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A Comparison between NMPC and LQG for the Level Control of Three Tank Interacting System

Nishant Parikh, Saruch Rathore, Rahul Misra and Anilkumar Markana

Abstract—**Modern industrial plants consist of many processes occurring simultaneously which are to be monitored and controlled at all time, during plant operation. Typically, industrial plants are multi-input multi-output type and they also exhibit strong non-linear dynamics. Three tank liquid level control is such a laboratory based benchmark multi-variable control problem for modeling, identification, fault detection & diagnosis and fault tolerant control system design. Multi-variable processes make monitoring and control difficult for conventional controllers. To overcome this problem most modern industries, use a model based controller as supervisory controller. However, these controllers are designed based on linear model of the process. Linear models often fail to capture the non-linear dynamics which results in the failure of control systems. In this article, we compared the performance of Linear Quadratic Gaussian Control (LQG) with the Non-linear Model Predictive Control (NMPC) to achieve the servo plus disturbance rejection and regulatory control of a three tank system in presence of changing valve position which serves as the disturbance input. As anticipated, the simulation results reveal better competency of NMPC over LQG in handling disturbances.**

I. INTRODUCTION

Most of the industrial processes are non-linear and multivariable which involves a large number of interactions between system variables. Study of such type of processes in a laboratory environment can greatly assist in developing desired models of the system as well as in implementing various control strategies on the same. The three tank system can be viewed as a prototype of common industrial process applications that involves storage systems such as a wastewater treatment plant, industrial chemical processes, food processing, iron and steel industries, nuclear power generation systems and other industries [1]. The liquid level control of such systems is of paramount importance since the quality of product depends greatly on the level controllers. The main objective of the controller is to control and stabilize the level of the two extreme end tanks by manipulating pump voltages in presence of changing bottom/interacting valve position which is an artificial disturbance. Conventional controllers are not able to handle multivariable interactions and constraints properly in presence of changing valve positions. For satisfactory performance, it would be a better choice to use controllers such as Model Predictive Control (MPC), Linear Quadratic Gaussian Control (LQG) or any other model based optimal control strategies. Plenty of researchers have used three tank system as a test bench to implement variety of control systems. Aixian and Yun [2] have designed a rough controller for three tank system. Kanagasabai and Jaya [3] designed a multi-loop control using a coefficient diagram method. Kovács et. al. [4] used a disturbance rejection LQ control which uses a linear model of the process to estimate control moves. Anilkumar. M. et. al. [14] presented EKF based extended MPC for the control of liquid in quadruple tank process. However, the performance of LQ control deteriorates as it faces difficulty in handling plant-model mismatch which arises due to change in bottom/interacting valve positions. In addition, it can't handle constraints explicitly. In recent time, EKF based non-linear MPC has become an increasingly popular and mature technology used in such type of situation.

In this work, we have used LQG and NMPC controller for three tank level control problem. A first principle based non-linear model of three tank systems (manufactured by Gurski TTS20 refer Figure 1), have been simulated using MATLAB to carry out various simulation studies. We compared the performance of both, LQG which uses linear model and NMPC which uses non-linear model to calculate the future control moves for the three tank level control problem under consideration. The changing valve position serves as the artificial disturbance for our simulation studies.

The rest of the paper is organized as follows:

Section II focuses on the problem descriptions. Section III deals with the LQG and NMPC control methodology. In section IV simulation results are discussed and the performance of both the controllers against the changing valve position is analyzed. Finally, Section V concludes the work.

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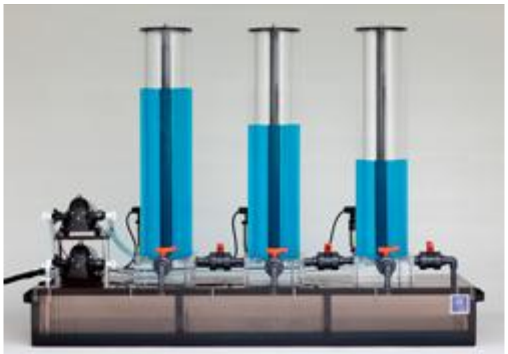

Figure 1. Laboratory setup of three tank interacting system [5]

II. PROBLEM STATEMENT

A. Level control of the three tank interacting system

Figure 2 shows the schematic of the three tank system. The system contains three identical interconnected tanks. Also, each tank is having a valve at the bottom of the tank, from which water drains out continuously to the reservoir. The inflow of liquid is through two pumps connected to Tank 1 and Tank 2. The flow of liquid can be either from tank 1 to tank 2 or from tank 2 to tank 1, via tank 3. The goal here is to control the level of tank 1 and tank 2 simultaneously at the desired levels despite changing bottom valve position. The difficulty here is that, due to changing valve position it is difficult to capture the dynamics through a linear model.

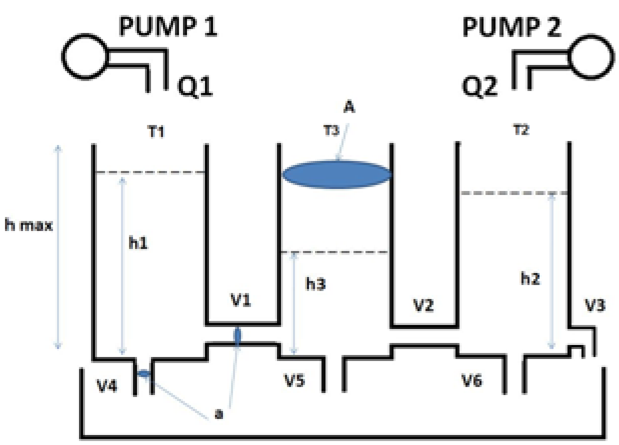

Figure 2. Schematic of three tank interacting system

B. Mathematical Modeling of Three Tank Interacting System

The model of three tank interacting system is based on the ideal properties of the liquid. The system contains three interconnected cylindrical tanks T1, T2 and T3 having cross-sectional area 'A' and maximum height h_{max}. A valve is provided at the bottom of each tank, from which the water drains out continuously to the reservoir. The connecting pipes and the bottom valves have a cross sectional area of 'a'. The pump P1 controls the inflow of tank T1 while pump P2 controls the inflow of tank T2. Q_1 and Q_2 are the flow rates of pump P1 and P2 respectively, which are controlled by analog signals ranging from 0V to 12V. v1, v2, v3, v4, v5 and v6 are the valves connecting the tanks to each other and to the reservoir.

The flow of liquid through a pipe can be derived from Bernoulli and continuity equations for an ideal liquid:

$$f = a_v\sqrt{2g\Delta h} \quad (1)$$

where, Δh is the difference between the level of tanks on both the sides of the pipe, g is the standard gravity, a_v is the effective flow area of the pipe. The effective flow area a_v can be controlled by valve position.

$$a_v = az_i * a \quad (2)$$

where, az_i is the coefficient representing valve position and 'a' is the total flow area of the pipe.

$$0 \leq az_i \leq 1 \quad (3)$$

$$A\frac{dh}{dt} = \text{sum of all occurring flow rates}$$

'A' being the cross-sectional area of the tank. Therefore, the change in tank level T1 can be written as follows,

$$\frac{dh_1}{dt} = S_1 - k_1\sqrt{|h_1 - h_2|}sign(h_1 - h_3) - k_4\sqrt{h_1} \quad (4)$$

where, k is a flow coefficient defined as follows,

$$k_i = az_i\frac{a\sqrt{2g}}{A} \quad (5)$$

$$i = 1,2,\ldots,6$$

and S is

$$S_i = \frac{Q_i}{A} \quad (6)$$

$$i = 1,2$$

Similarly, equations for the other two tanks can be derived and are as follows:

$$\frac{dh_2}{dt} = S_2 - k_2\sqrt{|h_2 - h_3|}sign(h_2 - h_3) - k_3\sqrt{h_2} - k_6\sqrt{h_2} \quad (7)$$

$$\frac{dh_3}{dt} = k_1\sqrt{|h_1 - h_3|}sign(h_1 - h_3) + k_2\sqrt{|h_2 - h_3|}sign(h_2 - h_3) - k_5\sqrt{h_2} \quad (8)$$

The values of different physical parameters of the actual three tank process are given in Table 1.

Table 1 Physical Parameters of Three Tank System

Parameter	Value
a	0.5 cm^2
A	154 cm^2
g	981 cm/s^2
h_{max}	63 cm
Q_{1max}, Q_{2max}	100 cm^3/s

Thus, Eq. 4, 7 & 8 represents the first principle based model of a three tank system. This model of three tank system has been used in many control system studies [11], [12], [13]. Empirical model has been developed in order to express pump inflow; Q_i in terms of pump input voltage, u_i using practical experiments on the laboratory based three tank system which is as follows:

$$m_i = (0.00682u_i^3 - 0.19104u_i^2 + 1.8601u_i + 3.0707)$$
$$i = 1,2 \qquad (9)$$

Where m_i is Q_i/u_i and u_i is the pump input voltage which ranges from 0 to 12V.

C. Linearization

The linearized model is obtained from a truncated Taylor series expansion of the non-linear differential equations. The non-linear dynamics are of the form:

$$\frac{dX}{dt} = F(X, U) \qquad (10)$$
$$Y = G(X, U)$$

Linearization of above system around the nominal operating point, $(\bar{X}, \bar{U})$ gives the linear system matrices,

$$A = \left[\frac{\partial F}{\partial X}\right], B = \left[\frac{\partial F}{\partial U}\right], C = \left[\frac{\partial G}{\partial X}\right], D = \left[\frac{\partial G}{\partial U}\right] \qquad (11)$$

Then, the linear approximation to the system is,

$$\frac{dx}{dt} = Ax + Bu \qquad (12)$$
$$y = Cx + Du$$
$$x(t) = X(t) - \bar{X},\ y(t) = Y(t) - \bar{Y},\ u(t) = U(t) - \bar{U} \qquad (13)$$

After linearization, the model is discretized under the following assumptions: (a) manipulated inputs are piecewise constant, (b) disturbance variables can be adequately represented by piecewise constant functions. Sampling time used for discretization is 5 sec. The discrete matrices thus obtained are,

$$\Phi = \begin{bmatrix} 0.7249 & 0.0345 & 0.2013 \\ 0.0345 & 0.7249 & 0.2013 \\ 0.2013 & 0.2013 & 0.5571 \end{bmatrix} \qquad (14)$$
$$\Gamma = \begin{bmatrix} 0.2788 & 0.0042 \\ 0.0042 & 0.2788 \\ 0.0390 & 0.0390 \end{bmatrix}$$
$$C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$
$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

III. Controller Formulations

A. Design of LQG Controller

1) Design of Feedback LQG Regulator

Consider the discrete linear state space representation of the three tank process given as:

$$x(k+1) = \Phi x(k) + \Gamma u(k) + \Gamma_d w(k) \qquad (15)$$
$$y(k) = Cx(k) + H_d w(k) + v(k) \qquad (16)$$

where, $x(k)$ represents vector of perturbed state variables, $u(k)$ represents perturbed manipulated inputs to process, $y(k)$ represents perturbed measured output, w and v are state and measurement noise, respectively. Here, $w(k)$ and $v(k)$ are assumed to be zero mean, normally distributed white noise sequence such that

$$R_1 = E[w(k)w(k)^T] \qquad (17)$$
$$R_{12} = E[w(k)v(k)^T] \qquad (18)$$
$$R_2 = E[v(k)v(k)^T] \qquad (19)$$

where, $E[\cdot]$ represents expectation operator.

The state feedback LQ control law for regulating the system at the origin can be implemented together with the Kalman predictor using estimated states as follows:

$$u(k) = -G_\infty \hat{x}(k|k-1) \qquad (20)$$

here, G_∞ is a regulator gain that can be obtained by minimizing the objective function,

$$J(u) = \sum_{i=0}^{\infty}(y(i)^T Q y(i) + u(i)^T R u(i)) \qquad (21)$$

through the solution of the algebraic Riccati equation [6]

$$G_\infty = (R + \Gamma^T S_\infty \Gamma)^{-1} \Gamma^T S_\infty \Phi \qquad (22)$$
$$S_\infty = [\Phi - \Gamma G_\infty]^T S_\infty [\Phi - \Gamma G_\infty] + Q + G_\infty^T R G_\infty \qquad (23)$$

When (Φ, Γ) is controllable and objective function is symmetric and positive definite, LQ controller will always give asymptotically stable closed loop behavior [6]. By selecting Q and R appropriately, it is easy to compromise between speed of recovery and magnitude of control signals.

The model described in (15) can be used to develop the optimal state estimation using Kalman filter, as follows:

$$e(k) = y(k) - C\hat{x}(k|k-1) \qquad (24)$$
$$\hat{x}(k+1|k) = \Phi\hat{x}(k|k-1) + \Gamma u(k) + L_p e(k) \qquad (25)$$

L_p is the steady state Kalman gain and is the solution of steady state Riccati equations:

$$L_p = [\Phi P_\infty C^T + R_{12}][C P_\infty C^T + R_2]^{-1} \qquad (26)$$
$$P_\infty = \Phi P_\infty \Phi^T + R_1 - L_p[C P_\infty C^T + R_2]L_p^T \qquad (27)$$

here, matrix P_∞ denotes steady state covariance of error in state estimation. It can be shown that, under the ideal conditions, the residual (or innovation) $\{e(k)\}$ is a zero mean Gaussian white noise process with covariance matrix $V_\infty = CP_\infty C^T + R_2$. The LQG design presented in this section is referred from [10].

2) Tracking and Unmeasured Disturbance Rejection for LQG Control

Linear quadratic regulator designed above can generate an offset if (a) the unmeasured disturbances are non-stationary, i.e. they have slowly drifting behavior (b) mismatch exists between the plant and the model. To deal with such a situation, it is necessary to introduce integral action in the control to deal with plant-model mismatch and reject unmeasured disturbances. Also, the regulator designed above only solves the restricted problem of moving the system from any initial state to the origin. If it is desired to move the system from any initial condition to an arbitrary setpoints, the state feedback control laws must be modified. The problem of regulation in the face of unknown disturbances/plant-model mismatch and tracking an arbitrary setpoints trajectory is solved by modifying the regulatory control law as follows:

$$u(k) = u_s(k) - G[\hat{x}(k|k-1) - x_s(k)] \quad (28)$$

where, $x_s(k)$ represents the final steady state target corresponding to setpoint, say $r(k)$, and $u_s(k)$ represents the steady state input necessary to reach this steady state.

When the model is perfect, the innovation sequence $\{e(k)\}$ is a zero mean white noise signal. However, in the presence of plant-model mismatch and/or drifting unmeasured disturbances, $E\{e(k)\} \neq 0$. The low frequency drifting mean of $\{e(k)\}$ can be obtained using a simple unity gain first order filter of the form.

$$e_f(k) = [\alpha I]e_f(k-1) + [(1-\alpha)I]e(k) \quad (29)$$

where, $0 \leq \alpha < 1$ is a tuning parameter.

Taking motivation from the observer error feedback based LQ control scheme developed by Deshpande et al. [7], steady state targets are computed by solving the following set of equations:

$$x_s(k) = \Phi x_s(k) + \Gamma u_s(k) + L_p e_f(k) \quad (30)$$

$$r(k) = C x_s(k) + e_f(k) \quad (31)$$

When numbers of outputs are equal to the number of measurements, the above equations reduced to

$$u_s(k) = K_u^{-1}\left[r(k) - K_e e_f(k)\right] \quad (32)$$

$$x_s(k) = (I - \Phi)^{-1}[\Gamma u_s(k) + L_p e_f(k)] \quad (33)$$

where,

$$K_u = C(I - \Phi)^{-1}\Gamma \quad (34)$$

$$K_e = C(I - \Phi)^{-1}L_p + I \quad (35)$$

The above feedback control law can be used for setpoint tracking as well as unknown disturbance rejection control problem.

B. EKF based NMPC Controller Formulation

1) Process Model

Nonlinear process model can be expressed through a set of nonlinear differential equations as follows:

$$\frac{dX}{dt} = F(X, U, D) \quad (36)$$

$$Y = G(X, D)$$

where, X is a state vector, U is a vector of manipulated inputs, Y is a vector of measured outputs and D is a vector of unmeasured disturbance variables. For digital controller design, U and D can be assumed to be piecewise constant between the sampling instants. The continuous process model (36) can be discretized with a suitable sampling time T_s and thus can be written as follows:

$$x(k) = F(x(k-1), u(k-1), d(k-1)) \quad (37)$$

$$y(k) = G(x(k), d(k)) \quad (38)$$

where $F(x(k-1),u(k-1),d(k-1))$ denotes the terminal state vector obtained by integrating ODE's (36) for one sampling time interval, T_s with the initial conditions of $x(k-1)$ and constant inputs of $u = u(k-1)$ and $d = d(k-1)$.

2) Objective Function

Control moves are calculated by minimizing the following quadratic objective function at each discrete time instant k.

$$\min_{\Delta u} J = \sum_{j=1}^{p} W_e\big(y(k+j|k) - r(k+j|k)\big)^2 + \sum_{j=0}^{q-1} W_u\big(\Delta u(k+j|k)\big)^2 \quad (39)$$

such that, the following constraints are satisfied.

$$\Delta u(k+q) = \cdots = \Delta u(k+p-1) = 0 \quad (40)$$

$$u^{low}(k+l) \leq u(k+l) \leq u^{high}(k+l), 0 \leq l \leq q-1$$

$$\Delta u^{low}(k+l) \leq \Delta u(k+l) \leq \Delta u^{high}(k+l), 0 \leq l \leq q-1$$

$$y^{low}(k+l|k) \leq y(k+l|k) \leq y^{high}(k+l|k),$$
$$0 \leq l \leq p$$

where, y and r represents the vector of predicted outputs and the corresponding setpoint over the prediction horizon p, respectively. Δu represents control moves over control horizon q, which is optimized at every sampling instant. W_e is a symmetric positive definite penalty matrix on the error between set-points and outputs. W_u is a symmetric positive definite weighing matrix on the rate of change of inputs in which $\Delta u(k+j|k) = u(k+j|k) - u(k+j-1|k)$. Please note that conventionally, the optimal control objective function is of set-point error minimization, although economic objective functions have also been demonstrated in the literature [8].

3) State Estimation: Extended Kalman Filter

We have used Extended Kalman Filter (EKF) for estimation of states [9]. EKF is an extension of optimal linear Kalman filter. The basic idea of EKF is to perform linearization at each time step and approximate the nonlinear system as a time varying system at each estimate and thereby apply optimal linear filtering theory to it.

4) Model Output Prediction

The optimal prediction of the controlled outputs for p (prediction horizon) future time steps, using local linearization of the process model, can be written as,

$$y(k+1|k) = S_{x(k)}\big(x(k|k), u(k-1)\big) + S_{u(k)}\Delta u(k) \quad (41)$$

$S_{x(k)}(x(k|k),u(k-1))$ is the vector of future controlled outputs and is calculated by integrating the nonlinear model equation (36) with the assumption of no change in the inputs. $S_{u(k)}$ is a constant matrix constructed from Jacobian matrices obtained using local linearization. The exact definitions for these matrices are given in [9].

5) Control moves calculation and implementation

When the output prediction equation (41) is substituted into the objective function (39), the optimization problem can be written as standard QP formulation and the objective function becomes,

$$\min_{\Delta u(k)} J = \frac{1}{2}\Delta u(k)^T H_k \Delta u(k) + \Delta u(k)^T F_k \quad (42)$$

where the Hessian for the QP, H_k and gradient vector, F_k is given by

$$H_k = 2[S_{u(k)}^T W_e S_{u(k)} + \Lambda^T W_u \Lambda] \quad (43)$$

$$F_k = -2[\left(r_k - S_{x(k)}\left(x(k|k), u(k-1)\right)\right)^T W_e S_{u(k)}] \quad (44)$$

The above optimization problem can be solved analytically under the absence of constraints at every sample time. Subject to linear constraints in (40), the same optimization problem can be solved using standard quadratic programming. First element of the computed control moves *Δu(k)* is implemented to the plant and the whole algorithm is to be continued to the next time step.

IV. SIMULATION RESULTS AND DISCUSSION

A. Simulation Details

As shown in Table 2, following case studies have been made by simulating proposed LQG and NMPC on non-linear plant:

Table 2. Case Study

Case	Type of Control	Strategy
A	Regulatory plus disturbance rejection	LQG and NMPC
B	Servo control plus disturbance rejection	LQG and NMPC

The non-linear model has been used for the formulation of the NMPC controller, whereas the linear discrete-time model obtained earlier has been used for the formulation of LQG controller. The total simulation time selected is 1800 sec. As the dynamics of three tank system is slow (open loop settling time is 500 sec), sampling time is chosen as 5 sec. The simulation details of LQG and NMPC are given as below:

1) LQG controller parameters

The input constraints are

$$u_{min} = 0 \quad \text{and} \quad u_{max} = 12$$

The standard deviation for measurement noise σ_{v1} and σ_{v2} are chosen as

$$\sigma_{v1} = 0.1 \quad \text{and} \sigma_{v2} = 0.1$$

The weighting matrices used in LQG design are as follows:

Output weighting matrix, $Q = \begin{bmatrix} 1000 & 0 \\ 0 & 1000 \end{bmatrix}$

and

Input weighting matrix, $R = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix}$

The steady state gain, G in (28) is calculated using dlqr command in MATLAB.

The innovation filter is used which is given by following

$$e_f(k) = [\alpha I]e_f(k-1) + [(1-\alpha)I]e(k) \quad (45)$$

where, $\alpha = \begin{bmatrix} 0.95 & 0 \\ 0 & 0.95 \end{bmatrix}$

Choice of the filter parameter influences the regulatory behavior of the LQG controller in the desired frequency band. Choosing $\alpha = 0$ sets $e_f(k) = e(k)$ and the filtering is eliminated which makes the controller quite aggressive.

2) NMPC controller parameters

The constraints as mentioned in (40) are:

$$u^{low} = 0 \quad \text{and} \quad u^{high} = 12$$

$$\Delta u^{low} = -1.5 \quad \text{and} \quad \Delta u^{high} = 1.5$$

$$y^{low} = 0 \quad \text{and} \quad y^{high} = 63$$

The prediction horizon, *p=400* and the control horizon, *q=2*.

B. Case Study

1) Regulatory Control Problem

Figure 3 & 4 presents the comparison between NMPC and LQG for regulatory control. A step change of 10 cm and 15 cm has been introduced in the heights of the liquid in tank 1 and tank 2 respectively at 250th sampling instant. After that both the setpoints are being kept constant throughout. The manipulated inputs for this case are the input voltages to the Pump 1 and the Pump 2. The valve positions are indicated by az_i, a decimal number ranging from 0 to 1 which represents that how much percentage of the valve is open (example: 0.5 means that the valve is 50% open). Initially az_1 (valve position for v1) and az_2 are 1 (100% open), az_3 is kept at 0 (closed), az_5 and az_6 are kept at 0.5. Valve 4 position, az_4, is manipulated at random sampling instants to introduce disturbances in the system. In this simulation experiment, az_4 is first kept at 0.5. It is then changed to 0.8 at the 650th sampling instant. Then, at the 1050th instant it is changed from 0.8 to 0.2. Later, at the 1450th instant it is changed from 0.2 to 0.6 and thereafter it has been kept constant. It is observed that there are oscillations in the water level in both the tanks as a result of manipulating valve 4 positions. Simulation result shows that, fewer oscillations are observed in case of NMPC as compared to LQG even for large changes in the valve position. Thus, NMPC seems better in terms of disturbance rejection compared to LQG. The similar results were obtained in other simulations (not shown here), where the different interacting/bottom valve positions were taken as the disturbances.

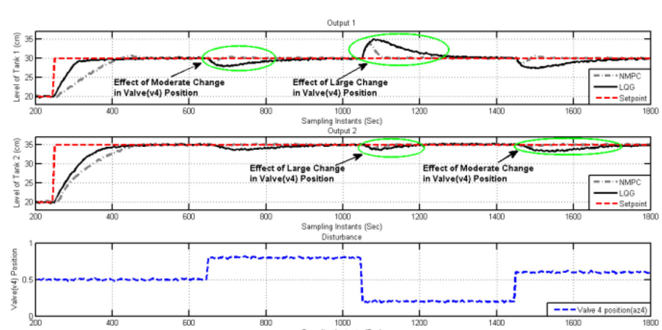

Figure 3. Comparison of NMPC and LQG for regulatory case

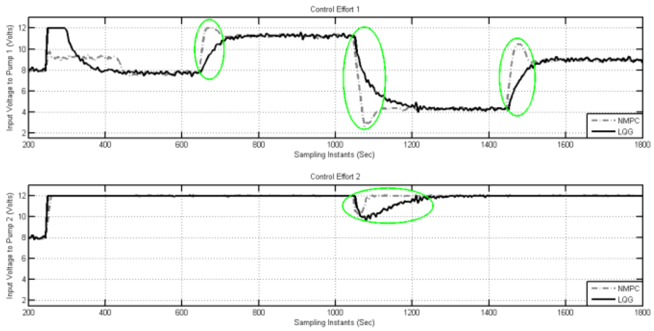

Figure 4. NMPC and LQG controller effort for regulatory case

2) *Servo Control plus Disturbance Rejection Problem*

Figure 5 shows the comparison between NMPC and LQG for servo control plus disturbance rejection case. The valve positions az_1 and az_2 are 1 (100% open), az_3 is kept at 0 (closed), az_4, az_5 and az_6 are kept at 0.5. The setpoints are being changed at different sampling instants. At 1301 sampling instant, simultaneous change in setpoints and valve-4 position have been introduced. The simulation results show that LQG performs marginally better than NMPC for setpoint tracking throughout. However, NMPC seems better when it comes to disturbance rejection. As shown if Figure 6, the controller efforts of LQG is aggressive as compared to NMPC.

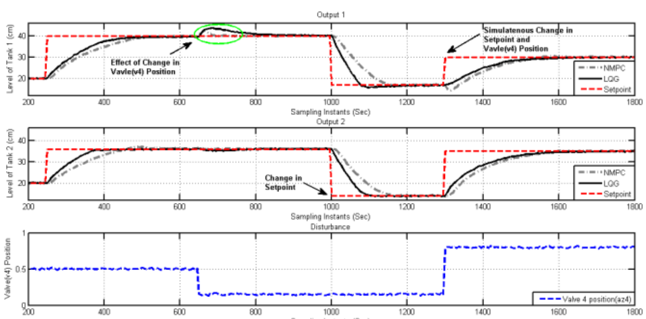

Figure 5. Comparison of NMPC and LQG for servo control plus disturbance rejection problem

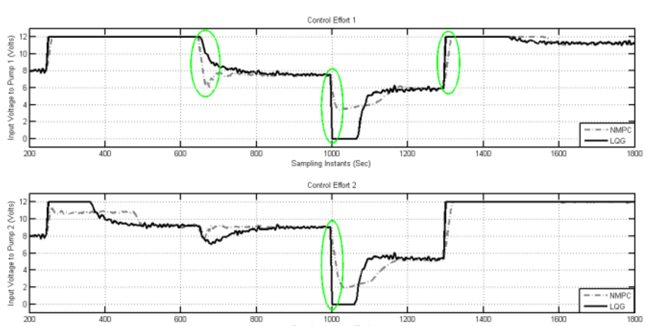

Figure 6. NMPC and LQG controller effort for servo control plus disturbance rejection problem

V. Conclusion

Model based control algorithms viz. EKF based NMPC and LQG have been simulated on a first principle based model of the laboratory three tank system. The comparisons of NMPC and LQG have been done for both regulatory control and set point tracking in presence of an artificial disturbance. The simulation results show that NMPC is better in handling disturbances compared to LQG but LQG outperforms when it comes to setpoint tracking. While comparing the controller efforts in case of set point tracking, we observed that the controller efforts for LQG is aggressive compared to NMPC. This can lead to chattering and damage to the actuator in this case the motors for the pumps 1 and 2. Thus, we conclude that NMPC is arguably a better choice than LQG for the control of a three tank interacting process in presence of disturbances.

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References

[1] *Amira, DTS2000Laboratory setup three tank system*, Duisburg: Amira GmbH, 1996.

[2] Pan Aixian, Gao Yun, "Design and Application of Rough Controller in Three-tank System", in *Computing, Control and Industrial Engineering (CCIE)2010 International Conference*, Vol. 2, pp. 144-148, 2010.

[3] N. Kanagasabai, N. Jaya, "Design of Multiloop Controller for Three Tank Process using CDM Technique," *International Journal on Soft Computing*, Vol. 5, No. 2, p.11, 2014.

[4] Kovács L., Borbély E., Benyó Z., "Optimal Control of the Three Tank System in H_2/H_∞ Space," in5*th* *Slovakian-Hungarian Joint Symposium on Applied Machine Intelligence and Informatics*, Poprad, Slovakia, 2007.

[5] *Gurski TTS20, Laboratory Setup Three Tank System*, Ingenieurbüro Gurski-Schramm & Partner, 2013.

[6] K.J. Astrom, B. Wittenmark, *Computer Controlled Systems*, Prentice Hall, Englewood Cliffs, NJ; 1990.

[7] A. Deshpande, U. Zamad, S. C. Patwardhan, On-line Sensor /Actuator Failure Isolation and Reconfigurable Control using Generalized Likelihood Ratio Method, *Ind. Eng. Chem. Res.*, vol. 48, 2009, 1522-1535.

[8] Tri Tran, KV Ling and Jan M Maciejowski, "Economic model predictive control- a review," In Proc. of Intl. Symposium on Automation and Robotics in Construction, ISARC 2014, 2014.

[9] Jay H Lee and N Lawrence Ricker, "Extended Kalman filter based nonlinear model predictive control," *Industrial & Engineering Chemistry Research*, 33(6):1530-1541, 1994.

[10] Nishant Parikh, Sachin Patwardhan, Santanu Bandyopadhyay and Ravindra Gudi, "Control of a Nuclear Steam Generator using Feedback-Feedforward LQG Controller," in *Proceeding of the 2011 4th International Symposium on Advanced Control of Industrial Processes*, Thousand Islands Lake, Hangzhou, P.R. China, 2011.

[11] P. Chalupa, J. Novák and V. Bobál, "Comprehensive Model of DTS200 Three Tank System in Simulink," *International Journal of Mathematical Models and Methods in Applied Science*, Issue 2, Volume 6, 2012.

[12] D. Henry and A. Zolghadri, "Norm-based design of robust FDI schemes for uncertain system under feedback control: Comparison of two approaches," *Control engineering practice*, 14, 2006, 1081-1097.

[13] L.Li and D. Zhou, "Fast and robust fault diagnosis for a class of nonlinear systems: detectability analysis," *Computers &Chemical Engineering*, 28, 2004, 2635-2646.

[14] Anilkumar Markana, Nitin Padhiyar and Kannan Moudgalya "Lexicographic optimization based MPC: Simulation and experimental study," *Computers & Chemical Engineering*, 88 (2016): 135-144.