time.
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The control horizon was chosen to be $5 \leq M \leq 10$. The proposed matrix depends on the suppression coefficient $\lambda$, proposed matrix, and other values created from the open-loop response of the original system.

Assume $G$ as the open-loop step response data of the system model. $G = [g_{i+1} \ g_{i+2} \ g_{i+3} \ g_{i+4} \ g_{i+5} \ \ldots \ \ g_{i+n}]$

Then, the proposed matrix $\mathcal{W}_{SMT}$ becomes as:

$$
\begin{bmatrix}
    1/2\omega_2 & h_{i+1} & h_{i+2} & h_{i+3} & h_{i+4} & h_{i+5} \\
    h_{i+1} & 1/2\omega_2 & g_{i+1} & 0 & g_{i+2} & 0 \\
    h_{i+2} & g_{i+1} & 1/2\omega_2 & g_{i+2} & 0 & g_{i+3} \\
    h_{i+3} & 0 & g_{i+2} & 1/2\omega_2 & g_{i+3} & 0 \\
    h_{i+4} & g_{i+3} & 0 & g_{i+4} & 1/2\omega_2 & g_{i+4} \\
    h_{i+5} & 0 & g_{i+4} & 0 & g_{i+5} & 1/2\omega_2 \\
\end{bmatrix}
$$

(6)

where $\omega_1, \omega_2$ are adjustable parameters mostly $\omega_1 = \omega_2 \equiv 1$ or 2. The effect of $\omega_1 < \omega_2$ decreased the rise time and selected with limited range to avoid the higher value of overshoot or disturbance. Denote the output sampled values as $y_1, y_2, \ldots, y_n$ and the input $u_1, u_2, \ldots, u_n$. Then, the incremental change in $u$ will be denoted as

$$
\Delta u_k = u_k - u_{k-1}
$$

(7)

The response $y(t)$, to a unit step change in $u$ at $t = 0$ (i.e., $\Delta u_0 = 1$) is shown in Fig. 1, where $g_i$ is step response coefficients, $h_i$ is impulse response coefficients, and the impulse response, $h_i = g_i - g_{i-1}$

![Fig. 1. Unit Step Response (sampling data).](image-url)
2.2. Condition number analysis

Basically, the conditioning of a matrix (or a system) represents its sensitivity to model mismatch, particularly in inverting the matrix. Since MPCs are essentially pseudo-inverses of the plant model, this matrix measure has deep applicability in the controller design and application. The numerical measure of ill-conditioning, known as the condition number [10].

The problems for condition numbers can be circumvented by scaling the transfer matrix with diagonal matrices in such a way that a minimum or “optimal” condition number is obtained [11]. Hugo [10] stated that the single loop structure is much more robust, as indicated by the large reduction in condition number between the two structures for reduction in condition number and its effect to improve the response behaviour. Small condition numbers frequently lead to a small transient response of the system.

In a brief introduction to MPC, Hovd [12] mentioned that there are two main ways of reducing the condition number of $A^T A + W$ by modifying the tuning matrix $W$.

The proposed matrix depends on the suppression coefficient $\lambda$. Marafioti [13] reported that the input weight $\lambda$ has benefits on the condition number, as it can improve robustness for optimization algorithms. Related to this suppression coefficient effect is the reduction in the condition number of the matrix that results from the state dependent input weight. As discussed, reducing the ill-conditioning of the matrix is a common approach to improve the robustness of industrial MPC.

The condition number for the exact and approximate $A_\lambda$ matrix as a function of the scaled move suppression coefficient $\lambda$, for different choices of the control horizon $M$, is calculated as [1]:

$$A_\lambda = \begin{bmatrix} \Phi & \Phi \\ \Phi & \Phi \end{bmatrix} + \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} = \begin{bmatrix} \Phi + \lambda & \Phi \\ \Phi & \Phi + \lambda \end{bmatrix}$$  \hspace{1cm} (8)
The singular values of $A_2$ are $M \Phi + \lambda^{-1}$ and $\lambda$. Also $P \to \infty$ as $|A_2|$ given by $A^T A_{M+M} = M \Phi \lambda^{M-1} + \lambda^M$ (9)

The condition number is a measure of how much a matrix is sensitive to errors, which can be computed by dividing the largest singular value over the smallest singular value.

$$CN_{M+M} = \frac{M \Phi}{\lambda} + 1$$ (10)

In recent years, [8] proposed a matrix called extended move suppression matrix $A_{EPC}$ where the analysis of the condition number is repeated for the extended move suppression matrix, as shown in Eq. (11). The determinant of EPC can be calculated as follows [8, 9]:

$$A_{EPC} = \begin{bmatrix} \Phi & \Phi \\ \Phi & \Phi \end{bmatrix} + \begin{bmatrix} 0 & -R_1 \lambda \\ -R_1 \lambda & 0 \end{bmatrix} = \begin{bmatrix} \Phi & \Phi - R_1 \lambda \\ \Phi - R_1 \lambda & \Phi \end{bmatrix}$$ (11)

The absolute determinant $A^T A$ of EPC is calculated as:

$$A^T A_{EPC} = R_1^{M-1} M \Phi \lambda^{M-1} - (M - 1) R_1^{M} \lambda^M$$ (12)

The condition numbers $CN$ of EPC is calculated as:

$$CN_{EPC} = MR_1 \left( \frac{\Phi}{\lambda} - R_1^{M-1} \right) + R_1^{M}$$ (13)

The new proposed move suppression matrix $A_{SMT}$ was simplified for determining the condition number $CN_{SMT}$ as below:

$$A_{SMT} = \begin{bmatrix} \Phi & \Phi \\ \Phi & \Phi \end{bmatrix} + \begin{bmatrix} \lambda / \omega & \omega \lambda h_{i+1} \\ \omega \lambda h_{i+1} & \lambda / \omega \end{bmatrix} = \begin{bmatrix} \Phi + \lambda / \omega & \Phi + \omega \lambda h_{i+1} \\ \Phi + \omega \lambda h_{i+1} & \Phi + \lambda / \omega \end{bmatrix}$$ (14)

where $h_{i+1} = g_{i+2} - g_{i+1}$. To simplify the analysis, assume $\omega = 1$, so the absolute determinant $A^T A_{SMT}$ of proposed method would be:

$$A^T A_{SMT} = M \lambda^{M-1} \Phi (1 - h_{i+1}) + \lambda^M (1 - h_{i+1}^M)$$ (15)

The condition numbers $CN$ of proposed method is:

$$CN_{SMT} = \frac{M \Phi}{\lambda} (1 - h_{i+1}) - (1 - h_{i+1}^M)$$ (16)

Figures 3 and 4 show the approximate and exact condition number and determination matrix with different method respectively, using Eqs. (10), (13), and (16), respectively. The results were obtained from a simulation for a process which has a SOPDT transfer function of the form [6, 8, 9]:

$$G_p = e^{-50s} \frac{s}{(150 s+1)(25 s+1)}$$ (17)

The condition numbers were determined for different control horizon $M = 2$, 4, and 6, to evaluate the condition number cases and estimate the ideal behaviour of $A^T A + \Psi$.

The reduction in condition number is value to improve the response behaviour [10]. The condition numbers in the proposed method showed good responses at all cases of $M = 2, 4$, and 6.
3. Regression Technique

Scientists and engineers often want to represent empirical data using a model based on mathematical equations. Using model and correct calculation can identify the important features of the data [14]. It can be used for data regression fitting. This section explains how to use regression analysis to obtain a dependent variable, the proposed Lambda - $\lambda_{pa}$, according to various independent variables “$K_p$, $\tau_r$, $t_d$, $P$, & $T_s$”. Adding several factors to the proposed model that are useful to explain $\lambda_{pa}$. Therefore, the regression analysis can be used to create better models to predict the dependent variable. A further advantage of the regression analysis is that it is possible to incorporate functional relationships. In simple regression model only on the basis of a single explanatory variable may appear in the equation. Multiple regression model allows much more flexibility. Regression technique is used with a fitting to find parameter values that best fit the data. This regression technique can be created a formula using simple transformations involve logarithms, inversions, and exponentials [15-18].

In every step, each one of the 150 FOPDT stable models was simulated with the DMC proposed algorithm, where each case was compared with optimal $\lambda_{oPDTu}$ and calculated empirically. The 150 FOPDT models were $K_p \times \tau_r \times t_d$ ordered as $5 \times 3 \times 10$ to cover a wide range of data as $K_p = 1, 2, 3, 4, 5$. $\tau_r = 1, 2, 3$, and $t_d$
=0.2, 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2 (Appendix A). Residuals versus other quantities were used to find failures of hypothesis especially in regression techniques, for the plot of residuals versus the fitted values. A null plot would indicate no failure of hypothesis, while curvature might indicate that the fitted mean function is inappropriate, and residuals that seem to increase or decrease in average magnitude with the fitted values might indicate nonconstant residual variance [19]. To estimate the goodness of fit of lines to different sets of data, “coefficient of determination, \( R^2 \)” needs to calculated. That value should be 1 to approve best fitting for set of data.

Figures 5 and 6 show the analysis of set of data in appendix 1 ordered in 30 group. Every group was calculated their norm of residual. The graphs clearly show that coefficient of determination \( R^2 \) was perfect in most cases, except case S7 which gave \( R^2=0.866 \), and case S12 which gave \( R^2=0.733 \), meaning 96.67% of the groups were perfect for its analysis of \( R^2 \) of data in this study.

Figure 6 shows that norm of residuals for set of each group S1-S30 had four groups out of confidence bounds of 0.4, whereas norm of residuals for 4 groups out of 30 group gave unbounds values, meaning 86.67% of the data are perfect.

![Fig. 5. Coefficient of determination \( R^2 \) for set of data S1-S30.](image)

![Fig. 6. Norm of residual for set of data S1-S30.](image)

The formula of \( \lambda_{pa} \) is given by:

\[
\lambda_{pa} = \alpha \ast \left( K_p - \left( \frac{\tau_r}{\tau_d} \right)^2 \right)^{1/2} \ast e^{-\frac{t_d}{\tau_s} \ast K_p} \]

(18)

The parameter \( \alpha \) depended on \( \frac{t_d}{\tau_r} \), where \( \frac{t_d}{\tau_r} \) was calculated every 0.5 which gave \( \alpha = 0.5 \).
4. Simulation Results

This section discusses the implementation of the proposed algorithm to different stable processes and comparison with previous methods. Although, the experimental implementation of the proposed strategy for pneumatic actuator force control had been achieved widespread industrial acceptance [20]. Nevertheless, the justifying of the control’s law potential, simulation examples with different orders is needed. According to the control law presented in the previous section:

All these methods have their own advantages, disadvantages and limitations. Most of the tuning methods were proposed with first order plus time delay (FOPDT) system to obtain the controller parameters, because those type of systems can explain the behavior of a wide range of processes.

4.1. Process 1

Consider the second order plus time delay process [6, 9, 21].

\[ G_{p1}(s) = \frac{e^{-50s}}{(150s+1)(25s+1)} \]

(19)

For simplicity, we chose the general first order plus dead time (FOPDT) model formulation that can be obtained by a step response test as the process model to calculate the controller parameters only. First order plus dead time (FOPDT) model for process 1 had gain \( K = 1 \), \( t_d = 70 \) s, and \( \tau_r \) was the FOPDT’s time constant equal to 157 s. Cooper [6] calculated the sampling time as \( T_s = 16 \) s, \( P=54 \), and \( M=4 \), \( \lambda = 0.14 \). Abu-Ayyad method (EPC) was calculated at the same controller parameters, in terms of predictive horizon \( P=54 \) and control horizon \( M = 4 \) and \( \lambda = 0.14 \). In the proposed algorithm, \( \omega_1 = 2 \), \( \omega_2 = 2 \) and the prediction horizon was calculated by adding 20% for the settling time, so the predictive horizon \( P \) became 66 to cover more sampling data that could affect the behavior of the response, where the prediction horizon was not large enough as approved [21]. The proposed control horizon, \( M=8 \) and \( \lambda_{pa} = 0.004 \).

In terms of rise time and disturbance rejection, the proposed method was perfect compared to others as shown in Fig .7 and Table 1. However, the manipulated variable has higher value but the proposed method achieved superior performance for output signal and the disturbance rejection.

<table>
<thead>
<tr>
<th>Method</th>
<th>Overshoot%</th>
<th>Rise Time(s)</th>
<th>Settling Time(s)</th>
<th>ISE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooper</td>
<td>0</td>
<td>276</td>
<td>603</td>
<td>117</td>
</tr>
<tr>
<td>Abu-Ayyad EPC</td>
<td>1.2</td>
<td>219</td>
<td>510</td>
<td>92</td>
</tr>
<tr>
<td>Proposed SMT</td>
<td>0.2</td>
<td>93</td>
<td>282</td>
<td>76</td>
</tr>
</tbody>
</table>

Table 1. A comparison between Cooper, EPC, and Proposed for process 1.
4.2. Process 2

Consider the following process with a right-half-plane (RHP) [6, 9].

\[
G_{p2} = \frac{(-50 s+1)e^{-10 s}}{(100 s+1)^{2}}
\]  

(20)

First order plus dead time (FOPDT) model for process 2 had gain \( K = 1 \), time delay \( t_d = 105 \) s, \( \tau_p \) was FOPDT’s time constant equal to 163 s. Cooper [6] calculated the sampling time as \( T_s = 24 \) s, \( P = 39 \), \( M = 4 \) and the suppression coefficient \( \lambda = 0.14 \). Abu-Ayyad method EPC was calculated at the same controller parameters in terms of \( P, T_s, M, \) and \( \lambda \). In the proposed strategy, \( \omega_1 = 1, \omega_2 = 1 \) and the prediction horizon was calculated as \( P \) became 46 to cover more sampling data that could affect the behavior of the response. The proposed method have control horizon \( M=10 \) and \( \lambda_{p\alpha} = 0.0005 \).

However, the proposed method shows higher starting manipulated variable, but superior performance achieved by the proposed method in terms of rise time and disturbance rejection as shown in Fig. 8, and Table 2.

<table>
<thead>
<tr>
<th>Method</th>
<th>Overshoot%</th>
<th>Rise Time (s)</th>
<th>Settling Time (s)</th>
<th>ISE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooper</td>
<td>1.80</td>
<td>127</td>
<td>395</td>
<td>220</td>
</tr>
<tr>
<td>Abu-Ayyad EPC</td>
<td>0.20</td>
<td>112</td>
<td>274</td>
<td>188</td>
</tr>
<tr>
<td>Proposed SMT</td>
<td>0.01</td>
<td>92</td>
<td>231</td>
<td>138</td>
</tr>
</tbody>
</table>

Table 2. A comparison between Cooper, EPC, and Proposed for process 2.
4.3. Process 3

Consider the following the higher order process [6, 9].

\[
G_{p3} = \frac{e^{-10s}}{(50s+1)^4}
\]  

(21)

First order plus dead time (FOPDT) model for process 3 is the gain \( K = 1 \), \( t_d = 99 \text{ s} \), \( \tau_r \) is the FOPDT’s time constant equal to 124 s. In Cooper method [6] the sampling time calculated as Cooper’s method \( T_s = 19 \text{ s} \), \( P=38 \), \( M=4 \) and the suppression coefficient \( \lambda \) is 0.05 while Abu-Ayyad method EPC calculated at same controller parameters in term of predictive horizon \( P=38 \) and Control horizon \( M=4 \) and the suppression coefficient. In the proposed algorithm \( \omega_1 = 1 \), \( \omega_2 = 2 \) and the prediction horizon \( P \) became 45 and the proposed control horizon \( M=5 \). \( \lambda_{pu} = 0.0001 \).

In term of rise time, settling time, error estimation, and disturbance rejection the proposed method gives better performance compare to others as shown in Fig. 9, and Table 3. However, EPC method mostly similar behaviour to the proposed SMT method.

<table>
<thead>
<tr>
<th>Method</th>
<th>Overshoot%</th>
<th>Rise Time (s)</th>
<th>Settling Time (s)</th>
<th>ISE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooper</td>
<td>4.3</td>
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<td>735</td>
<td>105</td>
</tr>
<tr>
<td>Abu-Ayyad EPC</td>
<td>0.05</td>
<td>118</td>
<td>296</td>
<td>89</td>
</tr>
<tr>
<td>Proposed SMT</td>
<td>0.01</td>
<td>113</td>
<td>294</td>
<td>82</td>
</tr>
</tbody>
</table>

Table 3. A comparison between Cooper, EPC, and Proposed for process 3.
5. Conclusion

An easy to use predictive control strategy using self-identification matrix technique \( W_{SMT} \) has been presented. This strategy applies simple rules based on the step response of the process with an analytical tool for tuning parameters. Regression methods were used to estimate a formula for the tuning move suppression coefficient. The method does not require complex numerical calculations just one formula achieved good results with the proposed matrix. The simulation results demonstrate the effectiveness of the proposed method in comparison with two different construction predictive methods. The proposed strategy achieves an ideal set point tracking with minimal overshoot, rise time, and disturbance rejection. This research focused on creating a new MPC strategy for stable processes. While, our on-going research will be extending a MPC strategy for unstable processes.

References


## Appendix A

### Estimation of optimal $\lambda_{OpTu}$ for 150 FOPDT models

<table>
<thead>
<tr>
<th>No</th>
<th>$\alpha_1$</th>
<th>$\tau_1$</th>
<th>$\varphi_1$</th>
<th>$\nu$</th>
<th>$\alpha_2$</th>
<th>$\tau_2$</th>
<th>$\varphi_2$</th>
<th>$\nu$</th>
<th>$\lambda_{OpTu}$</th>
<th>$\Delta\lambda_{OpTu}$</th>
<th>set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5</td>
<td>5</td>
<td>0.01</td>
<td>0.01</td>
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*Development of Predictive Control Strategy Using Self-Identification Matrix . . . 1929*