

Model Predictive Control of a Serial Link Robot Manipulator

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Abstract—this paper presents a new approach for a model predictive control dynamics of a two-link manipulator robot. This technique consists of linearizing a nonlinear dynamic model of the robot by using a feedback linearization control. Once, the linear model has been obtained, a predictive control approach will be developed. We have introduced a quadratic criterion and these parameters are calculated to have a specific behaviour of the closed-loop system. Here, the objective is to control the arm robot from an initial configuration to the final configuration using a predictive control approach and it is obtained by minimizing a quadratic criterion. To show the efficiency of the proposed method, some simulation results are given.

Keywords—*Two DOF robot arm; Dynamic model; Nonlinear control; Model predictive control.*

I. INTRODUCTION

Industrial robots are most widely used in applications such as welding, paint spraying, punching, drilling, bending, multi-axis machining, exploration, heavy load transport, neutralization of explosives maintenance in harmful and dangerous environments. For these kinds of processes, they are expected to move the manipulator one place to another place with almost precision control and continue the process. But robot manipulators are systems highly nonlinear in nature. The nonlinear system can be linearized around the operating point and the controlled is to be designed. While designing the controller for such a nonlinear system to meet the desired performance is a critical one. In most of the application, robot manipulator is designed a serial rigid link. For example, SCARA (Selective Compliant Articulated Robot Arm) type with two degrees of freedom is considered and PID control of this type of robot arm and the stability analysis is carried out using Lyapunov's theory [1]. Wheel-leg robot has more than one arm have controlled. WLR has more degrees of freedom than other robots [2]. Mobile manipulators are used in multiple applications. An approach for dynamic modelling and PID control are in detail [3]. Human-like behaviour has emerged in the robotic manipulator. Modelling and ANN-based control approach for the regression relationship between robots pose and swivel motion angle [4]. Close collaboration between the robot and humans in various processes. In particular case robot and human share, the workspace [5]. A robust adaptive Takagi-Sugeno-Kang fuzzy cerebellar model articulation controller (RATFC) is proposed and applied to a robot manipulator to achieve high-precision position and speed control [6]. Manipulators' models are obtained using the Lagrange equation. The manipulator configuration consists of five rotational joints and four links [7]. Aerial Manipulators are modelled and controlled using the Lagrangian model. The nonlinear model is linearized through the feedback linearization technique [8]. Kinematic and dynamic models of two robots with a physical link that is employed to deal with actuator failures for two-wheel drive (2WD) mobile robots are proposed and dynamic controller is designed [9]. A novel transformable aerial robot called DRAGON which is multi-degree

freedom. The dynamic is derived based on the centre of gravity. Decouples the thrust force control and rotor gimbal control to guarantee the optimal regulator for thrust force. The Linear-Quadratic-Integral optimization technique is utilized [10]. Hybrid Electric-Pneumatic actuator for the robot is designed and PID controllers are used. [11]. Playing robot for badminton requires high precision, hybrid electric-pneumatic actuators are used to develop a humanoid robot arm. This robot with seven degrees of freedom that roughly reproduce the motion of humans [12]. Load frequency control (LFC) strategy based on model predictive control (MPC) to regulate the system frequency. Frequency fluctuation caused by wind power integration; an effective MPC-based LFC strategy is proposed for a power system with wind turbine generators [13]. A whole-body optimal control framework to jointly solve the problems of manipulation, balancing, and interaction, as one optimization problem for an inherently unstable robot. The optimization is performed using a model predictive control (MPC) approach [14].

Model Predictive Control is an emerging control method for a vast amount of control applications.

II. Dynamic Model

A serial link manipulator having two degrees of freedom can be represented in the figure:1.

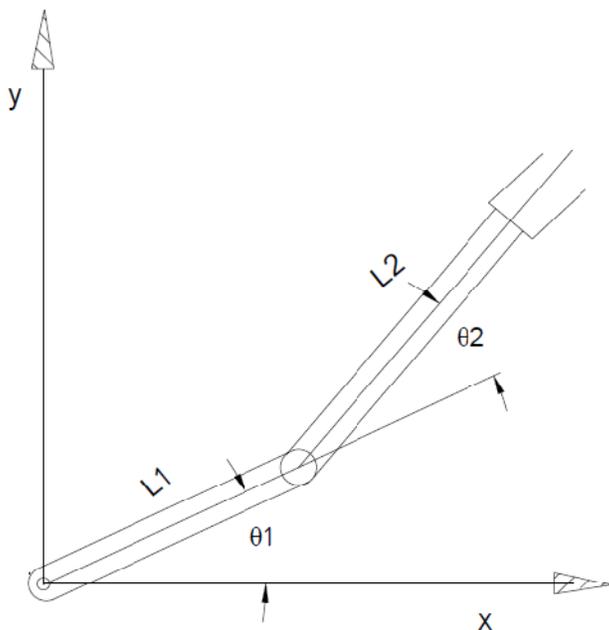


Figure: 1: Two degrees of freedom Manipulator

Where θ_i , L_i , and M_i ($i=1,2$) are respectively the joint angle, length, and the mass of the first link ($i=1$) and the second link ($i=2$). The gravitational force (g) is noted.

The Mathematical dynamic model of this robot is based on kinetic and potential energy. There are arrived by using the basic geometric model (BGM) [15]

$$\{ x_1 = L_1 \cos(\theta_1)$$

$$y_1 = L_1 \sin(\theta_1)$$

$$x_2 = L_1 \cos(\theta_1) + L_2 \cos(\theta_1 + \theta_2)$$

$$y_2 = L_1 \sin(\theta_1) + L_2 \sin(\theta_1 + \theta_2) \} \tag{1}$$

Kinetic Energy can be written as

$$KE = \frac{1}{2} M_1 \dot{x}_1^2 + \frac{1}{2} M_1 \dot{y}_1^2 + \frac{1}{2} M_2 \dot{x}_2^2 + \frac{1}{2} M_2 \dot{y}_2^2$$

$$KE = \frac{1}{2} (M_1 + M_2) L_1^2 \dot{\theta}_1^2 + \frac{1}{2} M_2 L_2^2 \dot{\theta}_1^2 + M_2 L_2^2 \dot{\theta}_1 \dot{\theta}_2 + \frac{1}{2} M_2 L_2^2 \dot{\theta}_2^2 + M_2 L_1 L_2 \cos \theta_2 (\dot{\theta}_1 \dot{\theta}_2 + \dot{\theta}_1^2) \tag{2}$$

Potential Energy can be written as

$$PE = M_1 g L_1 \cos(\theta_1) + M_2 g L_1 \cos(\theta_1) + L_2 \cos(\theta_1 + \theta_2) \tag{3}$$

To find the robot motion equations, we use the formalism of Lagrange(L):

L=KE-PE

$$L = \frac{1}{2} (M_1 + M_2) L_1^2 \dot{\theta}_1^2 + \frac{1}{2} M_2 L_2^2 \dot{\theta}_1^2 + M_2 L_2^2 \dot{\theta}_1 \dot{\theta}_2 + \frac{1}{2} M_2 L_2^2 \dot{\theta}_2^2 + M_2 L_1 L_2 \cos \theta_2 (\dot{\theta}_1 \dot{\theta}_2 + \dot{\theta}_1^2) - M_1 g L_1 \cos(\theta_1) - M_2 g L_1 \cos(\theta_1) - L_2 \cos(\theta_1 + \theta_2) \tag{4}$$

The Lagrange-Euler formulation for link 1, gives the torque $\tau_1 = \frac{d}{dt} \left(\frac{\partial L}{\partial \dot{\theta}_1} \right) - \frac{\partial L}{\partial \theta_1}$ (5)

$$\tau_1 = ((M_1 + M_2) L_1^2 + M_2 L_2^2 + 2 M_2 L_1 L_2 \cos \theta_2) \ddot{\theta}_1 + (M_2 L_2^2 + M_2 L_1 L_2 \cos \theta_2) \ddot{\theta}_2 - M_1 L_1 L_2 \sin(\theta_2) (\dot{\theta}_1 \dot{\theta}_2 + \dot{\theta}_1^2) - (M_1 + M_2) g L_1 \sin(\theta_1) - M_2 g L_2 \sin(\theta_1 + \theta_2) \tag{6}$$

The Lagrange-Euler formulation for link 2, gives the torque $\tau_2 = \frac{d}{dt} \left(\frac{\partial L}{\partial \dot{\theta}_2} \right) - \frac{\partial L}{\partial \theta_2}$ (7)

$$\tau_2 = (M_2 L_2^2 + M_2 L_1 L_2 \cos \theta_2) \ddot{\theta}_1 + M_2 L_2^2 \ddot{\theta}_2 - M_2 L_1 L_2 \sin \theta_2 \dot{\theta}_1 \dot{\theta}_2 - M_2 g L_2 \sin(\theta_1 + \theta_2) \tag{8}$$

Developing the equation (5) and (7), the dynamic model of a robotic arm with two degrees of freedom (DOF) is given by the following formula [15]:

$$\left\{ \begin{array}{l} M(\theta)\ddot{\theta} + \dot{C}(\theta, \dot{\theta}) + G(\theta) = \tau \\ Y = \theta \end{array} \right\} \tag{9}$$

Where:

$\theta = [\theta_1 \theta_2]^T$ is a joint variable vector;

$\tau = [\tau_1 \tau_2]^T$ is torque vector (control input);

Y is the output vector;

$$G(\theta) = \begin{bmatrix} -(M_1 + M_2) g L_1 \sin(\theta_1) - M_2 g L_2 \sin(\theta_1 + \theta_2) \\ - M_2 g L_2 \sin(\theta_1 + \theta_2) \end{bmatrix}$$

is a vector of gravity torquing;

$$C(\theta, \dot{\theta}) = \begin{bmatrix} -M_2 L_1 L_2 (2\dot{\theta}_1 \dot{\theta}_2 + \dot{\theta}_1^2) \sin(\theta_2) \\ -M_2 L_1 L_2 \sin(\theta_2) \dot{\theta}_1 \dot{\theta}_2 \end{bmatrix}$$

$M(\theta) = \begin{bmatrix} D_1 & D_2 \\ D_3 & D_4 \end{bmatrix}$ is the inertia matrix;

With:

$$D_1 = (M_1 + M_2)L_1^2 + M_2L_2^2 + 2M_2L_1L_2 \cos(\theta_2)$$

$$D_2 = M_2L_2^2 + M_2L_1L_2 \cos(\theta_2)$$

$$D_3 = D_2$$

$$D_4 = M_2L_2^2$$

III. CONTROLLER DESIGN

In this section, linearize the dynamic model (9) using feedback linearization technique. Model Predictive Control is designed for the developed the linearized dynamic model.

a. Feedback Linearization

The nonlinear dynamics of the system can be linearized using feedback linearization technique. [15]

Differentiate the output Y until the control input τ appears. In our case, the control input τ appears in the second derivative of the output Y. This implies that the relative degree is equal to two. The second derivative of Y is given by the following formula:

$$\ddot{Y} = \ddot{\theta} = M(\theta)^{-1}(-C(\theta, \dot{\theta}) - G(\theta) + \tau) = v \tag{10}$$

Where:

$$V = [v_1 v_2]^T \text{ is a synthetic control vector.}$$

The feedback linearization control law is obtained from eqn.(10)

$$\tau = M(\theta)v + C(\theta, \dot{\theta}) + G(\theta) \tag{11}$$

Applying the control law (10) to the nonlinear system (9), the dynamic model of the manipulator robot with two DOF, becomes a linear system double integrator. Hence, the system behaves as second order system. By using the control law (11), we obtain a complete linearization of the nonlinear system (9) and we get a linear system for each joint variable

$$\frac{\theta_1(p)}{v_1(p)} = \frac{1}{s^2} \text{ and } \frac{\theta_2(p)}{v_2(p)} = \frac{1}{s^2} \tag{12}$$

Where s is a Laplace variable

b. Model Predictive Control

In this, we propose a Model Predictive Control for the dynamic model associated with the second-order system. MPC is an advanced control technique that can be implemented in many ways, depends on the models used. Dynamic Matrix Control is one of the algorithms used in this paper.

(i) Dynamic Matrix Control

DMC was developed by Shell Oil Company, based on a step response model. The step response model is given below in the form.[17]

$$\hat{y}_k = S_1 \Delta u_{k-1} + S_2 \Delta u_{k-2} + \dots + S_1 \Delta u_{k-N+1} + S_N \Delta u_{k-N} \quad (13)$$

Which is written in the form

$$\hat{y}_k = \sum_{i=1}^{N-1} S_i \Delta u_{k-i} + S_N u_{k-N} \quad (14)$$

Where

k -the model prediction at a timestep

u_{k-N} is the manipulated input N steps in the past.

The model-predicted output is unlikely to be equal to the actual measured output at time step k . The difference between the measured output (y_k) and the model prediction is called the additive disturbance.

$$d_k = y_k - \hat{y}_k \quad (15)$$

$$\hat{y}_k = \hat{y}_k + d_k$$

The corrected predicted output at the first-time step in the future can be written as

$$\hat{y}_{k+1}^c = \hat{y}_{k+1} + \hat{d}_{k+1} + y \quad (16)$$

$$\hat{y}_{k+1}^c = \sum_{i=1}^{N-1} S_i \Delta u_{k-i} + S_N u_{k-N} + \hat{d}_{k+1} \quad (17)$$

$$\hat{y}_{k+1}^c = S_1 \Delta u_k + \sum_{i=2}^{N-1} S_i \Delta u_{k-i} + S_N u_{k-N} + \hat{d}_{k+1} \quad (18)$$

So, for the j th step into the future, we find

$$\hat{y}_{k+j}^c = \hat{y}_{k+j} + \hat{d}_{k+j} \quad (19)$$

$$\hat{y}_{k+j}^c = \underbrace{\sum_{i=1}^j S_i \Delta u_{k-i+j}}_{\text{effect of future control moves}} + \underbrace{\sum_{i=1}^{N-1} S_i \Delta u_{k-i} + S_N u_{k-N+j}}_{\text{effect of past control moves}} + \underbrace{\hat{d}_{k+j}}_{\text{correction term}} \quad (20)$$

Separate the effects of past and future control moves

$$\begin{aligned} \hat{y}_{k+j}^c &= S_1 \Delta u_{k+j-1} + S_1 \Delta u_{k+j-2} + \dots + S_1 \Delta u_k \{ \text{effect of current and future moves} \\ &\quad + S_N u_{k-N+j} + S_{j+1} \Delta u_{k-1} + S_{j+2} \Delta u_{k-2} \{ \text{effect of past moves} \\ &\quad + \dots + S_{-(N-1)} \Delta u_{-(k-N+j+1)} \{ \text{effect of past moves} \\ &\quad + \hat{d}_{k+j} \{ \text{correction term} \quad (21) \end{aligned}$$

The correction term is constant in the future.

$$\hat{d}_{k+j} = \hat{d}_{k+j-1} = \dots = d_k = y_k - \hat{y}_k \quad (22)$$

There are no control moves beyond the control horizon of M steps, so

$$\Delta u_{k+M} = \Delta u_{k+M+1} = \dots = \Delta u_{k-p-1} = 0 \quad (23)$$

Prediction horizon of P steps and a control horizon of M steps, yields

$$\underbrace{\begin{bmatrix} \hat{y}_{k+1}^c \\ \hat{y}_{k+2}^c \\ \vdots \\ \hat{y}_{k+j}^c \\ \vdots \\ \hat{y}_{k+P}^c \end{bmatrix}}_{\substack{P \times 1 \\ \text{Corrected output} \\ \text{predictions,}}} = \begin{bmatrix} s_1 & 0 & 0 & \dots & 0 & 0 \\ s_2 & s_1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ s_j & s_{j-1} & s_{j-2} & \dots & \dots & s_{j-M+1} \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ s_P & s_{P-1} & s_{P-2} & \dots & \dots & s_{j-M+1} \end{bmatrix} \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \Delta u_{k+M-2} \\ \Delta u_{k+M-1} \end{bmatrix}$$

$$+ \begin{bmatrix} s_1 & 0 & 0 & \dots & 0 & 0 \\ s_2 & s_1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ s_j & s_{j-1} & s_{j-2} & \dots & \dots & s_{j-M+1} \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ s_P & s_{P-1} & s_{P-2} & \dots & \dots & s_{j-M+1} \end{bmatrix} \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \Delta u_{k+M-2} \\ \Delta u_{k+M-1} \end{bmatrix}$$

$$+ \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \Delta u_{k+M-2} \\ \Delta u_{k+M-1} \end{bmatrix} + \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \Delta u_{k+M-2} \\ \Delta u_{k+M-1} \end{bmatrix} \quad (24)$$

using matrix-vector notation in (21).

$$\hat{y}_{corrected\ predicted\ output}^c = \underbrace{S_f \Delta u_f}_{\text{effect of current and future moves}} + \underbrace{S_{past} \Delta u_{past} + S_N u_P}_{\text{effect of past moves}} + \underbrace{\hat{d}}_{\text{predicted disturbances}} \quad (25)$$

The above equation (25) corrected-predicted output response is naturally composed of a "forced response" and a "free response" (the output changes that are predicted if there are no future control moves).

The difference between the setpoint trajectory, r, and the future predictions can be written

$$r - \hat{y}_{corrected\ predicted\ Error.E^c}^c = r - \underbrace{[S_{past} \Delta u_P + S_N u_P + \hat{d}]}_{\text{Unforced error (if no current future control moves were made), E}} - S_f \Delta u_f \quad (26)$$

$$E^c = E - S_f \Delta u_f \quad (27)$$

Least square function is as follows

$$\Phi = \sum_{i=1}^P (e_{k+i}^c)^2 + w \sum_{i=0}^{M-1} (\Delta u_{k+i})^2 \quad (28)$$

$$\sum_{i=1}^P (e_{k+i}^c)^2 = [e_{k+1}^c \ e_{k+2}^c \ \dots \ e_{k+p}^c] \begin{bmatrix} e_{k+1}^c \\ e_{k+2}^c \\ \vdots \\ e_{k+p}^c \end{bmatrix} \quad (29)$$

$$= (E^c)^T E^c \quad (30)$$

$$w \sum_{i=0}^{M-1} (\Delta u_{k+i})^2 = w \cdot [\Delta u_k \ \Delta u_{k+1} \ \dots \ \Delta u_{k+M-1}] \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \Delta u_{k+M-1} \end{bmatrix} \quad (31)$$

$$= w \cdot [\Delta u_k \ \Delta u_{k+1} \ \dots \ \Delta u_{k+M-1}] \begin{bmatrix} w & 0 & 0 & 0 \\ 0 & w & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & w \end{bmatrix} \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \Delta u_{k+M-1} \end{bmatrix}$$

$$= \Delta u_f^T W \Delta u_f \quad (32)$$

$$\emptyset = (E^c)^T E^c + (\Delta u_k)^T W \Delta u_f \quad (33)$$

$$\emptyset = (E - S_f \Delta u_f)^T (E - S_f \Delta u_f + (\Delta u_f)^T W \Delta u_f) \quad (34)$$

$$\Delta u_f = \underbrace{(S_f^T S_f + W)^{-1} S_f^T}_k \underbrace{E}_{unforced\ errors} \quad (35)$$

Unforced error vector (E) is proportional to the current and future control move vector (Δu_f). Controller gain matrix, K , multiplies the unforced error vector.

Current control move is implemented as

$$\Delta u_k = K_1 E \quad (36)$$

$$K = (S_f^T S_f + W)^{-1} S_f^T \quad (37)$$

where K_1 represents the first row of the K matrix.

IV. Simulation Results

For controller design, after modeling and linearization of the manipulator system has double integration present in torque equation. Hence the robot arm two DOF is considered as a second-order system. The ultimate aim of the proposed work is to control torque in the joint of manipulator.

A standard second-order transfer function model is given as $G(s) = \frac{\omega_n^2}{s^2 + 2\epsilon\omega_n s + \omega_n^2}$. (38)

Generally, the velocity of a manipulator is very slow in some applications like movement in the water.

The behavior of the second-order system depends on the ω_n and ϵ . Based on the velocity of the manipulator, the settling time of the system response gets changed.

For the required settling time in a certain application, the value of ω_n is computed from the known value of ε . In this project, the settling time of the system is considered as 3 seconds. The value of ε is chosen as 1 where the system is said to be critically damped. The critically damped system shows a better response without oscillating in nature. So, the reference model as $G_m(s) = \frac{1.78}{s^2 + 2.66s + 1.78}$

Figure 2 and 3 shows the PID controller of the desired response of the system. In case some of the application position control of robot manipulator can be very precisely and quickly. And also controlling time can be varied on different occasion in the process. So that we have to modify the system parameters is a complicated one. Instead of modifying the system parameters to reach the desired response, we can easily vary the control method. By DMC control by varying the tuning parameters to desired response at various settling time.

Figure 4 shows the DMC controller for the same system parameters but the performance characteristics of the system are changed, that is settling time of the system response gets changed. So, the cost of the system design at various performance can be neglected, hence the cost of the single design is less to meet the different performance with one system. Change of system parameter is difficult, once system is designed.

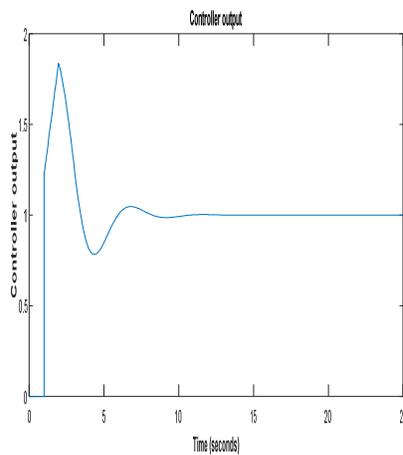


Fig:2 Controller output-PID

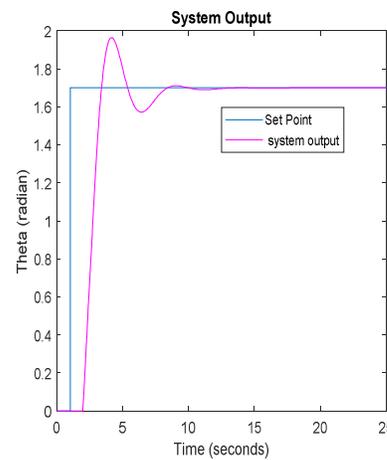


Fig:3 System Output-PID

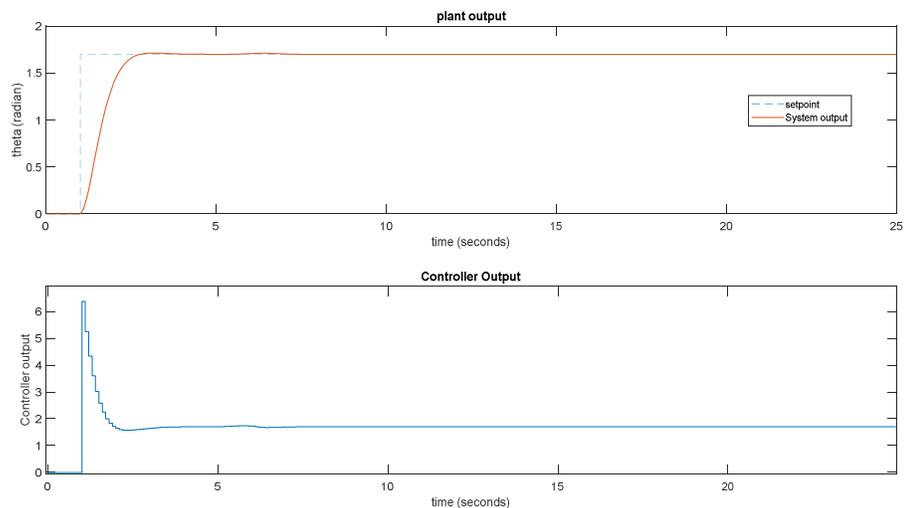


Fig:4 DMC system output and Controller output.

V. Conclusion

Controller	Settling Time in seconds
PID	12
DMC	3

Hence the settling time of the system responses gets changed when the DMC control is used instead of a PID controller. This saves the cost of system design, with simple changes in the type of controller. The performance of the DMC is better than the conventional PID controller.

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