

# Optimization of a Quadruple Fire Fighting Reservoir System Using Model Predictive Control

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## **ABSTRACT**

This work does an extensive exhibition investigation of Model Prescient Regulator (MPC) for a changed variant of benchmark of a Quadruple Firefighting Reservoir System which is a Multi-Input Multi-Output (MIMO), exceptionally nonlinear coupled framework. The goal is to control the foam concentrate level of Quadruple Reservoir Framework with the Optimization of objective cost function of system error while satisfying input amplitude constraints. Simulation have been carried out with MATLAB R2018A and results are reasonably contrasted with PI and LQR regulators. Results broadcast that the unified MPC with an adequately huge expectation skyline and prediction horizon is better choice when compared with decentralized PI and incorporated LQR regulator as it measures the deficiency of execution and loss of performance due to the linear nature of the prediction model. The Nonlinear model of the Quadruple Reservoir System is linearized and a check for controllability and observability is carried out for both operating conditions I.e. Minimum and Non-minimum phase systems using MATLAB.

## **INTRODUCTION**

Genuine modern practices are truly challenging to control since they may possess time delays, strong interaction among the variables and non-minimum phase dynamics [1]. Control of such frameworks is done either by centralized, or decentralized/decoupled techniques. In completely decentralized control, the MIMO system is approximated as a set of independent SISO systems. When applicable, the advantage of completely decentralized control is that one can apply the simpler SISO theory on complex MIMO systems [2], [3]. Appropriateness of this guess relies upon the disregarded collaboration elements, which can be seen as demonstrating blunders, heartiness investigation can be applied to decide their effect. Odds of coming out on top are expanded by wisely matching inputs and outputs by using Relative Gain

Array (RGA) or feed forward techniques [4]. Feedforward is often a very effective tool for MIMO systems. Interactions are then thought of as disturbances; this is an approximation, because the interactions involve feedback, whereas disturbance analysis presumes disturbances to be independent inputs. Some MIMO problems can be better treated as SISO problems if a pre-compensator is first used. When complex MIMO systems are decoupled, obviously the degree of interaction among the

# ARTICLE INFO

Article History Received: June, 2022 Received in revised form: August, 2022 Accepted: November, 2022 Published online: December, 2022

#### **KEYWORDS**

Quadruple, Fire, Fighting, Reservoir, Preventive

variables decreases significantly [5], [6]. Although, a simpler SISO control theory can easily be applied to the decoupled MIMO systems but control engineer has to compromise with the desired performance which in many cases may not be acceptable [7], [8]. Beside decoupled control, there are several other ways to quantify interactions in multivariable systems including their structure and their strength. Interactions can have a completely general structure (every input potentially affects every output) or display patterns, such as triangular or dominant diagonal; they can also display frequency-dependent patterns, such as being statistically coupled or band-decoupled. The lower the strength of interaction, the more nearly a system behaves like a set of independent systems that can be analyzed and controlled separately [8]. Weak coupling can be due to the nature of the interacting dynamics or to a separation in frequency range or time scale. The stronger the interaction, the more important it becomes to view the MIMO system and its interactions.

Sliding Mode Control (SMC) is an advanced, centralized and nonlinear control method that alters the dynamics of a nonlinear system by application of a discontinuous control signal that forces the system to slide along a cross-section of the system's normal behavior. Despite of the practical benefits it offers the drawback of undesirable oscillations with finite amplitude and frequency. This

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destructive phenomenon, so called 'chattering', may lower control accuracy or incur unwanted wear of mechanical components. Furthermore, Linear Quadratic Regulator (LQR) is also an advance controller that falls under the class of optimal control strategies [9]. The theory of optimal control is concerned with operating a dynamic system at minimum objective function. The case where the system dynamics are described by a set of linear differential equations and the cost is described by a quadratic function is called the LQ problem [10], [11]. Although, LQR is an optimal controller which like Model Predictive Controller (MPC) calculates the control signal also by minimizing an objective function. But the main difference between the working schemes, thus in the performance of LQR and MPC lies in the fact that MPC in addition to the minimization of an objective function, calculates the control signal while considering the predicted future behavior of the process to be controlled [12]. Therefore, MPC performs better than LQR [13-15]. MPC has been utilized for a very long time, and has been acknowledged as a significant apparatus in many cycle industry applications due to the benefits it offers over customary regulators, for example, the basic treatment of multivariable cycles and the capacity to deal with requirements on the state factors and the signs [16]. It is a high level control structure which decides a webbased answer for an improvement issue which goes with it a characteristic decision for MIMO nonlinear coupled frameworks which have requirements among factors. As its name infers, MPC utilizes forecasts representing things to come conduct to settle on control choices. In the event that those forecasts are questionable, care should be taken to guarantee that the control activities don't prompt requirements infringement. Since the control activity relies upon tackling a compelled mathematical improvement issue, guaranteeing that a solution is essential to the enhancement issue exists. Model based strategies like entomb model regulators and dynamic network regulators have additionally been utilized for MIMO, Multivariable frameworks [14]. However, MPC is most popular and widely used controller, as it can accept models in the form of state

space representation, which reduces the computational time and complexity [16-21]. The main objective of this work is to maintain the water level of lower tanks at the reference value with minimum Mean squared error (MSE). The remainder of the paper is coordinated as follows, segment II delineates the framework depiction to be controlled. Segment III

depicts its state space model and detailing of the control conspire. Segment IV shows the comprehensive simulation studies for different controllers and lastly conclusions are drawn in the last Seament.

# SYSTEM DESCRIPTION

Because of solid connection among the variables, highly nonlinearity and non-minimum phase characteristics, the level control of Quadruple firefighting reservoir System is a complex control problem. It consists of four tanks, two pumps and a reservoir [9]. The controlled input variables are pump voltages and output are levels of lower two tanks. The outflow of each pump is divided into two tanks using split valves 1& 2. Pump-1 feeds Tank-1 and Tank-4 whereas pump-2 feeds Tank-2 and Tank-3. Tanks 3 and 4 discharges into Tanks-1 and 2 respectively while Tanks-1 and 2 discharges directly into the reservoir situated at the bottom. To increase the complexity, an additional interconnection between lower two tanks is introduced to make it more effective for firefighting as shown in Fig.1. The objective of present work is to control the water levels of lower two tanks with the optimization of objective cost function. The dynamics of the Quadruple firefighting reservoir System are described in [22]. The nominal values of parameters are given in Table 1.







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In deriving the mathematical model for the quadruple fire-fighting reservoir system from physical data, while having on mind that the target is the control of the levels in the two lower tanks. There is just one way of developing the model of the foam concentrate interaction in the 4-tank. The mathematical model of the four-tank process can be derived by using mass balances and Bernoulli's law. The mass balance for i<sup>th</sup> tanks can be written as,

 $A_i \frac{dh_i}{dt} = q_{i \text{ out}} + q_{i \text{ in}}$  Equation 1

Where q<sub>in</sub> and q<sub>out</sub> are inflow and outflow of a tank respectively that can be modeled using Bernoulli's law.  $A_i$  is the cross-section area of i<sup>th</sup> tank and the potential energy in the tank will be equal to kinetic energy of the liquid in the tank such that,

$$
mgh = \frac{1}{2}mv^2
$$
 Equation 2  
Solving above equation for gives

Solving above equation for gives,

 $v = \sqrt{2gh}$  Equation 3 Multiplying the equation (3) with an area of the outlet hole (a) of the tank gives the volumetric flow rate qout as,

$$
q_{out} = av = a\sqrt{2gh}
$$
 Equation 4  
Then the outflow of  $i^{th}$  tanks can be written as,

 $q_{out} = a_1 a_1 = a_1 \sqrt{2gh_i}$  Equation 5

The flow from pump 1 is  $k_1u_1$  that split into a flow  $q_{1in} = \gamma_1 k_1 u_1$  to the tank 1 and a flow  $q_{4in} = (1-\gamma_1)$  $\gamma_1$ )k<sub>1</sub>u<sub>1</sub> to tank 4. Similarly, the flow from the pump 2 is  $k_2u_2$  that split into a flow  $q_{2in} = \gamma_2k_2u_2$  to the tank 2 and a flow  $q_{3in} = (1-\gamma_2)k_2u_2$  to tank 3. The level measurement signals are  $k_c$  \*h<sub>i</sub>. By using equation (1) and (5) mass balance and Bernoulli's law can be extended for the quadruple firefighting reservoir system as,

$$
A_1 \frac{dh_1}{dt} = -q_{1out} + q_{3out} + q_{1in} \text{ Equation 6}
$$
\n
$$
A_2 \frac{dh_2}{dt} = -q_{2out} + q_{4out} + q_{2i} \text{ Equation 7}
$$
\n
$$
A_3 \frac{dh_3}{dt} = -q_{3out} + q_{3in} \text{ Equation 8}
$$
\n
$$
A_4 \frac{dh_4}{dt} = -q_{4out} + q_{4in} \text{ Equation 9}
$$
\nSubstituting the inflow q<sub>in</sub> and outflow q<sub>out</sub> of the tanks yield,  
\n
$$
A_1 \frac{dh_1}{dt} = -a_1 \sqrt{2gh_1} + a_3 \sqrt{2gh_3} +
$$
\n
$$
y_1 k_1 u_1 \text{Equation 10}
$$
\n
$$
A_2 \frac{dh_2}{dt} = -a_2 \sqrt{2gh_2} + a_4 \sqrt{2gh_4} +
$$
\n
$$
y_2 k_2 u_2 \text{Equation 11}
$$

$$
A_3 \frac{d h_3}{d t} = -a_3 \sqrt{2gh_3} + (1 - y_2) k_2 u_2
$$
  
Equation 12

$$
A_4 \frac{dh_4}{dt} = -a_4 \sqrt{2gh_4} + (1 \cdot y_1 k_1 u_1)
$$
  
Equation 13

The nonlinear model of the quadruple firefighting reservoir is described in above four differential equations and the parameter description is given in Table 2 below.





# LINEARIZATION OF THE QUADRUPLE FIREFIGHTING RESERVOIR NONLINEAR MODEL

The nonlinear differential equations (10) - (13) can be linearized at operating point given at the levels in the tanks hi<sup>0</sup> and  $u<sup>0</sup>$ . Considering the variables such that  $h = h_i - h_i^0$  and  $u_i = u_i - u_i^0$ . The linearized state space model is given by

$$
A_1 \frac{dh_i}{dt} = Ax + Bu
$$
  
\n
$$
y = Dx
$$
  
\n
$$
Q_1 = 0
$$
  
\n
$$
\frac{dh}{dt} =
$$
  
\n
$$
\begin{bmatrix}\n-\frac{1}{T_1} & 0 & \frac{A_3}{A_1 T_1} & 0 \\
0 & -\frac{1}{T_2} & 0 & \frac{A_4}{A_1 T_2} \\
0 & 0 & -\frac{1}{T_3} & 0 \\
0 & 0 & 0 & -\frac{1}{T_4}\n\end{bmatrix}\n\begin{bmatrix}\nh_1 \\
h_2 \\
h_3 \\
h_4\n\end{bmatrix}\n\begin{bmatrix}\n\frac{y_1 k_1}{A_1} & 0 \\
0 & \frac{y_2 k_2}{A_2} \\
0 & \frac{(1 - y_1)k_2}{A_3} \\
0 & \frac{(1 - y_1)k_1}{A_3} \\
0\n\end{bmatrix}\n\begin{bmatrix}\nu_1 \\
u_2 \\
u_3\n\end{bmatrix}
$$

 $\begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$ 

$$
y = \begin{bmatrix} k_c & 0 & 0 & 0 \\ 0 & k_2 & 0 & 0 \\ 0 & 0 & k_2 & 0 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{bmatrix}
$$

The time constant for tank I can be calculated as,

$$
T_1 = \frac{A_1}{a_1} \sqrt{2gh_1^0} \quad \text{for } l = 2, \dots 4
$$

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#### LINEAR TRANSFER FUNCTION OF THE QUADRUPLE FIREFIGHTING RESERVOIR **SYSTEM**

The linear transfer function of the quadruple firefighting reservoir system can be formulated by Laplace transform of equations (15) and (16)

 $\left[\begin{matrix} y_1(\mathcal{S}) \\ \vdots \\ y_n(\mathcal{S}) \end{matrix}\right]$  $\begin{bmatrix} y_1(S) \\ y_2(S) \end{bmatrix} = G(S), \begin{bmatrix} u_1(S) \\ u_2(S) \end{bmatrix}$  $u_2(S)$ Equation 17  $G(S) = D(sI - A^{-1}B)$ Equation 18  $G(s) = \begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{12}(s) & G_{13}(s) \end{bmatrix}$  $G_{21} (s) G_{22} (s)$ Equation 19

Substituting above terms into the equation

$$
(19), we have
$$

$$
G(s) = \begin{bmatrix} \frac{y_1 c_1}{(1 + sT_1)} & \frac{(1 - y_2)c_1}{(1 + sT_1)(1 + sT_3)} \\ \frac{(1 - y_1)c_2}{(1 + sT_2)(1 + sT_4)} & \frac{y_2 c_2}{(1 + sT_2)} \end{bmatrix} \dots \dots .20
$$

Where  $c_1$  and  $c_2$  in equation (20) are defined as,  $c_1 = T_1K_1C_1/A_1$  and  $c_2 = T_2K_2C_2/A_2$ 

According to the equations (17) and (19), the relationship between inputs and output will be as follows,

 $y_1(s)G_{11}(s)u_1 + G_{12}(s)u_2(s)$  Equation 21  $y_2(s)G_{21}(s)u_1(s) + G_{22}(s)u_2(s)$  Equation 22 It will be used for input-output pairing to see

how the change in inputs  $u_1$  or  $u_2$  affects the outputs  $y_1$ or y2.

#### MODEL PREDICTIVE CONTROLLER

MPC predicts future result values with the assistance of current and past way of behaving. It utilizes a framework model to compute an anticipated result signal over a forecast skyline later on. Another improvement is made at each control span inside the forecast skyline by taking another control info and taking care of it into the framework at each time step, while considering the constraints. This ability to handle constraints is integrated in the structure of MPC and this has made it more popular and more advantageous than other classical controllers such as PID and LQR. The structure of MPC is shown in Figure 2.

The limitation to the process are known as constraints, and MPC becomes the standard control strategy due to its constraints handling abilities. In this work, input amplitude constraints are considered, such as:

> $0 \le u_1 \le 5$  $0 \le u_2 \le 5$



#### STATE-SPACE FORMULATION OF MPC

Any linear dynamic system can be represented as,  $X_{k+1} = AX_k + Bu_k$  Equation 23  $Y_k = DX_k$  Equation 24 For  $k = k + 1$ ; where k is present time instant and  $k+1$ is one step ahead,  $Y_{k+1} = DX_{k+1}$  using Egn. (23), Egn. (24) yields,  $Y_{k+1} = D (AX_k + Bu_k)$  Equation 25  $Y_{k+1}$  = DAX<sub>k</sub> + DBu Equation 26 for  $K = K + 2$ ,  $Y_{k+2} = DAX_{k+1} + DBu_{k+1}$  $Y_{k+2}$  = DA<sup>2</sup> $X_k$  + DB<sub>uk</sub> + DB<sub>u<sub>k+1</sub>Equation 27</sub> for  $K = K + 3$ ,  $Y_{k+3} = DAX_{k+2} + DBu_{k+2}$  $Y_{k+3} = DA^3X_k$  + = DA<sup>2</sup>Bu<sub>k</sub> + DABu<sub>k+1</sub>+DBu<sub>k+2…</sub> 28  $y_{k+2}^{\kappa+1}$  $y_k$  $y_{k+1}$  $\begin{bmatrix} y_{k+2} \\ y_{k+2} \\ y_{k+3} \end{bmatrix} = \begin{bmatrix} y_{k+1} \\ y_{k+2} \\ y_{k+3} \end{bmatrix}$ D DA  $DA^2$  $D_A^3$  $x_k$  +  $\mathsf{I}$ 0 0 0 DB 0 0<br>DAB DB 0  $\begin{bmatrix} DAB & DB & 0 \\ DA^2B & DAB & DB \end{bmatrix}$  $\begin{bmatrix} 0 & 0 & 0 \ DB & 0 & 0 \ DA^2B & DAB & DB \end{bmatrix} \begin{bmatrix} u_k \ u_{k+1} \ u_{k+1} \end{bmatrix}$  $u_{k+1}$  $u_{k+2}$  $Y_{k|4}$  $0<sub>4</sub>$  $H_4^d$  $u_{k|4}$  ... 29  $Y_{k|4}$ = data matrix of output variables

 $u_{k|4}$  = data matrix of input variables

 $O_4$  = extended observability matrix for pair (D, A)  $H_4^d$  = lower block triangular Toeplitz matrix for D, A, B matrices.

Eqn. (29) can also be written as,

 $Y_{K|4} = 0_4 x_k + H_4^d u_{k|3}$ Equation 30

for prediction horizon of L, Eqn. (30) can be rewritten as

 $Y_{K|L} = O_L x_k + H_L^d u_{k+1|L-1}$ ........Equation 31 Similarly,

 $Y_{K|L} = O_L x_k + H_L^d u_{k+1|L-1}$ ........Equation 32 Substituting the values from Eqn. (24), Eqn. (32) becomes,

$$
Y_{K+1|L} = O_L A x_k + O_L B U_k +
$$

 $H_L^d u_{k+1|L-1}$  Equation 33 Which can be represented in matrix form as

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$$
Y_{K+1|L} = O_L A x_k + (O_L B H_L^d) \begin{bmatrix} u_k \\ u_{k+1|L-1} \end{bmatrix}
$$
  
\nEquation 34  
\nWhere, p<sub>L</sub> =  $O_L A x_k F_L$ ;  $F_L = (O_L B H_L^d)$   
\n
$$
u_k = \begin{bmatrix} u_k \\ u_{k+1|L-1} \end{bmatrix}; Y_{K+1|L} = p_L + F_L U_{K|L}
$$
  
\nEq. (34) represents the predictive model of the s

iystem to be controlled and now MPC determines the predicted output based on this predictive model. The objective cost function to be optimized is given as,

$$
J_K = (y_{k+k|L} - r_{k+k|L})^T Q (y_{k+k|L} - r_{k+k|L}) +
$$
  

$$
u_{k|L}^T P u_{k|L} . 35
$$

Substituting prediction model from the equation (35) into the cost function given in equation (36), we have

$$
J_{K} = (F_{L}u_{k|L} + P_{L} - r_{k+k|L})^{T} Q(F_{L}u_{k|L} + P_{L} - r_{k+k|L})^{T} + u_{k|L}^{T} P u_{k|L}
$$
  
\n
$$
J_{K} = u_{k|L}^{T} (F_{L}^{T} Q F_{L} + P) u_{k|L}^{T}
$$
  
\n
$$
2F_{L}^{T} Q (P_{L} - r_{k+k|L}) u_{k|L} + (P_{L} - r_{k+k|L})^{T}
$$
  
\n
$$
Q (P_{L} - r_{k+k|L}) u_{k|L} + (P_{L} - r_{k+k|L})^{T}
$$
  
\nEquation 37  
\n
$$
J_{K} = u_{k|L}^{T} H u_{k|L} + 2F^{T} u_{k|L} + J_{0}
$$
  
\nEquation 38

Where:

H =  $F_L^T Q F_L + P$  $f = F_L^T Q (P_L - r_{k|L})$  $J_0 = (P_L - r_{k+k|L}^T Q (P_L - r_{k+k|L})$ 

Minimizing the cost function given in equation (38) with respect to  $u_{k|L}$ 

 $\frac{\partial J_k}{\partial u_{k}} = u_{k|L} H u_{k|L} + 2f^T u_{k|L} + J_0$  Equation 39  $\overline{\partial u_{\mathbf{k|L}}}$ 

The equation (2.52) becomes the future optimal control, where only the first element  $u_{klL}$ , of control vector  $u^*_{kl}$  is used for control purpose.  $u_{k|L}^* = H^{-1*}f$  Equation 40

Eq. (40) represents the optimal controlled input vector in which only the first element is fed to the system, practically.

#### SIMULATION RESULTS

Control plot has been mimicked on MATLAB (R2017a) stage with Intel (R) Center (TM) i5- 5200U central processor @2.20 GHz. To approve the exhibition of MPC, its outcomes are decently contrasted and the Proportional-Integral (PI) and LQR regulators. The Control objective is to follow the setfocuses changes in water levels of Tank-1 and Tank 2 with the improvement of goal cost function of framework blunder while satisfying input amplitude constraints. At first degrees of Tanks-1 and Tank-2 are 4.5 cm and 5.5 cm separately, inspecting period 0.1 sec, expectation skyline length 25 are picked.

The reactions of PI, LQR, MPC and their control endeavors are displayed in Fig. 3 and 4. All regulators can follow the set-point changes however the reactions of MPC are superior to PI and LQR regulators. As at each time moment the water level of tanks is changing consequently making the framework model to change consistently. The boundaries of PI regulator are fixed and picked for arbitrary reasons by involving experimentation technique for whole control skyline which is improper for time changing framework model. Both LQR and MPC falls under the class of optimal controllers however they contrast in such manner that in expansion to the optimal minimization of the cost function MPC chips away at future expectations. In spite of the fact that LQR can handle serious areas of strength for the between Tank-1 and Tank-2 in any case, the reactions are lazy when contrasted with MPC. It is noted from reenactment results that reactions of MPC are better than other compared controllers. The values of MSEs for PI, LQR and MPC are moreover determined which are viewed as 0.0058, 0.0035 and 0.0022 respectively.



Fig. 3. Response and control input for Tank-1



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## CONCLUSIONS

In this work, the consequences of the MPC for a quadruple firefighting reservoir system have been presented. In this benchmark, three distinct control methodologies are applied to a nonlinear, MIMO intuitive fourfold tank lab model framework. Right off the bat, a decentralized PI control conspire is executed by finding a suitable information yield matching utilizing RGA examination. True to form, the outcomes recommend that a concentrated approach might give a superior presentation. This motivated the application of advanced optimal control strategies.

The experimental results affirm the need of more perplexing control algorithms when rigid execution is conceived. Reproduced results show that both brought together LQR and MPC can handle the nonlinear, MIMO interactive system but centralized MPC is much more efficient comparatively as it measures the loss of performance due to the linear nature of the prediction model with a sufficiently large prediction horizon.

## REFERENCES

- [1] Seborg et al, "Process dynamics and Control," Wiley India.
- [2] P. Campo and M. Morari, "Achievable closed-loop properties of systems under decentralized control: conditions involving the steady-state gain," IEEE Transactions on Automatic Control, vol. 39(5), pp. 392-394, 1994.
- [3] K. Åström, K. Johansson and Q. Wang, "Design of decoupled PID controllers for MIMO systems," Proceeding of the American Control Conference, Arlington, VA., pp. 2015-2020, 2001.
- [4] E. Bristol, "On a new measure of interaction for multivariable process control," IEEE Transactions on Automatic Control, vol. 11, pp. 133– 134, 1966.
- [5] J. Freudenberg and R. Middleton, "Design rules for multivariable feedback systems," Proceedings of the Conference on Decision and Control, Kobe, Japan, pp. 1980-1985, 1996.
- [6] S. Skogestad and I. Postlethwaite, "Multivariable" Feedback Control: Analysis and Design," Wiley, New York, 1996.
- [7] F. Garrelli, R.J. Mantz and H. De Battista, "Limiting interaction in decentralized control of MIMO systems," Journal of Process Control, vol. 16(5), pp. 437-483, 2006.
- [8] W.J. Cai, W. Ni, M.J. He and C.Y. Ni, "Normalized Decoupling-A New Approach for MIMO Process Control System Design," Ind. Eng. Chem. Res., vol. 47 (19), pp. 7347-6356, 2008.
- [9] W. Bequette, "Process Control: Modeling, Design and Simulation," Prentice Hall professional, 2003.
- [10] Anderson et. al., "Optimal Control: Linear Control Methods," Prentice-Hall International Editions, 1989.
- [11] Doyle, J. C., "Guaranteed Margins for LQR Regulators," IEEE Transactions on automatic control, 23(4), pp. 756-757, 1978.
- [12] Abubakar, U., Z. Haruna, A.-R. Yusuf, N.S. Usman, A.Y. Zubairu, A. Awhanni-mi, and A. Abubakar, "Model Predictive Control of Blood Pressure and Urine Production Rate for a Physiological Patient Model", Covenant Journal of Informatics Communication Technology (CJICT), 2022. 10(2): p. 1-15.
- [13] Eduardo F Camacho, "Model predictive control," second edition Springer.
- [14] David Di Ruscio, "Model Predictive Control with Integral Action: A simple MPC algorithm," Modeling, Identification and Control, Vol. 34, No. 3, 2013, pp. 119–129, ISSN 1890–1328.
- [15] Liuping Wang, "Model Predictive control system design and implementation." Springer.
- [16] Lars Grune, "Non-linear Model Predictive Control, theory and Algorithm," Springer.
- [17] Masood Askari, Mahmoud Moghavvemi, Hasider A.F. Almurib, "Multivariable Offset-free model Predictive controller for Quadruple tank system," IEEE Transactions on Industry Applications, Vol.52, No.2, March/April 2016.
- [18] B. Vatankhah and M. Farrokhi, "Offset-free adaptive nonlinear model predictive control for pneumatic servo system," in Proc. 2nd RSI/ISM Int.Conf. Robot. Mechatron. (ICRoM'14), 2014, pp. 896–901.
- [19] K. Horváth, E. Galvis, M. G. Valentín, and J. Rodellar, "New offset free method for model predictive control of open channels," Control Engineering Practices, vol. 41, pp. 13–25, 2015.
- [20] V. Kirubakaran, T. K. Radhakrishnan, and N. Sivakumaran, "Distributed multiparametric model predictive control design for a quadruple tank process," Measurement, vol. 47, pp. 841–854, Jan. 2014.
- [21] A. Abdullah and M. Zribi, "Control schemes for a quadruple tank process," Int. J. Computer, Communication, Control, vol. 7, pp. 594– 605, 2014.
- [22] K.H. Johansson, "The Quadruple Tank process: a multivariable Laboratory process with an adjustable zero," IEEE Transactions on Control system technology, 8, (3), 2000, pp. 456-465.

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