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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 $\mathcal{W}_{SMT}$. A new formula is produced for the main controller tuning parameter $\lambda_{p\alpha}$. In the novel formula, $\lambda_{p\alpha}$ 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, $i = 1,2, \dots, n$
$\mathcal{W}$	The weight matrix
$\mathcal{W}_{EPC}$	The weights matrix of EPC
$\mathcal{W}_{SMT}$	The proposed weight matrix
y_i	The output sampled values, $i = 1,2, \dots, n$

Greek Symbols

λ	The move suppression coefficient.
$\lambda_{p\alpha}$	The proposed formula for move suppression coefficient
λ_{TuOp}	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, *Ts*. Two weighting

matrices Q and R assuming that $Q = I$ and choose $R=\lambda I$. The parameter λ, 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 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/τ_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 "λ" 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, $\mathcal{W}_{EPC}$. The structure of $\mathcal{W}_{EPC}$ matrix is designed to have three parameters of weights, R_1, R_2, and λ, 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, λ] 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 $\mathcal{W}_{STM}$. 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 technics. (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:

$$\min_{\Delta u} J = [e - A\,\Delta u]^T [e - A\,\Delta u] + \Delta u^{\,T}\,\mathcal{W}\,\Delta u \tag{1}$$

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 Δu is the vector of manipulated variable moves. The form of the control law is given by:

$$\Delta u = (A^T A + \mathcal{W})^{-1} A^T e \tag{2}$$

2.1. Problem formulation

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

$$G_p = \frac{K_p e^{-td\,s}}{\tau_r\, s+1} \tag{3}$$

where K_p is the system's DC-gain, t_d is the dead time, τ_r is the FOPDT's time constant.

The systems dynamic matrix A was made up of the control horizon M columns of the systems step response appropriately, shifted down in order.

$$A = \begin{bmatrix} g_1 & 0 & \dots & \dots & \dots & 0 \\ g_2 & g_1 & \dots & \dots & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ g_M & g_{M-1} & \dots & \dots & \dots & g_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ g_P & g_{P-1} & \dots & \dots & \dots & g_{P-M+1} \end{bmatrix} \tag{4}$$

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

$$A^T A = K_p^2 \begin{bmatrix} \Phi_{11} & \Phi_{12} & \dots & \Phi_{1M} \\ \Phi_{12} & \Phi_{22} & \dots & \Phi_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \Phi_{M1} & \Phi_{M2} & \dots & \Phi_{MM} \end{bmatrix} \tag{5}$$

Let $\Phi_{ij} = P - k - \frac{3}{2}\frac{T_s}{\tau_p} + 3 - \frac{1}{2}(i+j) \;\; i,j = 1,2,\dots,M$

The parameter k is the discrete dead time calculated as $k = \tau_r/T_s + 1$, and T_s is the sampling time, and τ_r is the time constant. Note that the approximate $A^T A$ 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 $A^T A$ 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, $\Phi_{11} \cong \Phi_{12} \cong \Phi_{13} \cong \cdots \cong \Phi_{MM}$ [8].

An analytical expression for move suppression coefficient λ 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 $\mathcal{W}_{EPC}$. The structure of $\mathcal{W}_{EPC}$ is designed to have three parameters of weights, R_1, R_2, and λ, 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

sampling data, and the control horizon was chosen to be $5 \leq M \leq 10$. The proposed matrix depends on the suppression coefficient λ, 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.

$G = [\, g_{i+1} \;\; g_{i+2} \;\; g_{i+3} \;\; g_{i+4} \;\; g_{i+5} \; \cdots\cdots \;\; g_{i+n}]$

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

$h_{i+1} = g_{i+2} - g_{i+1}$

$h_{i+2} = g_{i+3} - g_{i+2}$

:

$h_{i+n-1} = g_{i+n} - g_{i+n-1}$

The proposed matrix is multiplied by the proposed tuning parameter $\lambda_{p\alpha}$ and defined as:

$$\mathcal{W}_{SMT} = \omega_1 \begin{bmatrix} 1/2\omega_2 & h_{i+1} & h_{i+2} & h_{i+3} & h_{i+4} & h_{i+5} \\ h_{i+1} & 1/2\omega_2 & g_{i+1} & 0 & g_{i+2} & 0 \\ h_{i+2} & g_{i+4} & 1/2\omega_2 & g_{i+2} & 0 & g_{i+3} \\ h_{i+3} & 0 & g_{i+3} & 1/2\omega_2 & g_{i+3} & 0 \\ h_{i+4} & g_{i+3} & 0 & g_{i+2} & 1/2\omega_2 & g_{i+4} \\ h_{i+5} & 0 & g_{i+2} & 0 & g_{i+1} & 1/2\omega_2 \end{bmatrix} \tag{6}$$

where ω_1, ω_2 are adjustable parameters mostly $\omega_1 = \omega_2 \cong 1$ 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

$$\Delta u_k = u_k - u_{k-1} \tag{7}$$

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, $h_i = g_i - g_{i-1}$

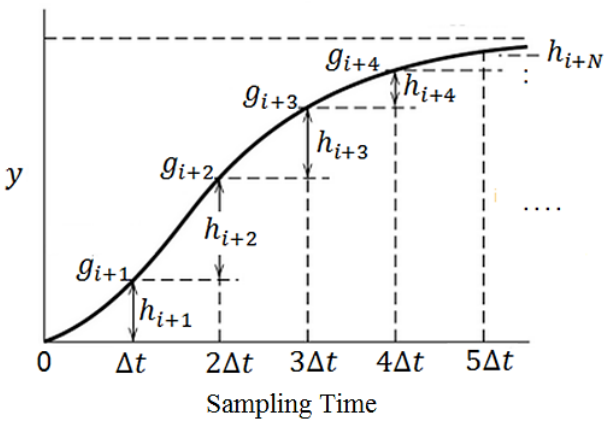

Fig. 1. Unit Step Response (sampling data).

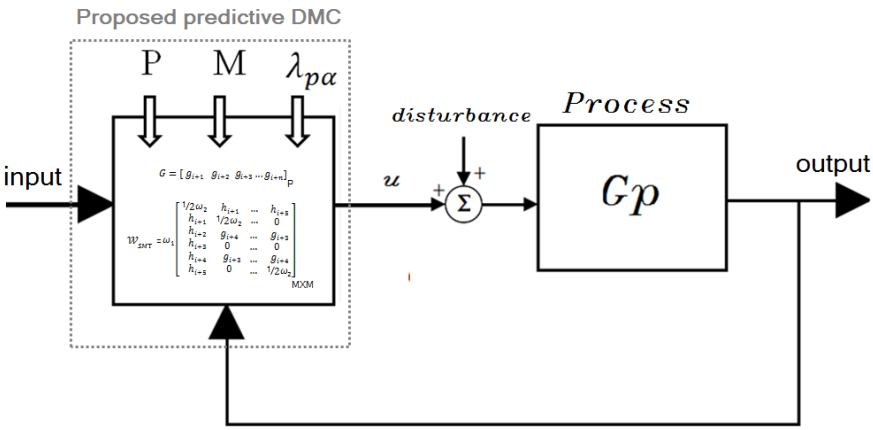

Fig. 2. Block diagram of the proposed predictive DMC.

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 Psuedo-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 $A^T A + \mathcal{W}$ by modifying the tuning matrix $\mathcal{W}$.

The proposed matrix depends on the suppression coefficient λ. Marafioti [13] reported that the input weight λ 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_λ matrix as a function of the scaled move suppression coefficient λ, for different choices of the control horizon M, is calculated as [1]:

$$A_\lambda = \begin{bmatrix} \Phi & \Phi \\ \Phi & \Phi \end{bmatrix} + \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} = \begin{bmatrix} \Phi + \lambda & \Phi \\ \Phi & \Phi + \lambda \end{bmatrix} \tag{8}$$

The singular values of A_λ are $M\Phi + \lambda^{-1}$ and λ. Also $P \to \infty$ as $|A_\lambda|$ given by

$$A^T A_{\lambda_{M\times M}} = M\Phi\lambda^{M-1} + \lambda^M \tag{9}$$

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.

$$CN_{\lambda_{M\times M}} = \frac{M\Phi}{\lambda} + 1 \tag{10}$$

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]:

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

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

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

The condition numbers CN of EPC is calculated as:

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

The new proposed move suppression matrix $A_{SM\mathrm{T}}$ was simplified for determining the condition number CN_{pro} as below:

$$A_{SM\mathrm{T}} = \begin{bmatrix} \Phi & \Phi \\ \Phi & \Phi \end{bmatrix} + \begin{bmatrix} \lambda/\omega & \omega\lambda h_{i+1} \\ \omega\lambda h_{i+1} & \lambda/\omega \end{bmatrix} = \begin{bmatrix} \Phi + \lambda/\omega & \Phi + \omega\lambda h_{i+1} \\ \Phi + \omega\lambda h_{i+1} & \Phi + \lambda/\omega \end{bmatrix} \tag{14}$$

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

$$A^T A_{SM\mathrm{T}} = M\lambda^{M-1}\Phi(1 - h_{i+1}) + \lambda^M\left(1 - {h_{i+1}}^M\right) \tag{15}$$

The condition numbers CN of proposed method is:

$$CN_{SM\mathrm{T}} = \frac{M\Phi}{\lambda}(1 - h_{i+1}) - \left(1 - {h_{i+1}}^M\right) \tag{16}$$

Figures 3 and 4 show the approximate and exact condition number and determination matrix with different method respectivly, 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]:

$$G_{p1} = \frac{e^{-50\,s}}{(150\,s+1)(25\,s+)} \tag{17}$$

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 $A^T A + \mathcal{W}$.

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.

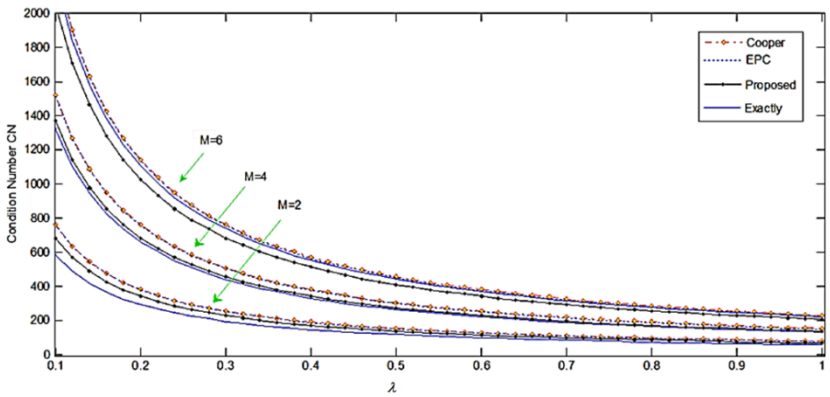

Fig. 3. The condition numbers versus λ within M = 2, 4 and 6.

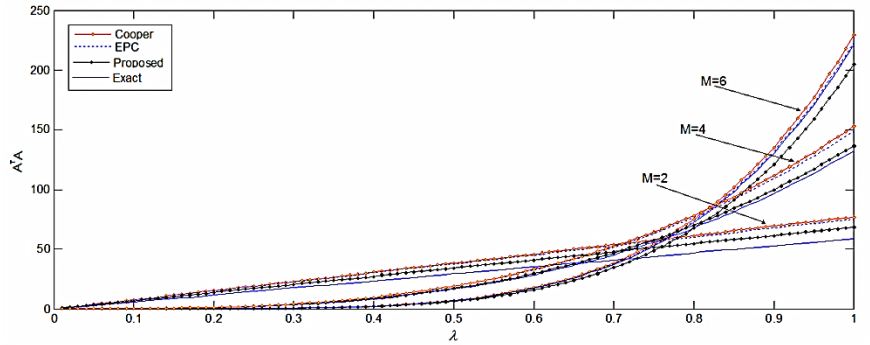

Fig. 4. The determination matrix versus λ within M = 2, 4 and 6.

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 - $\lambda_{p\alpha}$, according to various independent variables *"K_p, τ_r, t_d, P, & T_s".* Adding several factors to the proposed model that are useful to explain $\lambda_{p\alpha}$. 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 λ_{OpTu} and calculated empirically. The 150 FOPDT models were $K_p \times \tau_r \times t_d$ ordered as 5×3×10 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 tehniques, 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 appindix 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 coinfidence 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.

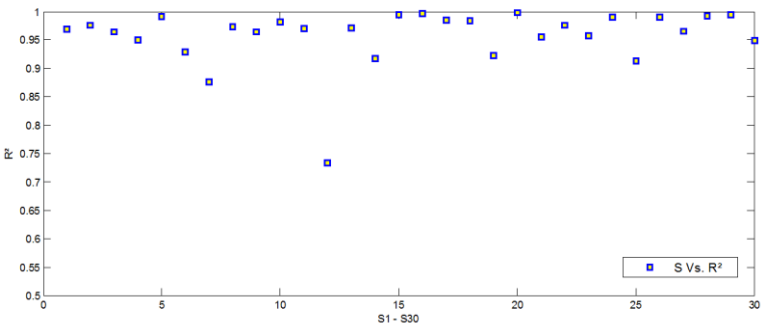

Fig. 5. Coefficient of determination R^2 for set of data S1-S30.

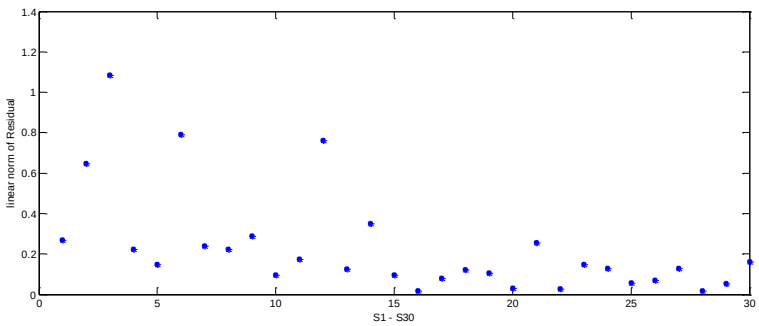

Fig. 6. Norm of residual for set of data S1-S30.

The formula of $\lambda_{p\alpha}$ is given by:

$$\lambda_{p\alpha} = \alpha * \left(\left[K_p - \left(\frac{\tau_r}{T_s} \right) \right]^2 \right)^{\frac{1}{20}} * e^{-\frac{t_d}{T_s}} * {K_p}^2 \tag{18}$$

The parameter α depended on t_d/τ_r ,where t_d/τ_r was calculated every 0.5 which gave α =$0.5^{\frac{(t_d/\tau_r)}{0.5}}$.

4. Simulation Results

This section discusses the implementation of the proposed alghorithm to different stable processes and comparison with previous methods. Although, the experimental implementation of the proposed strategy for pnumatic 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 (FOPTD) 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].

$$G_{p1} = \frac{e^{-50\,s}}{(150\,s+1)(25\,s+)} \tag{19}$$

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 τ_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 $\lambda_{p\alpha} = 0.004$.

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 1. A comparison between Cooper, EPC, and Proposed for process 1.

Method	Overshoot%	Rise Time(s)	Settling Time(s)	ISE
Cooper	0	276	603	117
Abu-Ayyad EPC	1.2	219	510	92
Proposed SMT	0.2	93	282	76

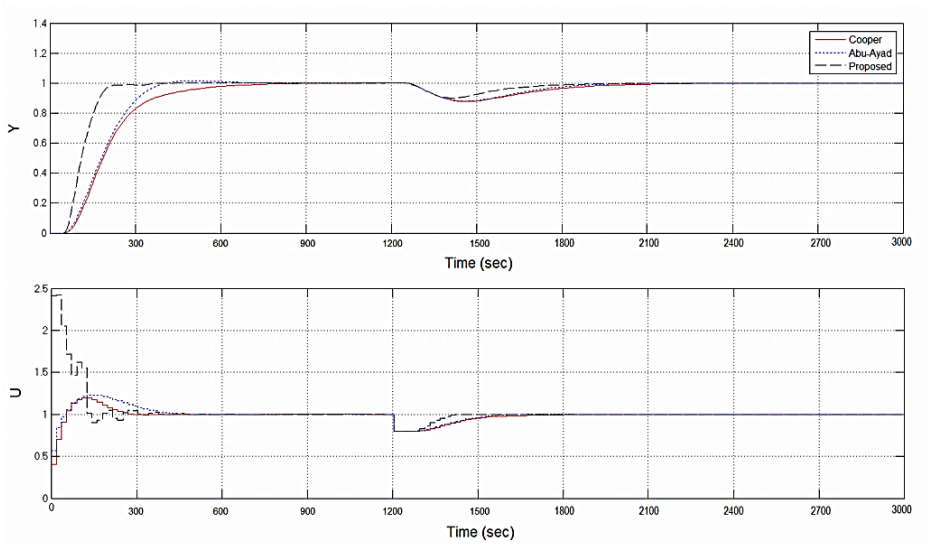

Fig. 7. A comparison between Cooper, EPC, and Proposed for process 1.

4.2. Process 2

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

$$G_{p2} = \frac{(-50\,s+1)e^{-10\,s}}{(100\,s+1)^2} \tag{20}$$

First order plus dead time (FOPDT) model for process 2 had gain K = 1, time delay t_d = 105 s, τ_r 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 λ=0.14. Abu-Ayyad method EPC was calculated at the same controller parameters in terms of P, T_s , M, and λ. 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 2. A comparison between Cooper, EPC, and Proposed for process 2.

Method	Overshoot%	Rise Time (s)	Settling Time (s)	ISE
Cooper	1.80	127	395	220
Abu-Ayyad EPC	0.20	112	274	188
Proposed SMT	0.01	92	231	138

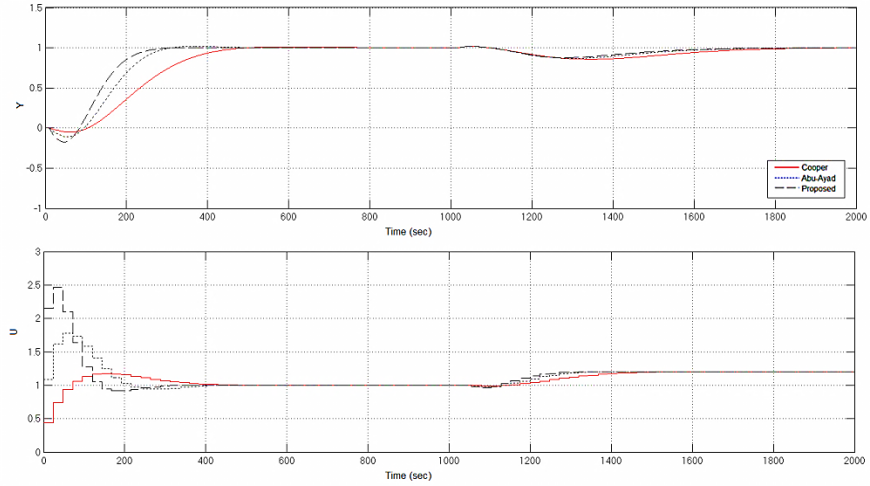

Fig. 8. A comparison between Cooper, EPC, and Proposed for process 2.

4.3. Process 3

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

$$G_{p3} = \frac{e^{-10\,s}}{(50\,s+1)^4} \tag{21}$$

First order plus dead time (FOPDT) model for process 3 is the gain K is 1, t_d is 99 s, τ_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 is 19 s, P=38, M=4 and the suppression coefficient λ 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. $\lambda_{p\alpha} = 0.0001$.

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

Method	Overshoot%	Rise Time (s)	Settling Time (s)	ISE
Cooper	4.3	118	735	105
Abu-Ayyad EPC	0.05	118	296	89
Proposed SMT	0.01	113	294	82

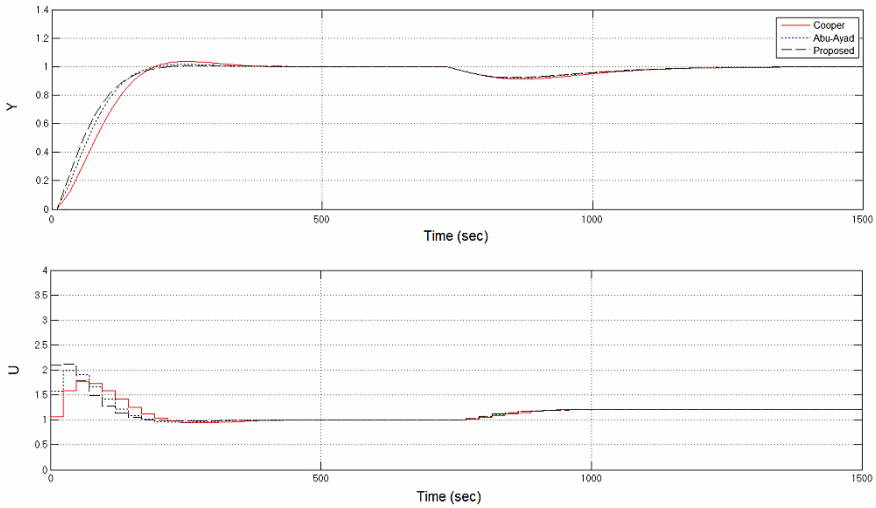

Fig. 9. A comparison between Cooper, EPC, and Proposed for process 3.

5. Conclusion

An easy to use predictive control strategy using self-identification matrix technique $\mathcal{W}_{SMT}$ has been presented. This strategy applies simple rules based on the step response of the process with analytical tool for tuning parameter. Regression method was 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.

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Appendix A

Estimation of optimal λ_{OpTu} for 150 FOPDT models

No	K_p	τ_d	τ_r	τ_d/τ_r	T_s	λ_{TryOpt}	$\lambda_{p\alpha}$	set	No	K_p	τ_d	τ_r	τ_d/τ_r	T_s	λ_{TryOpt}	$\lambda_{p\alpha}$	set
1	1	0.2	1	0.2	0.1	0.11	0.084		76	1	1.2	1	1.2	0.6	0.02	0.016	
2	2	0.2	1	0.2	0.1	0.4	0.333		77	2	1.2	1	1.2	0.6	0.08	0.061	
3	3	0.2	1	0.2	0.1	0.55	0.74	S1	78	3	1.2	1	1.2	0.6	0.2	0.157	S16
4	4	0.2	1	0.2	0.1	1.7	1.295		79	4	1.2	1	1.2	0.6	0.4	0.295	
5	5	0.2	1	0.2	0.1	2.5	1.987		80	5	1.2	1	1.2	0.6	0.6	0.477	
6	1	0.2	2	0.1	0.2	0.33	0.229		81	1	1.2	2	0.6	0.6	0.045	0.037	
7	2	0.2	2	0.1	0.2	1.2	0.906		82	2	1.2	2	0.6	0.6	0.17	0.139	
8	3	0.2	2	0.1	0.2	2.5	2.011	S2	83	3	1.2	2	0.6	0.6	0.3	0.273	S17
9	4	0.2	2	0.1	0.2	4.7	3.521		84	4	1.2	2	0.6	0.6	0.8	0.52	
10	5	0.2	2	0.1	0.2	5.8	5.401		85	5	1.2	2	0.6	0.6	1.2	0.89	
11	1	0.2	3	0.067	0.3	0.33	0.32		86	1	1.2	3	0.4	0.6	0.1	0.078	
12	2	0.2	3	0.067	0.3	1.4	1.264		87	2	1.2	3	0.4	0.6	0.4	0.302	
13	3	0.2	3	0.067	0.3	3	2.807	S3	88	3	1.2	3	0.4	0.6	0.9	0.653	S18
14	4	0.2	3	0.067	0.3	4.7	4.913		89	4	1.2	3	0.4	0.6	1.2	1.083	
15	5	0.2	3	0.067	0.3	5.8	7.538		90	5	1.2	3	0.4	0.6	1.5	1.254	
16	1	0.4	1	0.4	0.2	0.1	0.078		91	1	1.4	1	1.4	0.7	0.02	0.016	
17	2	0.4	1	0.4	0.2	0.5	0.302		92	2	1.4	1	1.4	0.7	0.1	0.064	
18	3	0.4	1	0.4	0.2	0.8	0.653	S4	93	3	1.4	1	1.4	0.7	0.13	0.159	S19
19	4	0.4	1	0.4	0.2	1.2	1.083		94	4	1.4	1	1.4	0.7	0.2	0.297	
20	5	0.4	1	0.4	0.2	1.8	1.254		95	5	1.4	1	1.4	0.7	0.5	0.48	
21	1	0.4	2	0.2	0.2	0.13	0.084		96	1	1.4	2	0.7	0.7	0.04	0.036	
22	2	0.4	2	0.2	0.2	0.7	0.333		97	2	1.4	2	0.7	0.7	0.18	0.133	
23	3	0.4	2	0.2	0.2	1	0.74	S5	98	3	1.4	2	0.7	0.7	0.3	0.251	S20
24	4	0.4	2	0.2	0.2	1.9	1.295		99	4	1.4	2	0.7	0.7	0.7	0.549	
25	5	0.4	2	0.2	0.2	2.8	1.987		100	5	1.4	2	0.7	0.7	1.1	0.913	
26	1	0.4	3	0.13	0.3	0.23	0.164		101	1	1.4	3	0.47	0.7	0.068	0.076	
27	2	0.4	3	0.13	0.3	0.96	0.649		102	2	1.4	3	0.47	0.7	0.3	0.294	
28	3	0.4	3	0.13	0.3	2	1.441	S6	103	3	1.4	3	0.47	0.7	0.8	0.625	S21
29	4	0.4	3	0.13	0.3	3.7	2.523		104	4	1.4	3	0.47	0.7	0.86	0.955	
30	5	0.4	3	0.13	0.3	4	3.87		105	5	1.4	3	0.47	0.7	1.4	1.636	
31	1	0.6	1	0.6	0.3	0.1	0.037		106	1	1.6	1	1.6	0.8	0.01	0.007	
32	2	0.6	1	0.6	0.3	0.3	0.139		107	2	1.6	1	1.6	0.8	0.05	0.033	
33	3	0.6	1	0.6	0.3	0.7	0.273	S7	108	3	1.6	1	1.6	0.8	0.12	0.081	S22
34	4	0.6	1	0.6	0.3	1.2	0.52		109	4	1.6	1	1.6	0.8	0.18	0.15	
35	5	0.6	1	0.6	0.3	1.3	0.89		110	5	1.6	1	1.6	0.8	0.25	0.241	
36	1	0.6	2	0.3	0.3	0.2	0.08		111	1	1.6	2	0.8	0.8	0.06	0.035	
37	2	0.6	2	0.3	0.3	0.5	0.316		112	2	1.6	2	0.8	0.8	0.17	0.126	
38	3	0.6	2	0.3	0.3	1	0.694	S8	113	3	1.6	2	0.8	0.8	0.3	0.284	S23
39	4	0.6	2	0.3	0.3	1.2	1.194		114	4	1.6	2	0.8	0.8	0.66	0.564	
40	5	0.6	2	0.3	0.3	2	1.78		115	5	1.6	2	0.8	0.8	0.8	0.927	
41	1	0.6	3	0.2	0.3	0.12	0.084		116	1	1.6	3	0.5	0.8	0.1	0.075	
42	2	0.6	3	0.2	0.3	0.55	0.333		117	2	1.6	3	0.5	0.8	0.3	0.286	
43	3	0.6	3	0.2	0.3	1.11	0.74	S9	118	3	1.6	3	0.5	0.8	0.7	0.592	S24
44	4	0.6	3	0.2	0.3	1.4	1.295		119	4	1.6	3	0.5	0.8	1	0.943	
45	5	0.6	3	0.2	0.3	2.78	1.987		120	5	1.6	3	0.5	0.8	1.63	1.73	
46	1	0.8	1	0.8	0.4	0.03	0.035		121	1	1.8	1	1.8	0.9	0.01	0.007	
47	2	0.8	1	0.8	0.4	0.2	0.126		122	2	1.8	1	1.8	0.9	0.04	0.033	
48	3	0.8	1	0.8	0.4	0.3	0.284	S10	123	3	1.8	1	1.8	0.9	0.15	0.081	S25
49	4	0.8	1	0.8	0.4	0.9	0.564		124	4	1.8	1	1.8	0.9	0.22	0.15	
50	5	0.8	1	0.8	0.4	1.3	0.927		125	5	1.8	1	1.8	0.9	0.26	0.242	
51	1	0.8	2	0.4	0.4	0.12	0.078		126	1	1.8	2	0.9	0.9	0.05	0.035	
52	2	0.8	2	0.4	0.4	0.2	0.302		127	2	1.8	2	0.9	0.9	0.13	0.116	
53	3	0.8	2	0.4	0.4	0.9	0.653	S11	128	3	1.8	2	0.9	0.9	0.47	0.297	S26
54	4	0.8	2	0.4	0.4	2	1.083		129	4	1.8	2	0.9	0.9	0.8	0.573	
55	5	0.8	2	0.4	0.4	2.5	1.254		130	5	1.8	2	0.9	0.9	1.2	0.937	
56	1	0.8	3	0.267	0.4	0.2	0.082		131	1	1.8	3	0.6	0.9	0.045	0.037	
57	2	0.8	3	0.267	0.4	1	0.321		132	2	1.8	3	0.6	0.9	0.15	0.139	
58	3	0.8	3	0.267	0.4	0.9	0.708	S12	133	3	1.8	3	0.6	0.9	0.5	0.273	S27
59	4	0.8	3	0.267	0.4	1.7	1.227		134	4	1.8	3	0.6	0.9	0.66	0.52	
60	5	0.8	3	0.267	0.4	2	1.854		135	5	1.8	3	0.6	0.9	1.07	0.89	
61	1	1	1	1	0.5	0.04	0.034		136	1	2	1	2	1	0.008	0.005	
62	2	1	1	1	0.5	0.08	0.092		137	2	2	1	2	1	0.025	0.034	
63	3	1	1	1	0.5	0.2	0.305	S13	138	3	2	1	2	1	0.11	0.082	S28
64	4	1	1	1	0.5	0.7	0.58		139	4	2	1	2	1	0.18	0.151	
65	5	1	1	1	0.5	1	0.944		140	5	2	1	2	1	0.32	0.243	
66	1	1	2	0.5	0.5	0.09	0.076		141	1	2	2	1	1	0.067	0.034	
67	2	1	2	0.5	0.5	0.4	0.29		142	2	2	2	1	1	0.1	0.092	
68	3	1	2	0.5	0.5	0.7	0.609	S14	143	3	2	2	1	1	0.43	0.305	S29
69	4	1	2	0.5	0.5	1.1	0.785		144	4	2	2	1	1	0.8	0.58	
70	5	1	2	0.5	0.5	1.5	1.692		145	5	2	2	1	1	1.19	0.944	
71	1	1	3	0.3	0.5	0.15	0.079		146	1	2	3	0.67	1	0.024	0.036	
72	2	1	3	0.3	0.5	0.45	0.311		147	2	2	3	0.67	1	0.2	0.135	
73	3	1	3	0.3	0.5	0.9	0.68	S15	148	3	2	3	0.67	1	0.33	0.214	S30
74	4	1	3	0.3	0.5	1.5	1.16		149	4	2	3	0.67	1	0.77	0.541	
75	5	1	3	0.3	0.5	2.4	1.692		150	5	2	3	0.67	1	0.95	0.907	