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New Framework of Unconstrained Model Predictive Controller with Enchantment of Anti-Windup Scheme in SISO SMISD Plant

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ABSTRACT

Steam temperatures have an important role in the overall dynamic in the Small-Medium Industry Steam Distillation (SMISD) plant and vital parameter in determining quality of essential oils. Therefore, an exact temperature control is required to regulate precisely to mitigate the effects of the heating process. This paper presents a new framework of unconstrained model predictive controller with enhancement of anti-windup scheme. The inspirations behind this action are the ability of Unconstrained Model Predictive Controller to predict future behaviour of the system but unable react fast enough due to input saturation (windup problem) and the ability of anti-windup strategy (back propagation) to minimize the effect of windup problem which normally occur with system with long dead time (temperature). It is interesting to combine both feature of conventional Unconstrained Model Predictive Controller and anti-windup strategy (back propagation) named UMPCAW which expected to produce better transient response. The UMPCAW is tune based on two most popular tuning rule which are Ziegler-Nichols (ZN) and Cohan-Coon (CC) named as UMPCAW-ZN and UMPCAW-CC respectively. The results demonstrated that UMPCAW-ZN and UMPCAW-CC are able to deliver better transient response while controlling SISO SMISD Plant.

Keywords: Unconstrained Model Predictive Controller, Anti-Windup Scheme, Back Propagation.

1. INTRODUCTION

Over recent years, there has been an explosive growth of interest in the usage of essential oil. It becomes an important commodity that is traded around the world and the demand has increased significantly over the past few decades. Estimately, the total export value is 20 billion annually. Essential oil is obtained through extraction process which separates the volatile component from the botanical plant which majorly is extracted using traditional steam distillation. Although this method can be consider as an old technique which had been used for hundreds of years, but still this method was preferred by the industries to gain mass oil production and at the same time consume low operational cost. In most literatures, the temperature is identified as the most significant parameter in determining quality and quantity in essential oil [1]-[2]. Consequently, due to prolonged exposure to high temperature the chemical composition in essential oil will suffer from the deterioration of the quality of the oil yield [2]-[3]. Furthermore, the use of unnecessary energy in return lead to operational inefficiency [4].

Therefore, an exact temperature control is required to regulate precisely to mitigate the effects of the heating process. By considering the factors mentioned, it is desirable to find a proper control technique for regulating the temperature of the Small-Medium Industry Steam Distillation (SMISD) plant. It is significant to minimize the mentioned problems by integrating the system with predictive controller and it is expected

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to execute a better control over operating conditions compared to the conventional controller since the predictive controller able to predict the behaviour of the system over the horizon. Model Predictive Controller (MPC) which is also called as Receding Horizon Control (RHC) or Moving Horizon Control (MHC) [5] in many published literatures. MPC is proven to be a useful framework for regulating systems that are subjected to large dead time [6]. For example, MPC shows better performances when controlling furnace temperature compared to the conventional PID lead and lag [7]. According to Martin and McGarel [8] stated that MPC performed superiorly in processes that are dominate by dead time. Due to the dynamic of steam along intricate interaction among other process variable, the system performances of conventional PID control will not be optimum.

The history of MPC can be tracked back to early 70s century [9]. MPC utilize nominal model of system to compute trajectory of the manipulated input such that the predicted future response of system as desired [10] and calculate the optimal control signal at each sampling time. Solution of optimization problems consisting the number of predicted optimal control input which is only the first of a term related to control input is implemented [11]. Qin and Badgwell reported in 2003 alone that there are more than 4600 of MPC application applied in the industry [12]. In the past 10 years, MPC has grown tremendously in term of theory and practical framework while several factors still need to be investigated. Computational burden is the new dimension that need further research as model-based control laws are usually computationally demanding [13]. This problem become bottleneck to establish MPC framework in real time studied. The standard practice in industry are to utilize Model Predictive Controller with terminal constraints to guarantee the stability and to ensure the performances are within the acceptable tolerated range. However, this technique requires higher computation effort to solve optimization problem on-line. Here, the authors introduce a new unorthodox technique, by utilizing the conventional unconstrained model predictive controller that is integrated with the anti-windup technique (back propagation).

The new technique is named as the Unconstrained Model Predictive Controller with Anti-windup (UMPCAW). Under this new technique, the authors use existing unconstrained model predictive controller framework where the system stability that is not guaranteed is couple with anti-windup technique. The anti-windup is the old technique which is originally used in the Proportional-Integral-Derivative Controller (PID) when encountered with the windup problem. The windup problem is the situation when the controller input exceeds the physical limitation of the system (for instance 0-5V, 4-20mA, and 3-15psi) and is unable to react fast enough response to change in error response. After a certain time, the controller control signal is built-up to extensive large due to the continuous rise the accumulated control signal as are response to persisting error occur to the system. However, when the system reaches the predetermined output or set point, the control signal begin to unwind/ decrease due change in error signal. But the controller do not response immediately due to the reasons stated above which resulted the control signal is far beyond the physical operating range of the actuator. It consumes significant amount of time (causes a lag in response) to unwind the accumulated control signal within the operating limit range of the actuator constrains.

The authors exploit the characteristics of anti-windup scheme (back propagation) which are combined with the conventional Unconstrained Model Predictive Controller. The motivation behind this action are due to the ability of the Unconstrained Model Predictive Controller to predict future behavior of the system but unable react fast enough due to input saturation (windup problem) and the ability of the anti-windup strategy (back propagation) to minimize the effect of the windup problem which normally occur with system with long dead time (temperature). It is interesting to combining both features of conventional Unconstrained Model Predictive Controller and anti-windup strategy (back propagation) which expectedly will produce a better transient response compare and less computation burden to conventional control. This experiment will be tested in the Small-Medium Industry Steam Distillation (SMISD) plant.

2. SMISD PLANT

The experiments are performed in Small-Medium Industry Steam Distillation (SMISD) plant that located at Faculty of Electrical Engineering Laboratory, Universiti Teknologi MARA (UiTM) Shah Alam. The detail descriptions have publish in [14]-[16].

3. MODEL PREDICTIVE CONTROLLER

Throughout this section, some aspects mathematical formation of UMPC. The formation will be discussed. The formation of (1)-(23) only applicable to Single Input Single Output (SISO) system [11].

3.1. Incremental model

Consider the following SISO state space nominal model:

$$x_n(k+1) = A_n\, x_n(k) + B_n\, u(k)$$
$$y(k) = C_n x_n(k) + D_n u(k) \tag{1}$$

Due to MPC works based on implementation of receding horizon principle where a current the plant utilize the current input for prediction and control, then we can implicitly assume that the input $u(k)$ cannot affect $y(k)$ instantaneously. This imply that in above equation where $D_n = 0$. The (1) can be rewrite as:

$$x_n(k+1) = A_n\, x_n(k) + B_n\, u(k)$$
$$y(k) = C_n x_n(k) \tag{2}$$

The nominal state space model can be extended by including the integral action to obtain the incremental model. The conversion from nominal model to incremental model is show in below:

Step 1: Introduce the difference operation on both sides of (1).

$$x_n(k+1) - x_n(k) = A_n(x_n(k) - x_n(k-1)) + B_n(u(k) - u(k-1)) \tag{3}$$

Note that:

$$\Delta x_n(k+1) = x_n(k+1) - x_n(k) \tag{3a}$$
$$\Delta x_n(k) = x_n(k) - x_n(k-1) \tag{3b}$$

And

$$\Delta u(k) = u(k) - u(k-1) \tag{3c}$$

Step 2: By taking consideration on (3a), (3b) and (3c).

$$\Delta x_n(k+1) = A_n \Delta x_n(k) + B_n \Delta u(k) \tag{4}$$

Step 3: Create new state variable $x(k)$ by connecting the Δx_n with $y(k)$

$$x(k) = \begin{bmatrix} \Delta x_n(k) \\ y(k) \end{bmatrix} \tag{5}$$

Note that: The output and incremental output is inform of:

$$y(k) = C_n x_n(k) \tag{6}$$

And

$$y(k+1) = C_n x_n(k+1) \tag{7}$$

Step 4: The difference between incremental output and output produce:

$$y(k+1) - y(k) = C_n(x_n(k+1) - x_n(k)) \tag{8}$$
$$y(k+1) - y(k) = C_n(\Delta x_n(k+1)) \tag{9}$$

Step 5: The incremental of state equation based on (1) is written as:

$$\Delta x_n(k+1) = A_n\, \Delta x_n(k) + B_n\, \Delta u(k) \tag{10}$$

Step 6: Substitute (10) into (9), then:

$$y(k+1) - y(k) = C_n(A_n \Delta x_n(k) + B_n \Delta u(k)) \tag{11}$$

$$y(k+1) = C_n(A_n \Delta x_n(k) + B_n \Delta u(k)) + y(k) \tag{12}$$

Step 7: Based on new state variable $x(k)$ in (5), then new incremental state variable $x(k + 1)$ write as:

$$x(k+1) = \begin{bmatrix} \Delta x_n(k+1) \\ y(k+1) \end{bmatrix} \tag{13}$$

Step 8: Substitute (10) and (12) into (13), then:

$$x(k+1) = \begin{bmatrix} A_n \Delta x_n(k) + B_n \Delta u(k) \\ C_n(A_n \Delta x_n(k) + B_n \Delta u(k)) + y(k) \end{bmatrix} \tag{14}$$

$$\begin{bmatrix} \Delta x_n(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} A_n \Delta x_n(k) + B_n \Delta u(k) \\ C_n(A_n \Delta x_n(k) + B_n \Delta u(k)) + y(k) \end{bmatrix} \tag{15}$$

Step 9: Rearrange in matrix form

$$\begin{bmatrix} \Delta x_n(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} A_n & O_n^T \\ C_n A_n & 1 \end{bmatrix} \begin{bmatrix} \Delta x_n(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} B_n \\ C_n B_n \end{bmatrix} \Delta u(k) \tag{16}$$

$$y(k) = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta x_n \\ y(k) \end{bmatrix}$$

Let:

$$A = \begin{bmatrix} A_n & O_n^T \\ C_n A_n & 1 \end{bmatrix}$$

$$B = \begin{bmatrix} B_n \\ B_n C_n \end{bmatrix}$$

$$C = \begin{bmatrix} O_n & 1 \end{bmatrix}$$

$$x(k+1) = \begin{bmatrix} \Delta x(k+1) \\ y(k+1) \end{bmatrix}$$

$$x(k) = \begin{bmatrix} \Delta x(k) \\ y(k) \end{bmatrix}$$

Note: On size depend on nominal matrix A. Let say if nominal matrix A have size 2 × 2, then $O_n = [0\ 0]$.

Step 10: Then incremental model can be written as:

$$\begin{aligned} x(k+1) &= Ax(k) + \Delta u(k) \\ y(k) &= Cx(k) \end{aligned} \tag{17}$$

3.2. Predictive Controller Parameter

Based on incremental model parameter (A, B, C), we can obtain the predictive controller parameter.

Step 1: The prediction of future system state can be achieved by iteration through (17) to determine the future state variable and the future prediction output.

Note: All predictions are formulated based on current state variable $x(k_i)$ and future control trajectory $\Delta u(k_i)$, $\Delta u(k_i + 1)$, $\Delta u(k_i + N_c - 1)$. The prediction horizon is denote as N_p, while control horizon is denote as N_c.

Form A:

$$\begin{aligned}
x(k_i + 1|k_i) &= Ax(k_i) + B\Delta u(k_i) \\
x(k_i + 2|k_i) &= Ax(k_i + 1) + B\Delta u(k_i + 1) \\
&= A(Ax(k_i) + B\Delta u(k_i)) + B\Delta u(k_i + 1) \\
&= A^2x(k_i) + AB\Delta u(k_i)) + B\Delta u(k_i + 1) \\
\vdots \quad & \vdots \quad \vdots \\
x(k_i + Np|k_i) &= A^{Np}x(k_i) + A^{Np-1} B\Delta u(k_i) + \ldots + A^{Np-Nc} B\Delta u(k_i + Nc - 1)
\end{aligned}$$

Step 2: The predicted output is obtained by substituting the predicted state

Form B:

$$\begin{aligned}
y(k_i + 1|k_i) &= CAx(k_i) + BC\Delta u(k_i) \\
y(k_i + 2|k_i) &= CAx(k_i + 1) + BC\Delta u(k_i + 1) \\
&= CA(Ax(k_i) + B\Delta u(k_i)) + BC\Delta u(k_i + 1) \\
&= CA^2x(k_i) + ABC\Delta u(k_i) + BC\Delta u(k_i + 1) \\
\vdots \quad & \vdots \quad \vdots \\
y(k_i + Np|k_i) &= CA^{Np}x(k_i) + CA^{Np-1} B\Delta u(k_i) + CA^{Np-Nc} B\Delta u(k_i - Nc - 1)
\end{aligned}$$

Step 3: The form B in compact form of matrix

$$Y = Fx(k_i) + \varnothing\Delta u \tag{18}$$

Where:

$$Y = \begin{bmatrix} y(k+1|k) \\ \vdots \\ y(k_i + N_p|k_i) \end{bmatrix}$$

$$\Delta u = \begin{bmatrix} \Delta u(k_i) \\ \Delta u(k_i + 1) \\ \vdots \\ \Delta u(k_i + N_c - 1) \end{bmatrix}$$

$$F = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{Np} \end{bmatrix}$$

$$\phi = \begin{pmatrix} CB & 0 & \cdots & 0 \\ CAB & CB & & 0 \\ \vdots & & \ddots & \vdots \\ CAB^{Np-1} & CA^{Np-2} & \cdots & CA^{Np-Nc}B \end{pmatrix}$$

3.3. Optimization

The objective of the optimization is to bring the predicted output as close as to the set point.

Step 1: To obtained an optimal sequence, the following performance index as shown in (19) must be minimize within the future horizon [11].

$$J = \left(R_{ref} - Y\right)^T \left(R_{ref} - Y\right) + \Delta U^T \bar{R} \Delta U \tag{19}$$

Where:

$Rref$	=	Np × Set point
Y	=	Predicted Output
ΔU	=	Control Parameter
$\bar{R}$	=	Tuning Parameter

Where the first term is refers as the objective function that minimize error between the prediction outputs with the set point. The second term refers to how big the input U must consider

Step 2: The (19) can be extended into (20) by taking:

$$J = \left(R_{ref} - \left(Fx\left(k_i + \phi \Delta U\right)\right)\right)^T \left(R_{ref} - \left(Fx\left(k_i + \phi \Delta U\right)\right)\right) + \Delta U^T \bar{R} \Delta U) \tag{20}$$

Step 3: To find the optimal control signal, it necessary to differentiate the cost function.

$$\frac{\delta J}{\delta \Delta u} = -2\phi^T \left(R_{ref} - Fx\left(k_i\right)\right) + 2\left(\phi^T \phi + \bar{R}\right)\Delta U \tag{21}$$

Step 4: To find minimum J, it necessary to have $\frac{\delta J}{\delta \Delta u} = 0$.

$$0 = -2\phi^T \left(R_{ref} - Fx\left(k_i\right)\right) + 2\left(\phi^T \phi + \bar{R}\right)\Delta U \tag{22}$$

Step 5: Rearrange the equation to find optimal control signal.

$$\Delta U = \left(\phi^T \phi + \bar{R}\right)^{-1} \left(R_{ref} - Fx\left(k_i\right)\right) \tag{23}$$

Then the optimal control signal can be obtained by solving the (23).

4. THE PROPOSE NEW PREDICTIVE CONTROLLERS

The proposed new predictive controller scheme is based on the well-known formation of unconstrained model predictive controller (UMPC) which is unbound in input and the output state is combined with anti-windup scheme. The authors take advantage of the characterizations of the anti-windup scheme (back propagation) which is combine with the conventional Unconstrained Model Predictive Controller. The

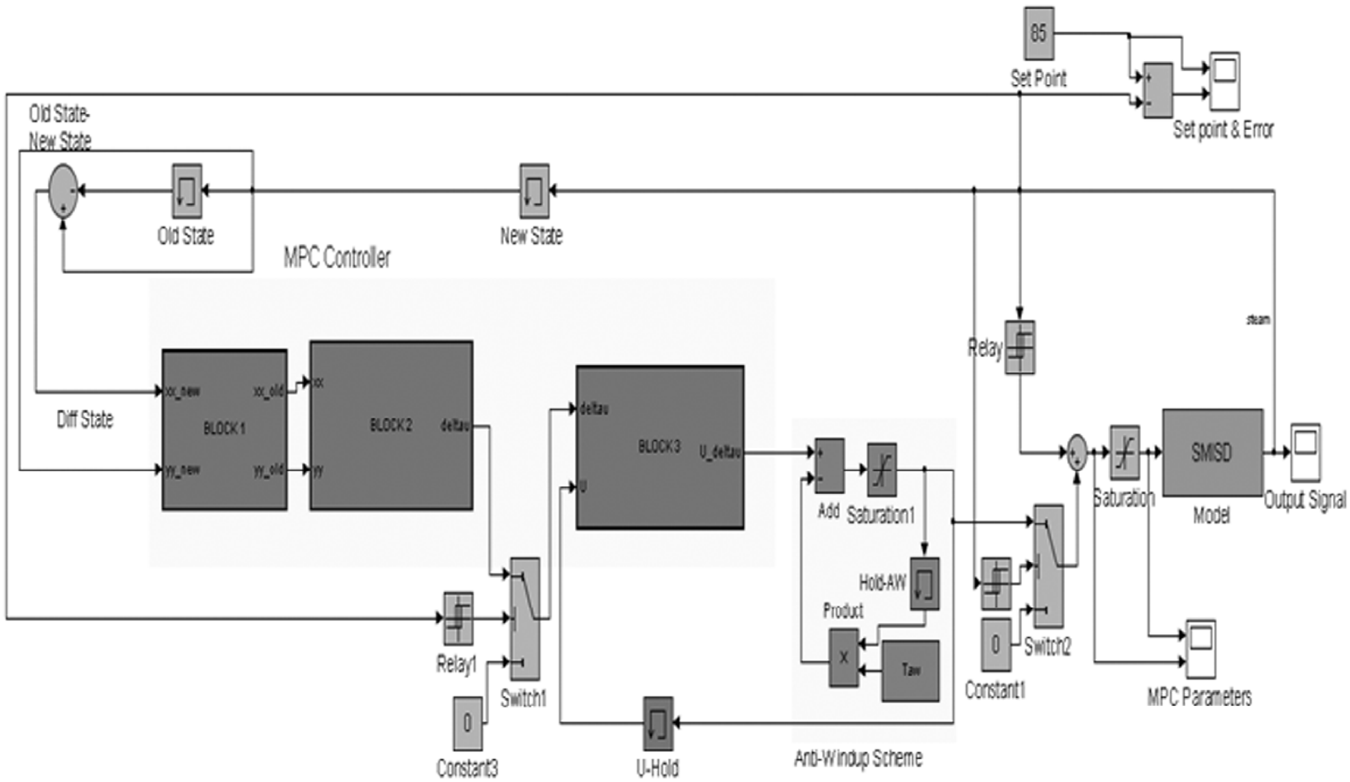

Figure 1: UMPCAW Scheme Block Diagram

inspiration behind this action are the ability of Unconstrained Model Predictive Controller to predict future behaviour of the system but it unable to react fast enough due to input saturation (windup problem) and the ability of anti-windup strategy (back propagation) to minimize the effect of windup problem which normally occur with system with long dead time (temperature). It is interesting to combining both feature of conventional Unconstrained Model Predictive Controller and anti-windup strategy (back propagation) which is expected to produce better transient response compare and less computation burden to conventional control. A block diagram of the proposed new predictive controller is shown in Figure. 1 which consists of 3 main component which is optimization block, integrator block and anti-windup scheme.

4.1. The Operation of UMPCAW

The initial value of $x(k_i)$ are loaded in the system which consisting of $[\Delta x(k); y(k)]$ that are derive from (16). The $\Delta x(k)$ and $y(k)$ represents the changing in system state (temperature) and the system state (temperature) itself respectively.

Next, the initial value of $x(k_i)$ is feed into the optimization block. As given in (23), the optimization routine is run based on this equation. The optimization routine produce number of sequences optimal input ($\Delta u(k_i)$, $\Delta u(k_i + 1)$, ... $\Delta u(k_i + N_c - 1)$). The number of the sequence optimal input depends on the number of control horizon, N_c. Only the first term is used for the later step which are passed to integrator block.

The framework behind integrator block where it used to aggregate the accumulation of the optimal input signal ($\Delta u(k_i)$ which are named as current input signal, $u(k_i)$. After a certain amount of time, the current input signal, $u(k_i)$, is transform to become past signal, $u(k_p)$ after it passes through the hold block. Note that the hold block is used to hold the data for 1 simulation time. The overall relationship is defined as $u(k_i) = \Delta u(k_i) + u(k_p)$. Up to this point are the standard formations of unconstrained model predictive controller.

The new key innovation in this paper is done by the introduction of the anti-windup (back calculation) at the far end of the integrator block. The anti-windup scheme consist of anti-windup gain (T_{AW}), saturation block and summation block. First of all, the saturation block represent the maximum/minimum (i.e. 0-5V, 4-20mA, 3-15psi) physical limitation of the actuator. For example, if the physical limitation of system are 0-5V and the current accumulated signal are 4V. This condition are called as unsaturated signal, which resulted the anti-windup scheme do not activated and if the value above saturated value (i.e. 6V), the scheme are activated. When the saturated block is active, it only permits 5V to pass through it. Then the summation block will take account the difference between saturated and unsaturated value (5-6 = –1). The resulted values are attenuate by tracking time constant (T_{AW}). However to used standard rule of thumb to calculate tracking time constant which is $\left(T_{AW} = \sqrt{T_I T_D}\right)$ does not work. The minor modification is done to rule of the thumb by divided the value by 100. By doing so, the new gain become $T_{AW} = \frac{T_I T_D}{100}$.

Subsequently, the optimal signal $u(k_i)$ are consigned to plant. Note that, output of system are equivalent to system state and Delta x is define as: $\Delta x(k) = \Delta x(k - 1) - \Delta x(k)$. Succeeding, the whole process are repeated by using new obtaining state of the system.

5. RESULT AND DISCUSSION

In this section, the proposed method are tested in simulation. The proposed method are executed in MATLAB software environment based on Window 7 platform. The transient response of propose method are analysed based on two criteria which is step response (transient performance-rise time, settling time, percentage overshoot) and set point tracking.

5.1. Step response/servo response

Step response test are most widely practiced owing to its implementation that simple test yet powerful tool in assessing overall process dynamics and time took to achieved steady state. In general, step response is define as how long system output took to achieved steady state when its input change is from zero to some arbitrary value. Same significant quantitative important information can be extracted from the system such as percentage overshoot, settling time and rise time.

Table 1 shows detail summary of step response of the develop controllers and Figure. 2 plot the controller response when subjected to step input. For all runs the step response experiment were controlled at a set

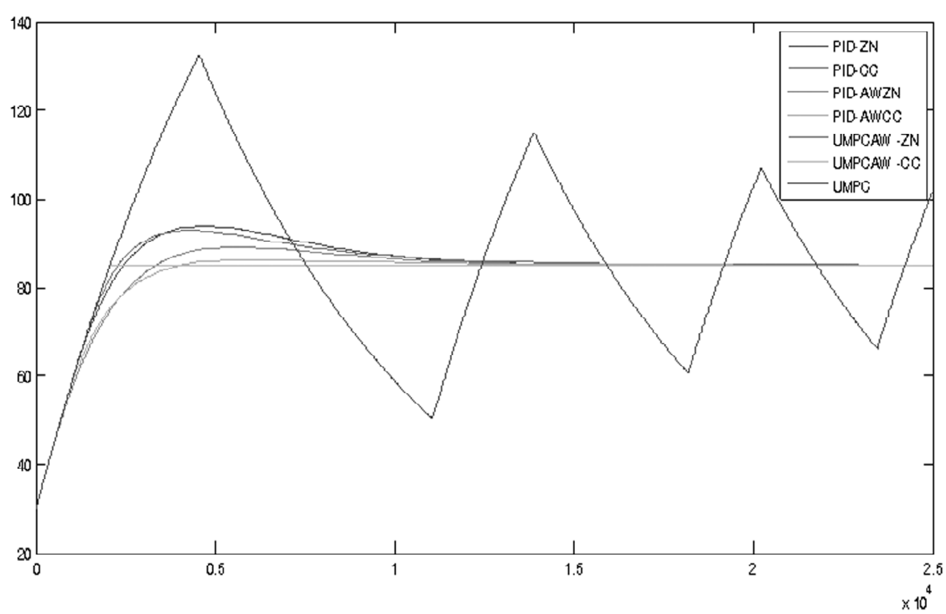

Figure 2: Simulation of servo response

Table 1
Transient response when subject to step response results

Controller	*Rise Time (Second)*	*Settling Time (Second)*	*Percentage Overshoot (%)*
PID-ZN	1821	9290	10.4523
PID-CC	1710	8946	9.2673
PID-AWZN	2349	8030	4.8760
PID-AWCC	2397	8091	1.4044
UMPCAW-ZN	1633	1930	0.3071
UMPCAW-CC	1633	1929	0.2677
UMPC	2252	24826	30.3306

point of 85 degree Celsius and initial temperature of 30 degree Celsius. This to ensure that the experiment is constant throughout the time. The step response plot demonstrates that the UMPCAW-ZN and UMPCAW-CC recorded the lowest rise time. This indicates that both controllers are capable to deliver satisfying results in shortest time compared to other controllers. From the analysis above, it is seen that UMPCAW-ZN and UMPCAW-CC have the smallest number of setting time, followed by UMP, PID-AWZN, PID-AWCC, PID-CC and lastly PID-ZN. Further analysis reveals that longer settling time is due to the presence of large dead time is the system. Due to this problem, it allows the control signal to built-up to extensive large value and take longer time for it unwind. This phenomena is known as windup phenomena. The controller (UMPCAW-ZN and UMPCAW-CC) are able to mitigate the effect of windup phenomena compare to other type tested controllers. Referring to the percentage overshoot result shows that the UMPCAW-CC and UMPCAW-ZN preference performance with 0.2677% and 0.3071% respectively. Followed by PID-AWCC (1.4044%), PID-AWZN (4.8760%), PID-CC (9.2673%), and PID ZN (10.4523%).

5.2. Set point tracking

The set point tracking test are aiming to determine the robustness of the developed controller. In this test, the controller left on the steady state before the reading are collected. Then calculate MSE/RMSE to determine the robustness of the system that data collected are start from 20000-25000 second.

Table 2 presents the quantitative results of controller's response to set point tracking which used the MSE/RMSE as visual indications of controlled performance. The criteria for fairy good set point controller is to have the lowest number of MSE/RMSE. The result shows that PID-AWCC have lower number of MSE/RMSE. It followed by PID-AWZN, PID-ZN, PID-CC, UMPCAW-ZN and UMPCAW-CC. The major cause of UMPCAW-ZN and UMPCAW-CC to have poor performance is cause by sustained oscillation

Table 2
Summary of set point tracking

Controller	*MSE*	*RMSE*
PID-ZN	2.8418e-04	0.0169
PID-CC	9.7471e-04	0.0312
PID-AWZN	1.0822e-04	0.0104
PID-AWCC	7.9681e-05	0.0089
UMPCAW -ZN	0.0274	0.1656
UMPCAW -CC	0.0313	0.1769
UMPC	139.5432	11.8128

which vary from 84.8 to 85.2 Celsius. However, this result indicate that the UMPCAW-ZN and UMPCAW-CC still in favour in term of performance due to it's operate within limit of 5% of settling time.

6. CONCLUSIONS

In this work, a new framework for UMPAW based on Ziegler-Nichols and Cohan-Coon tuning rule is proposed. The employment of anti-windup scheme in UMPC able to ensure the stability of the systems. The UMPCAW-CC achieved slightly better performance in transient response than UMPCAW-ZN but in overall both are very similar. This indicated that both tuning for Unconstrained of Model Predictive Control seems do not have so much difference. Further work is needed to determine the general rule of thumb for gain of anti-windup. It should be noticed that both develop controllers achieved superior performances in transient response (rise time, settling time, percentage overshoot) but have acceptable performance in set point tracking.

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