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# The comprehensive study of control optimization system with Model Predictive Control (MPC) for the plant of Multi Input Single Output (MISO)

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***Abstract***- For the predictive controller's performance to be high, accurate modeling is required. The Predictive Control Model (MPC) or Predicted Control Model (PCM) is the optimal choice. In this research, we use a Predicted Control Model to zero in on the optimal control configuration for a plant with multiple inputs and a single output (MISO). Using the linear time invariant Mismatch technique and character arrays storing the control actions given by the MPC optimal control system, the impact of modifications to the Kalman amplifier state estimator may be studied. The study is carried out in MATLAB, and the experimental results demonstrate that modifying the Kalman amplifier yields a more organized graph compared to the MPC Controller and various times(t) with varying constraints(u) supplied by linear time invariant functions..

**Keywords** — Predictive Control Model(MPC),Control Optimization system, Multi Input Single Output (MISO),Plan,Mismatch method,Kalman amplifier, linear time invariant

## 1. Introduction

In the era of the 4.0 revolution in industry, it is no longer possible to turn back the clock on technological progress. Everyone is racing to incorporate new technologies into their everyday routines and stay current of emerging technologies so they can stay competitive.Innovations in technology have an impact on the long-term viability of human endeavors. These changes have led to what is known as Automation[1]. In fact, managing a system boils down to a series of calculations. In the industrialized world, this is felt often. Companies now use automated operating systems to keep up with the times, and this feeling of being under control of the system permeates people's everyday routines[2]. The role of control system is to maintain the stability of a plant in line with objective goals, reduce mistakes, and increase system performance. The Predicted Control Model (MPC) is a state-of-the-art technique for controlling a process such that it operates within a given set of limitations. The process industries have been making use of it since the 1980s [3]. One of the most prominent methods of process control investigated in recent times is the Predicted Control Model (MPC), which is a synthesis of many technologies used to foretell future control actions and control routes based on the knowledge of existing input and output variables and expected control signals. It may be claimed that the MPC method is based on the explicit use of a process model and process metrics to create values for process inputs as a solution to an online optimization problem (in time real) to anticipate the future behavior of the process[4].
To do this, MPC solves an online optimization algorithm to determine the best course of action to take in order to get the predicted output closer to the reference. It's capable of handling MIMO systems, including those with feedback loops between inputs and outputs. It also has the capability of controlling access and egress. By incorporating future reference information into the control issue, MPC may enhance the controller's performance[5,6]. MPC provides preview capabilities. The MPC model is a kind of control that relies on foresight to direct action [7,8]. To produce an optimum control rule, MPC relies on long-term prediction of the process's output to set a minimum goal for one or more of the function criteria [10,11]. MPC employs the same cost function as LQR, namely the quadratic cost function, but its design approaches vary based on the dynamic model of the process, the process or measurement noise, and the cost function that has to be minimized [12,13,14]. Based on this cost function, MPC generates optimum input control for some time to come (prediction result), but only the present input control is applied to the installation. Up next: a cost-benefit analysis1.The procedure is run again, but this time the current set of input controls is used. MPC is helpful since it considers the limitations of both input and output values [15]. In this study, we'll talk about using MPC to optimize control systems for MISO plants.

## 2. Basic structure and circuit model of MPC

Traditional feedback controllers work by adjusting the control action in response to a change in the output set point of a system[15]. Model Predictive Control (MPC) is a technique that focuses on building controllers capable of adjusting the control action before a change in the output set point actually occurs [16]. This predictive ability, when combined with traditional feedback operation, allows a controller to make adjustments that are smoother and closer to optimal control action values. Fig 1 shows the basic structure of MPC and Fig 2 shows its circuit model.

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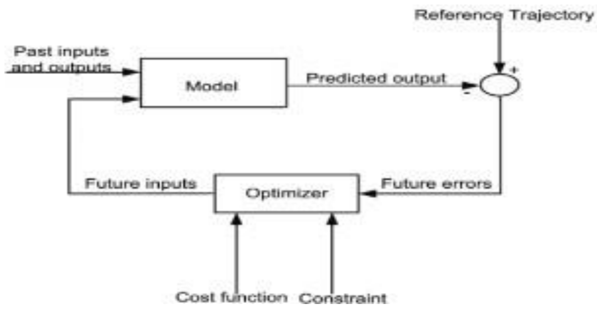


Fig1. basic structure of MPC

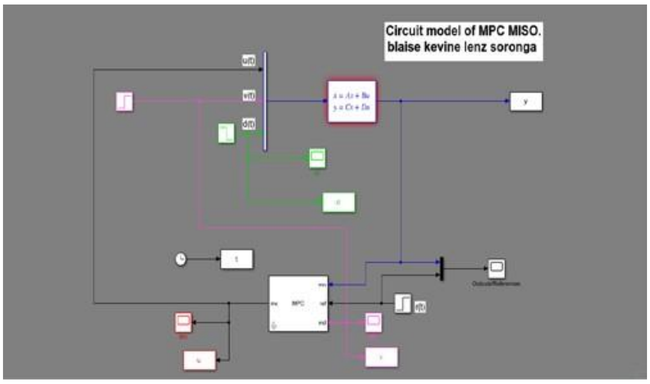


Fig2. Circuit model of MPC MISO

The plant input signals u(t), v(t), and d(t) represent the manipulated variable, measured input disturbance, and unmeasured input disturbance, respectively, while y(t) is the measured output. The block parameters are the matrices forming the state-space realization of the continuous-time plant, and the initial conditions for the five states. MISO is an antenna technology for wireless communication where multiple antennas are used at the source. Antennas are combined to minimize errors and optimize data.

### 3. Analysis and discussion

The design of this control system is made with an MPC which has one measured output and 3 inputs, namely onemanipulated variable (MV), one measured disturbance (MD), and one unmeasured disturbance (UD). The sytem is a closed loop and simulated via Matlab. In this study, the system used has inputs and output of 3 and 1 respectively. The state space ofthe system in this study can be written with equation (1)

sys = ss(tf({1,1.2,1.3},{[1 .5 1.3],[1 1.3],[0.9 0.7 1.3]}))     (1)

The system is taken from input 1 to output can be written with the equation(2)

$$G(s) = \frac{1}{s^2+0.5s+1.3} \qquad (2)$$

While the system arises from input 2 to output can be obtained with the equation (3).

$$G(s) = \frac{1}{s+1.3} \qquad (3)$$

Whereas the system from input 3 to output can be presented with the equation (4).

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$$G(s) = \frac{1}{0.9s^2+0.7s+1.3} \quad (4)$$

```
From input 1 to output:
         1
 -----------------
 s^2 + 0.5 s + 1.3

 From input 2 to output:
   1.2
 -------
 s + 1.3

 From input 3 to output:
           1.3
 ---------------------
 0.9 s^2 + 0.7 s + 1.3

Continuous-time transfer function.
```

Then using the state space function (ss) in matlab software, the transfer function of 1x3 can be transformed into the state space model. Via the script of sys = ss (sys) in matlab command window, we can get the following matrices of A, B, C and D. Fig 3, shows the command result.

```
Command Window
  >> sys = ss(tf({1,1.2,1.3},{[1 .5 1.3],[1 1.3],[0.9 0.7 1.3]}))

  sys =

    A =
              x1       x2       x3       x4       x5
     x1     -0.5     -1.3        0        0        0
     x2        1        0        0        0        0
     x3        0        0     -1.3        0        0
     x4        0        0        0  -0.7778   -1.444
     x5        0        0        0        1        0

    B =
         u1  u2  u3
     x1   1   0   0
     x2   0   0   0
     x3   0   1   0
     x4   0   0   1
     x5   0   0   0

    C =
            x1     x2     x3     x4     x5
     y1      0      1    1.2      0  1.444

    D =
         u1  u2  u3
     y1   0   0   0

fx Continuous-time state-space model.
```

Fig.3 the command window result

The simulation of Closed-Loop Response of our optimal control system with MPC with Model Mismatch, gives us the performances for input and output that can be seen in Figure 4 and Figure 5 respectively.

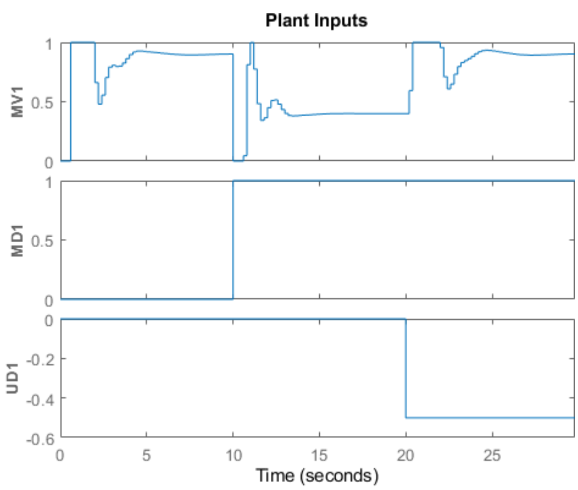


Figure 4 input performances

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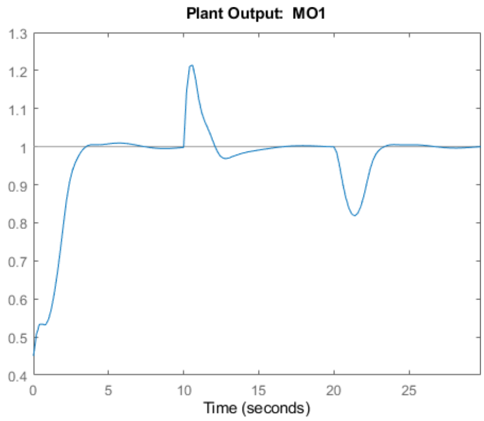


Figure 5 output performaces.

The Kalman amplifier is used to estimate the conditions, disturbances and noise that produces in a model being worked on. This is pre-existing data,by changing the Kalman amplifier and at each time step, the MPC controller calculates the manipulated variable by solving a constrained quadratic optimization problem which depends on the current state of the installation. Since plant condition is often not directly measurable, the controller defaults to a linear Kalman filter as an observer to estimate plant condition and disturbance and noise models. Therefore, the states of the controller are the states of this Kalman filter, which in turn are the estimates of the states of the increased discrete time plant. Figure 6 shows the output response that have been estimated by the default observer.

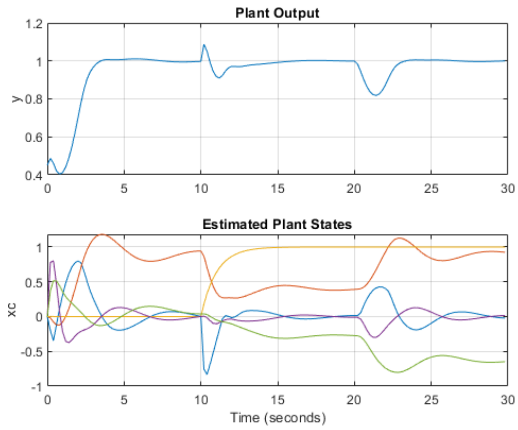


Fig 6 output response that have been estimated by the default observer.

The MPC controller may be thought of as behaving like a linear controller in the absence of restrictions. Keep in mind that the optimum feedback gain changes with time for a finite-time unconstrained linear quadratic regulator issue with a non-leaking finite horizon, since the value function is time sensitive. On the other hand, MPC's constantly retreating horizon ensures a constant value function and, hence, a time-invariant feedback gain. Closed-loop simulation results with no controller limitations are shown in Figures 7 and 8, while the corresponding character arrays for these actions are shown below.

| t (time) | u (Constraints in the inputs) | Provided by |
|---|---|---|
| 0.00 | 5.2478 | LTI |
| 0.20 | 3.0134 | LTI |
| 0.40 | 0.2281 | LTI |
| 0.60 | -0.9952 | LTI |
| 0.80 | -0.8749 | LTI |
| 1.00 | -0.2022 | LTI |

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| | | |
|---|---|---|
| 1.20 | 0.4459 | LTI |
| 1.40 | 0.8489 | LTI |
| 1.80 | 1.0511 | LTI |
| 2.00 | 1.0304 | LTI |
| 2.20 | 1.0053 | LTI |
| 2.40 | 0.9920 | LTI |
| 2.60 | 0.9896 | LTI |
| 2.80 | 0.9925 | LTI |
| 3.00 | 0.9964 | LTI |
| 3.20 | 0.9990 | LTI |
| 3.40 | 1.0002 | LTI |
| 3.60 | 1.0003 | LTI |
| 3.80 | 1.0004 | LTI |
| 4.00 | 1.0001 | LTI |
| 4.20 | 1.0000 | LTI |
| 4.40 | 0.9999 | LTI |
| 4.60 | 1.0000 | LTI |
| 4.80 | 1.0000 | LTI |

Table- character arrays containing the control actions

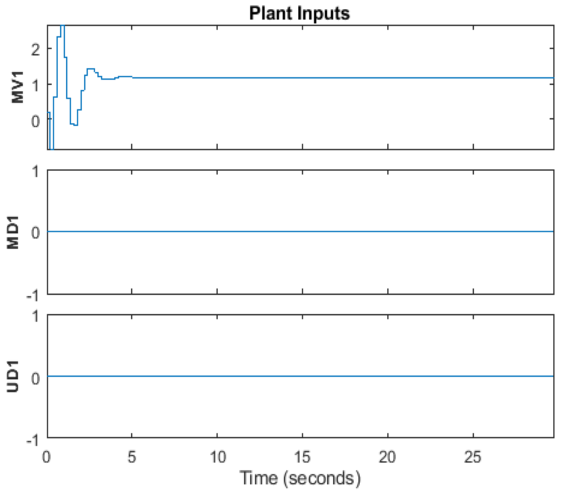


Figure 7 input performance with zero constraints

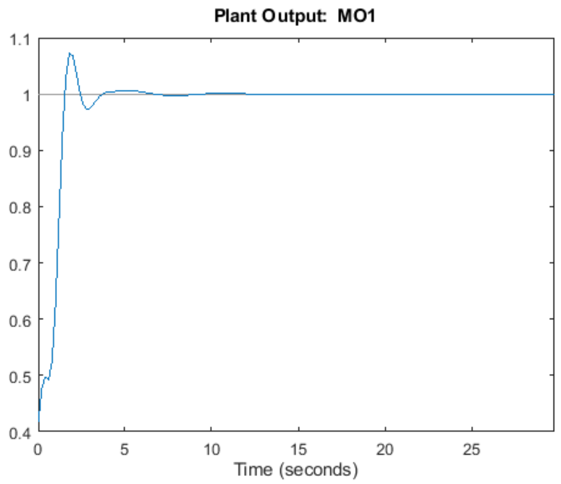

Fig.8 Output performance with zero constraints

## 4. Conclusion

In this research, an MPC control optimization system was shown, in which numerous inputs fed into a single output. The outcomes of a process in progress may be forecasted using MPC control. Errors in a process may be greatly reduced with the use of this. The Kalman filter allows for more orderly forecasting of outcomes. Without the presence of restrictions, an MPC controller operates similarly to a linear controller.To estimate plant condition and disturbance and noise models, we can see that the controller uses a linear Kalman filter by default as an observer. The states of the controller are the states of this Kalman filter, which are estimates of the states of the extended discrete time; and for a finite-time unconstrained linear quadratic regulator problem with a non-leaking finite horizon, the value function is time dependent, so the optimal feedback gain varies over time, and the result shows us different times(t) with different constraints(u) provided by LTI.

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