International Journal of Scientific Engineering and Applied Science (IJSEAS) – Volume-8, Issue-1, January 2022
ISSN: 2395-3470
www.ijseas.com

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

Blaise Kevine Lenz Soronga

* Electrical Engineering and Renewable Energy School, China Three Gorges University, 8 University Avenue, Yichang, Hubei province, China.

E-mail: blaisekevine@protonmail.com

Abstract- A modeling with a good predictive rate is necessary to create a good performance of the predictive controller . The correct and better model to use is the Predictive Control Model (MPC) or the Predicted Control Model. This study determines the control optimization system with the Predicted Control Model for the plant of Multi Input Single Output (MISO). The MPC optimal control system designed for the closed-loop Mismatch method, the effect of changes in the Kalman amplifier state estimator and the character arrays containing the control actions provided by linear time invariant with different constraint values . MATLAB is used to complete this work and the results of these experiments show that the output by changing the Kalman amplifier produces more structured graph compared to MPC Controller and different times(t) with different constraints(u) provided by linear time invariant.

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

1. Introduction

Today technology's development cannot be reneged, especially in the age of industry revolution 4.0. All parties have flocked to take advantage of technology in the course of their daily activities and to keep abreast of technological developments so as not to be left behind.Technological developments also affect the sustainability of human activities. With these developments, the world is facing with what is called Automation[1]. Come to think of it, control in a system becomes a calculation. This is felt a lot in the industrial world. Companies have changed their operating systems to be automatic in order to keep up with the age of development and the control of the system is also felt in the daily life of people[2]. The function of control system is to maintain the stability of a plant in accordance with target goals, minimize errors, and improve system performance. Predicted Control Model (MPC) is an advanced method of process control that is used to control a process while satisfying a set of constraints. It has been used in the process industries since the 1980s [3]. Predicted control Model (MPC) is one of the main process control techniques explored in the recent past; it is the fusion of different technologies used to predict future control action and future control paths knowing the current input and output variables and future control signals. It can be said that the MPC scheme is based on the explicit use of a process model and process metrics to generate values for process inputs as a solution to an online optimization problem (in time real) to predict the future behavior of the process[4].
MPC uses a model of the system to make predictions about the future behavior of the system and solves an online optimization algorithm to find the optimal control action that directs the expected output to the reference. It can manage multi-input multi-output systems which can have interactions between their inputs and their outputs. It can also manage entry and exit constraints. MPC has preview capability; it can incorporate future reference information into the control problem to improve the performance of the controller[5,6]. The MPC model is a control system that uses predictive results to issue input controls [7,8]. The basic concept of MPC is the use of long-term prediction of the output of the process to make a minimal target for one or more of the function criteria in order to obtain an optimal control law [10,11]. There are different design methodologies of MPC depending on the dynamic model of the process, the process or measurement noise, and the cost function that needs to be minimized and MPC uses the same cost function as LQR, namely the quadratic cost function [12,13,14]. Based on this cost function, MPC produces optimal input control for some time to come (prediction result), but only the current input control is applied to the installation. Next time, the cost-based calculation1.The function is repeated and only the current input controls are applied, and so on. One of the advantages of MPC is that this technique takes into account the constraints of input and output values [15]. In this paper we will discuss the control optimization system with MPC for plant Multi Input Single Output (MISO).

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.

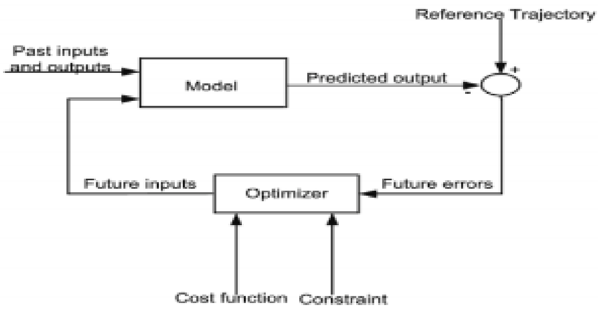

Fig1. basic structure of MPC

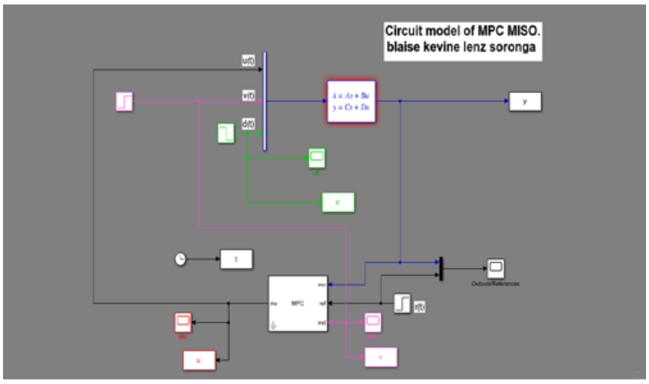

Fig2. Circuit model of MPC MISO

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 one manipulated 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 of the 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).

```
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.
```

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

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

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.

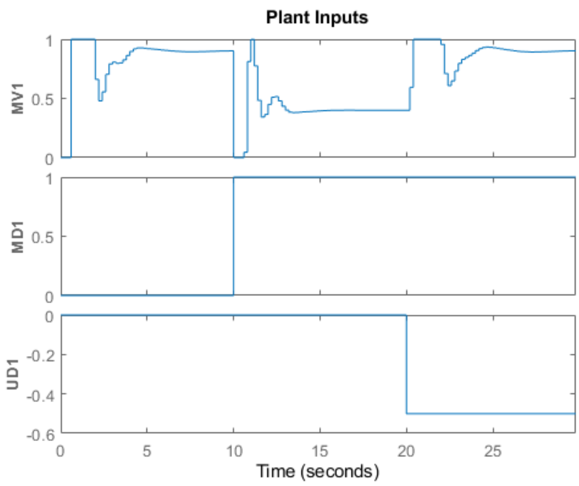

Figure 4 input performances

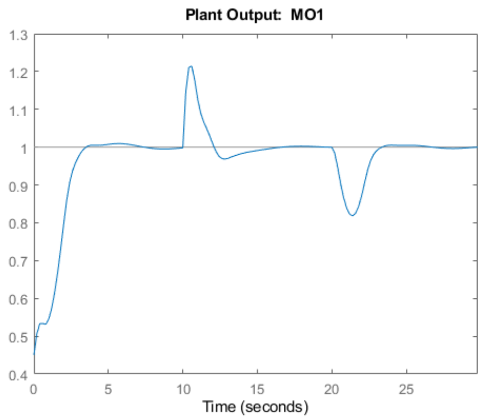

Figure 5 output performaces.

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.

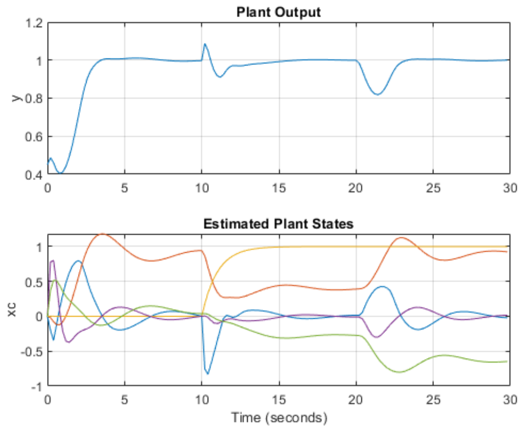

Fig 6 output response that have been estimated by the default observer.

By considering this case when constraints are not active, the MPC controller behaves like a linear controller. Note that 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. In contrast, in MPC the horizon has a constant length because it is always receding, resulting in a time invariant value function and hence an optimal time invariant feedback gain. The following table present the character arrays containing the control actions provided by linear time invariant and Fig 7 ,Fig 8 present respectively the closed-loop simulation result in which all controller constraints are turned off .

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

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

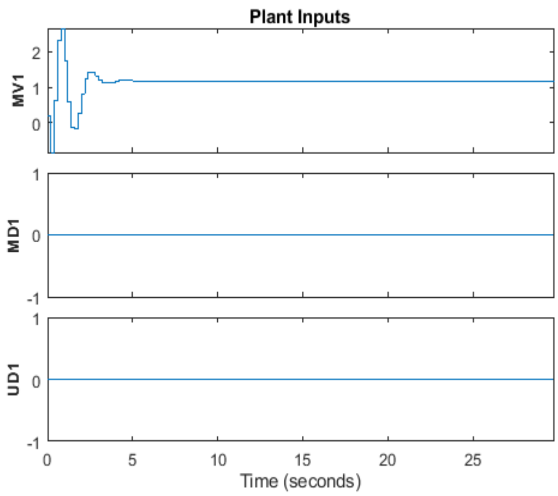

Figure 7 input performance with zero constraints

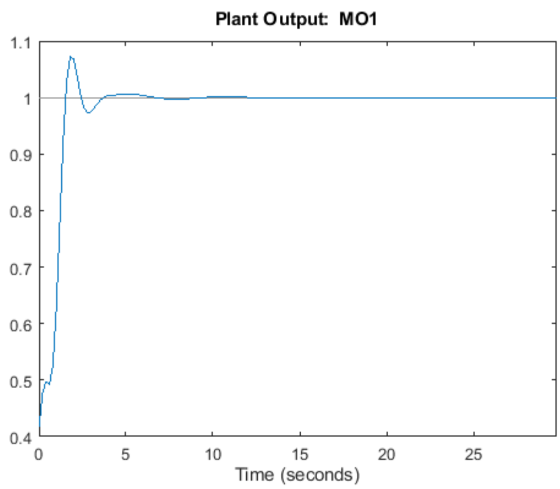

Fig.8 Output performance with zero constraints

4. Conclusion

This study showed the application of MPC control optimization system with multiple inputs and single output. MPC control can predict the results of an ongoing process. This is very useful in order to minimize errors during a process. With the Kalman filter, the results can be predicted in a more structured way. When there is not any activiness of constraints ,MPC controller behaves like a linear controller.we can also see that 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 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.

References

[1] Liping F, Zhang J, Huang X, Huang D. 2012. The design of the MISO Model Predictive Controller for Bioreactor. TELKOMNIKA.10(6). 1163-1170

[2] Nur H, Fatchul A, Dessy I, Muslikhin, Zainal A. (2017). Teaching Aid For Diagnosing Motorcycle Damages Using Back Propagation Artificial Neural Network. Jurnal Pendidikan Teknologi dan Kejuruan (JPTK), 26(2).

[3] Michèle Arnold, Göran Andersson. "Model Predictive Control of energy storage including uncertain forecasts" https://www.pscc-central.org/uploads/tx_ethpublications/fp292.pdf.

[4] Ohtsuka, Toshiyuki (2004). "A continuation/GMRES method for fast computation of nonlinear receding horizon control". Automatica. 40 (4): 563–574. doi:10.1016/j.automatica.2003.11.005.

[5] Ali D, Jalel G, Hassani M. 2007. Robust Predictive Control using a GOBF Model for MISO Systems. International Journal of Computers, Communications & Control. II(4): 355-366. C.Ekanayake, S.M. Gubanski, K.D.Mularachchi and M.A.R.M. Fernando, "Diagnostic of power K.D.Mularachchi and M.A.R.M. Fernando, "Diagnostic of power transformers in Sri Lanka application of dielectric spectroscopy in frequency domain"in Proc. Electrical Insulation Conference and Electrical Manufacturing and Coil Winding Conference, Cincinnati, 2001, pp.593-596..

[6] Serela G, Fiorentini M, Capozzoli A, Bernardini D. 2018. Model Predictive Control (MPC) for EnhancingBuilding and HVAC System Energy Efficiency:Problem Formulation, Applicationsand Opportunities. Energi. 11(631): 1-35.

[7] Khairudin M,Mohamed Z, Husain AR. 2011. Dynamic model and robust control of flexible link robot manipulator. Telkomnika 9 (2) ,pp.279. **[8]** Rawlings JB, Mayne DQ, Diehl MM. 2019. Model Predictive Control:Theory, Computation, and Design. Nob Hill Publishing. LLC.

[9] Nwobi CC., Stanley O, Anthony CI. 2016. Performance evaluation of Multi Input Single Output (MISO) production process using transfer function and fuzzy logic: case study of a brewery. Ain Shams Engineering Journal. 7 (3) : 1001-1010.

[10] Khairudin, M.,Wijaya, H.A.,Muslikhin. 2020. Converter matlab fuzzy inference to arduino Csystem. Journal of Physics: Conference Series 1456 (1)

[11] Azagra JR, Martinex MG, Elso J. 2014. Quantitative Feedback Control of Multiple Input Single Output Systems. Mathematical Problems in Engineering. 2014.

[12] Shun Y, Smith R, Hwang S. 2020. Development of model predictive control system using an artificial neural network: A case study with a distillation column. Journal of Cleaner Production. 277.

[13] Gango D, T. P´eni, R. Toth. 2019. Learning based approximate Model Predictive Control for nonlinier system. IFAC- PapersOnLine. 52 (28) : 152-157.

[14] Nelson JR, Johnson NG. 2020. Model predictive control of microgrids for real-time ancillary service market participation. Applied Energy. 269. **[15]** Dou T, Lopes YK, Rockett P. 2020. Model predictive control of non-domestic heating using genetic programming dynamic models. Applied Soft Computing. Properties and Applications of Dielectric Materials, Xi¡¯an,2000, vol.2, pp.825-830.

[16]https://www.halvorsen.blog/documents/tutorials/resources/Model%20Predictive%20Control%20in%20LabVIEW.pdf.

Blaise Kevine Lenz Soronga, born in DR. Congo**,** currently he is B.S student in China Three Gorges University, Yichang, China.