JOURNAL OF ENGINEERING RESEARCH

Refereed and issued twice annually by the
Faculty of Engineering - University of Tripoli

Issue 27 March 2019

INVESTIGATION OF CONSTRAINED MODEL PREDICTIVE CONTROL TUNING STRATEGY FOR MULTIVARIABLE PROCESSES

Mohamed Shtewi M. Daw, Ali said Zayed* and Abdulbaset Mohamed Alemam**

Department of Electrical and Electronic Engineering, Higher Institute of Sciences and Technology -AL Zahra, Libya
*Department of Electrical and Electronic Engineering, University of Sabrata
**Department of Mechanical and Industrial Engineering, University of Tripoli
Email: Mohamed_shtwi@yahoo.com

الملخص

تلقى أنظمة التحكم المتعددة المدخلات والمخرجات اهتماماً واسعاً في المجالين الأكاديمي والصناعي. كما تتمتع المتحكمات التكهنية بإنتشار كبير في جميع مجالات التحكم بما في ذلك العمليات الصناعية مثل مصانع البتروكيماويات. الهدف الرئيسي من استخدام هذا النوع من المتحكمات هو الحصول على أنظمة تحكم فعالة ومتينة للأنظمة الصناعية الغير خطية، حيث إن هذه المتحكمات التنبوئية مبنية على العديد من النماذج الخطية لتغطية مدى كبير من الظروف التشغيلية المختلفة لغرض الحصول على النموذج الرياضي المناسب الذي يتم من خلاله تصميم المتحكم الملائم لكي يعطي تنبؤات دقيقة لتحسين أداء المنظومة. إلا إن أداء أنظمة التحكم التكهنية يعتمد اعتماداً كبيراً على بعض المتغيرات التصميمية التي يتم اختيارها من قبل المصمم للحصول على النتائج المرجّوة.

تم في هذه الورقة البحثية تطبيق المتحكم التكهني المقيد للأنظمة المتعددة المدخلات والمخرجات المقترح من قبل الباحثان (محمد ميلود وعلي زايد) [1] للتحكم في حالتي دراسة وهما؛ برج تقطير لمصفاة نفطية وشبكة مبادل حراري اللتين سبق دراستهما في المراجع [2 ,3] على التوالي.

إن الغرض الرئيسي من هذه الدراسة هو تحديد أي هذه المعاملات التصميمية أكثر تأثيراً على الأداء الكلي للأنظمة المتعددة المتغيرات لكي يؤخذ بعين الإعتبار في عملية ضبط المتحكم لاحقا.

ABSTRACT

Multivariable processes and multivariable control have received wide attention from both the academic and industrial societies. Model predictive control (MPC) applications are very popular in industrial systems such as petrochemical processes. The aim of this control strategy is to provide a robust control to be implemented for a nonlinear industrial process. The scheme utilizes multiple linear models to cover wider ranges of operating conditions in order to obtain the suitable process model that further is used in control design computations. The model based nature of this control methodology focuses on improving performance and robustness of control systems by using accurate prediction. However, tuning of multivariable MPC is quite challenging because of the number of adjustable parameters that affect closed-loop performance. In this paper, the constrained multivariable MPC controller developed by (Milaud, M and Zayed, A) [1] is applied to (two by two) distillation column used by (Sridhar, R and Cooper, D) [2] and the (four by four) heat exchanger network (HEN) [3], in order to determine the most sensitive tuning parameter to be considered as MPC controller primary tuning parameter.

KEYWORDS: Multivariable; Model Predictive Control; Heat Exchanger; Distillation Column; Self-tuning Control; Multi-Variable Control; Tuning; Nonlinear Control.

INTRODUCTION

Industrial processes such as petrochemical industry, the food and beverage industry and the power industry are typically a number of input (manipulated) and output (controlled) variables which should be satisfactory response. The main problem which effecting the control objective is the coupling between inputs and outputs [4], where each manipulated variable can interact with controlled variables. These process interactions may induce undesirable interactions between two or more control loops [4, 5].

During the last decade numerous promising control approaches have appeared in the literature and become available such as classical Ziegler-Nicolas, minimum variance control, fuzzy logic, genetic algorithms and model predictive control (MPC) methods [6].

In this paper, the MPC control which is considered as one of the most widely used control methods in industry is implemented into two different multivariable systems namely (distillation column and heat exchanger network). This control method is especially used for controlling constrained multivariable processes.

In the next section, the model predictive control will be explained, in particular, the "quadratic dynamic matrix control algorithm" (QDMC). Then, two case-studies, distillation column process and heat exchanger network will be used to demonstrate and investigate the effect of the various MPC tuning parameters. Concluded remarks and the recommendations for future work are presented at the end.

MODEL PREDICTIVE CONTROL

A great deal of attention has been given to model predictive control (MPC) by both academic and industrial societies. MPC uses a reliable model to predict the effect of past control moves on future outputs “prediction horizon” (V), assuming no future moves, and using the same model to compute the optimal control (M) “horizon moves” [7]. This methodology based on an explicit `internal model' which is used to obtain predictions of system behavior over some future time interval, assuming some trajectory of control variables. The control variable trajectory is chosen by optimizing some aspect of system behavior over this interval. Only the initial segment of the optimized control trajectory is implemented. The whole cycle of prediction and optimization is repeated, typically over an interval of the same length.

In quadratic dynamic matrix control (QDMC) algorithm all necessary computations are performed on-line. The main feature of the controller is its ability to naturally handling control of multivariable plant constraints. It is combining linear dynamic models with linear inequalities. The various MPC algorithms propose different performance index or cost functions for obtaining the control law [8, 9]. The general aim of the cost function is that the future output $\hat{y}(k+j/k)$ on the considered horizon should follow a predefined reference signal $r(k+j)$ (set point tracking), at the same time the control action $\Delta u(k)$ should be penalized. The cost function is usually formulated as a quadratic function subject to equality and inequality constraints. The general expression for the performance index is:

$$J(\Delta u(k), \hat{y}(k)) = \sum_{j=1}^{V} \left\| \hat{y}(k+j/k) - r(k+j/k \right\|_{Q}^{2} + \sum_{j=0}^{U-1} \left\| \Delta \hat{u}(k+j/k) \right\|_{R}^{2} \tag{1}$$

$\|X\|_Q^2 = X^T Q X$ Where X is a vector, and $Q \in \Re^{V \times V}, R \in \Re^{U \times U}$ are weighting matrices with $Q \geq 0$ and $R \geq 0$.The weights are used as tuning parameters for the predictive controller, they are adjusted to give satisfactory dynamic performance.

Quadratic Dynamic Matrix Control

Quadratic dynamic matrix control (QDMC) is one of the most popular model predictive controller's algorithm used in wide ranges of industrial processes [9]. For that, this paper is presented in the context of tuning a QDMC controller. Therefore, the problems of tuning of both unconstrained and constrained multi-input multi-output (MIMO) QDMC have been addressed by an array of researchers. These include systematic trial and error tuning procedures and formal tuning techniques such as move suppression methods and principal component selection [9, 10]. A major part of QDMC's appeal in industry stems from the use of a linear finite step response model of the process and a simple quadratic performance objective function. The objective function which includes the controller parameters minimized over a prediction horizon to compute the optimal controller output moves as a least-squares problem. The candidate parameters for developing a systematic tuning strategy for QDMC include the prediction horizon, V, the control horizon, U, and the move suppression coefficient, λ. The appropriate choice of these parameters is strongly depended on the choice of sampling time and the nature of the process. Over the past decade, detailed studies of QDMC parameters have provided a wealth of information about their qualitative effects on closed-loop performance [11].

MPC Tuning Strategy

It instantly becomes obvious that tuning of MIMO QDMC is quite challenging because of the number of adjustable parameters that affect closed-loop performance. The main problem that needs to be addressed is the selection of appropriate tuning parameters (N, V, U, Q, R and T). Practical limitations often restrict the availability of sample time, T, as a tuning parameter as it may sometimes depend on the computer running the application [11, 12]. The model horizon is also not an appropriate tuning parameter since truncation of the model horizon, N, misrepresents the effect of past moves in the predicted output and leads to unpredictable closed-loop performance. The proposed strategy is a systematic approach of determining the tuning parameters based on first order plus delay time (FOPDT) process dynamics. The approach is summarized in Table (1) [2]. In order to realize the multivariable tuning procedure, the Laplace transform model for the multivariable process can be approximated by the following relationship:

$$\frac{y_i(s)}{u_j(s)} = \frac{K_{ij}\, e^{\theta^{ij} s}}{\tau_{ij}\, s+1} \quad (i = 1, 2, \dots, ϸ\, ; \;\; j = 1, 2, \dots, m) \qquad (2)$$

Where: $y_i(s)$ is the i^{th} output of the multivariable process and $u_j(s)$ is the j^{th} input of the process to be controlled, and θ^{ij} is the time delay between the i^{th} output and the j^{th} input. In this case K_{ij} is the steady state gain between $y_i(s)$ and $u_j(s)$. However, in this work only square processes are considered ($ϸ = m$).

Table 1: QDMC Tuning Strategy

1	Approximate the process dynamics of all controller output-process variable pair with first order plus dead time (FOPDT) models as stated in equation (2).
2	Select the sampling time as close as possible to: $T = Min(Max(0.1\tau_{ij}, 0.5\theta_{ij})) \quad (i = 1, 2, ..., \beta;\ j = 1, 2, ..., m)$
3	Compute the prediction horizon, V, and the model horizon, N as the process settling time in samples (rounded to the next integer): $$V = N = Max\left(\frac{5\tau_{ij}}{T} + d_{ij}\right) \quad (\mathrm{i} = 1, 2, \ldots, \beta;\ \mathrm{j} = 1, 2, \ldots, \mathrm{m})$$ Where $d_{ij} = (\frac{\theta_{ij}}{T} + 1)$ is the dead time samples.
4	Select the control horizon, U equal to 63.2% of the settling time of the slowest sub-process in the multivariable system [2]. $$U = Max\left(\frac{\tau_{ij}}{T} + d_{ij}\right) \quad (\mathrm{i} = 1, 2, \ldots, \beta;\ \mathrm{j} = 1, 2, \ldots, \mathrm{m})$$
5	Select the controlled variable weights, q_i to scale process variable measurements to similar magnitudes.
6	Compute the move suppression coefficients λ_j [5]: $$\lambda_j^{\,2} = \frac{U}{500} \sum_{i=1}^{\beta} \left[q_i^{\,2} K_{ij}^2 \left\{ V - d_{ij} - \frac{3\tau_{ij}}{2T} + 2 - \frac{(U-1)}{2} \right\} \right] \quad (i = 1, 2, ..., \beta;\ j = 1, 2, ..., m)$$
7	Implement DMC using the traditional step response matrix of the actual process and the computed parameters in steps 1 to 6.

In order to investigate the effect of MPC tuning parameters using the suggested tuning strategy, two different case-studies are implemented. The first is the distillation column [2] and the second is the heat exchanger network [1, 3]. Besides, three simulation experiments were carried out to ensure the effect of each tuning parameter.

FIRST CASE-STUDY: DISTILLATION COLUMN PROCESS

Distillation is used in many chemical processes for separating feed streams and for purification of final and intermediate products. It is known that high-purity distillation columns are highly nonlinear, and the composition interaction between the stages due to the counter flow of vapour and liquid is also large [13]. Thus, the control of columns to give multiple products of constant composition is very difficult. Various methods of controlling distillation columns have been reported in the literature (e.g., internal model control method, non-interacting control, fuzzy control, model predictive control [13, 14]. In this case-study we consider a multivariable process with dead-time (2x2) distillation column which was used by many control studies, including model predictive control [12]. The transfer function matrix is given as:

$$\begin{bmatrix} X_D(s) \\ X_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{16.7s+1} & \frac{-18.9e^{-3s}}{21.0s+1} \\ \frac{6.6se^{-7s}}{10.9s+1} & \frac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} W_F(s) \\ D_V(s) \end{bmatrix}$$

Where (X_D) and (X_B) are percentages of methanol in the distillate and percentage of methanol in the bottom products, respectively. Also $W_F(s)$ and $W_F(s)$ are reflux flow rate and steam flow rate in the reboiler, respectively. Looking at the system matrix, the sampling time is chosen for the slowest process, and is obtained in (2 minutes) and this gives 50 step response coefficients for a steady state time of (100 minutes). The control weights are taken as: $q_i = 1$, (1,2) and the input weights $r_1 = 20, r_2 = 35$.

Effect of Prediction Horizon

In order to clearly see the effect of the prediction horizon (V) on the performance of closed-loop systems, a simulation experiment was performed by considering three different values of V (i.e. V=5, V=25, V=50). Figure (1) shows the effects of the prediction horizon V on the MIMO (2x2) with dead-time process. Similarly, the control action is more aggressive, and the system response is faster as the prediction horizon V is decreased.

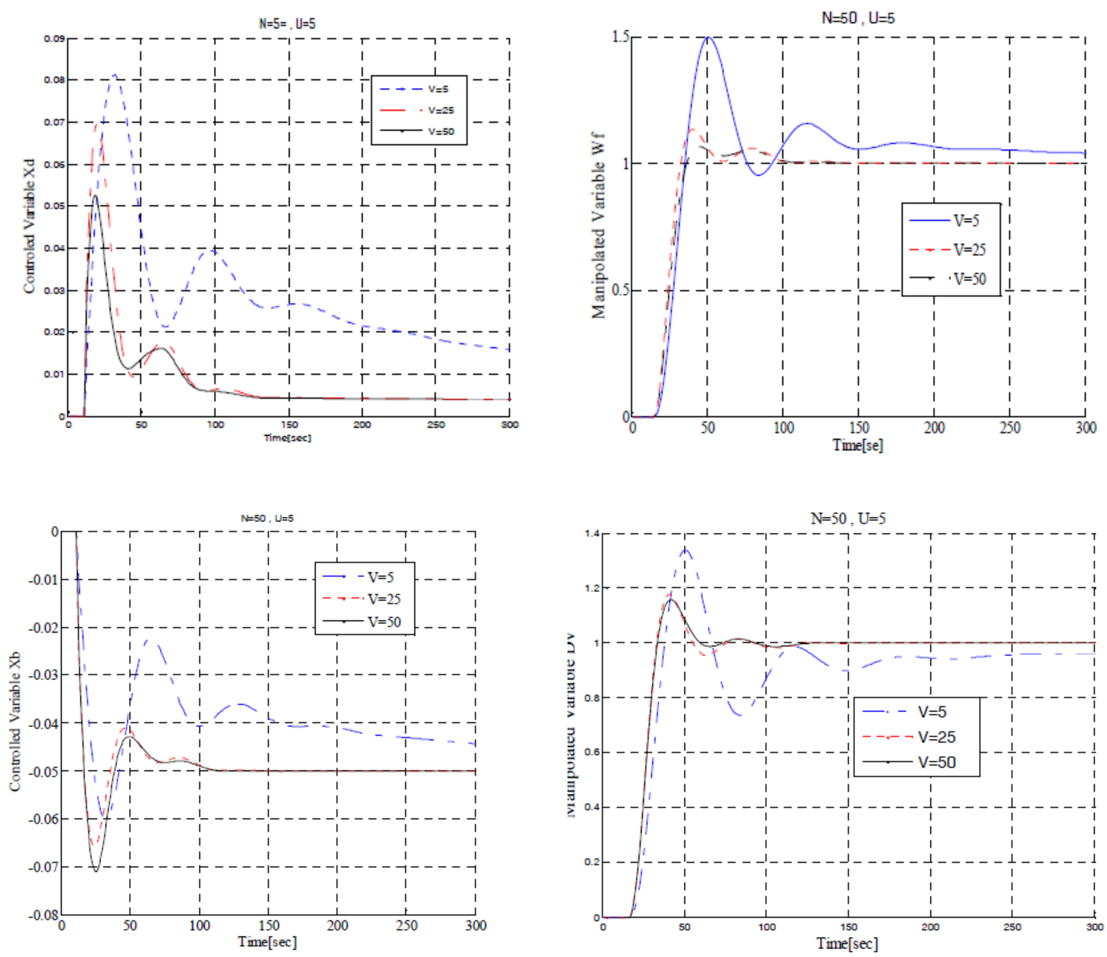


Figure 1: Effect of Prediction Horizon

Effect of Control Horizon

To observe the effect of the control horizon (U) on the performance of closed-loop systems, a simulation experiment was performed by considering three different values of U (i.e. U=3, U=5, U=10).

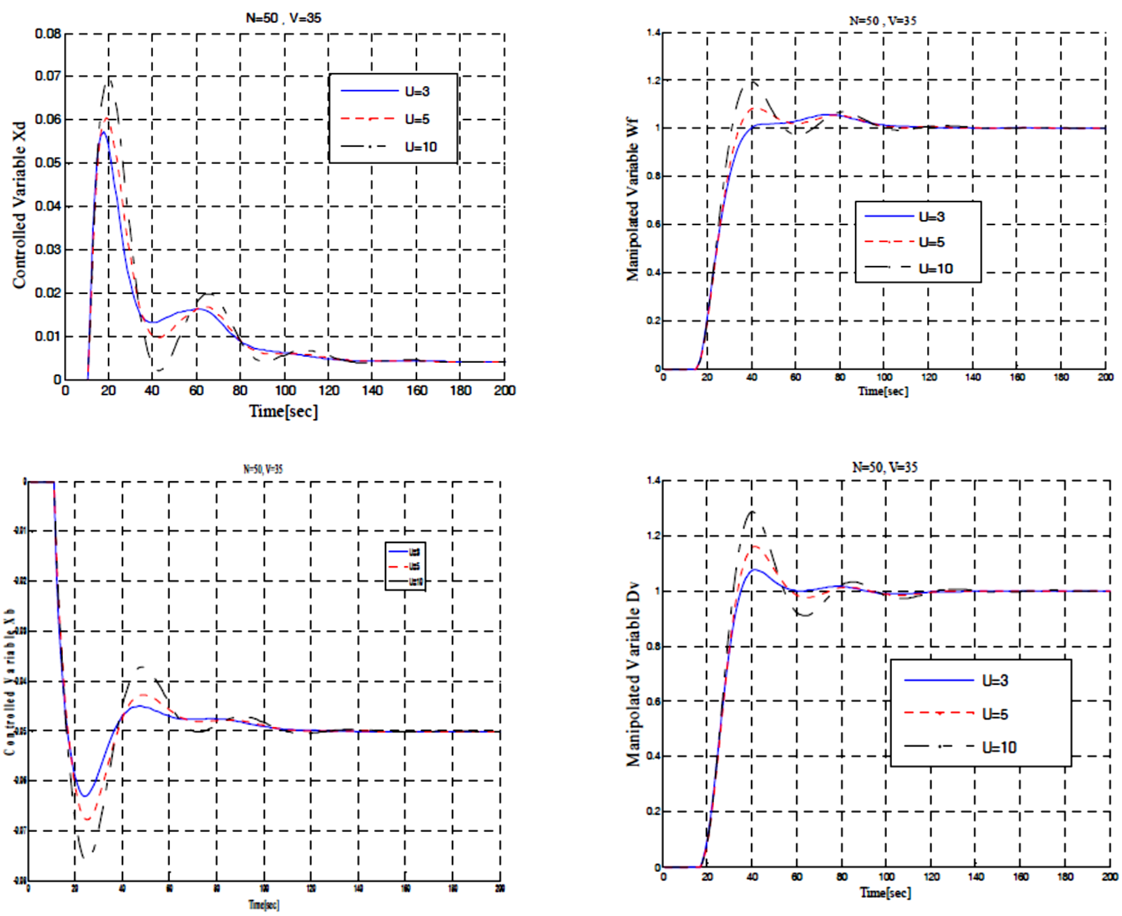


Figure 2: Effect of Control Horizon (U)

Figure (2) shows the effects of the control horizon U on the MIMO (2x2) with dead-time process. It shows also that the control action is more aggressive, and the system response is faster as the control horizon U is increased. Once the control horizon is increased from 3 to 10, the performance does not change significantly. The only noticeable effect is a slight increase in overshoot for a larger control horizon and this is due to the additional degree of freedom from a larger control horizon. This allows more aggressive initial moves that are later compensated by the extra moves available.

Effects of Input Weights

In order to see the influence of the input weights (r1, r2) on the performance of closed-loop systems, a simulation experiment was performed by considering three different values of (r). Figure (3) shows the effects of the input weights (r1, r2) on the MIMO (2x2) with dead-time process. Also, it can be seen that a larger move suppression coefficient results in a slower response. Further increasing r can lead to an undesirable sluggish response.

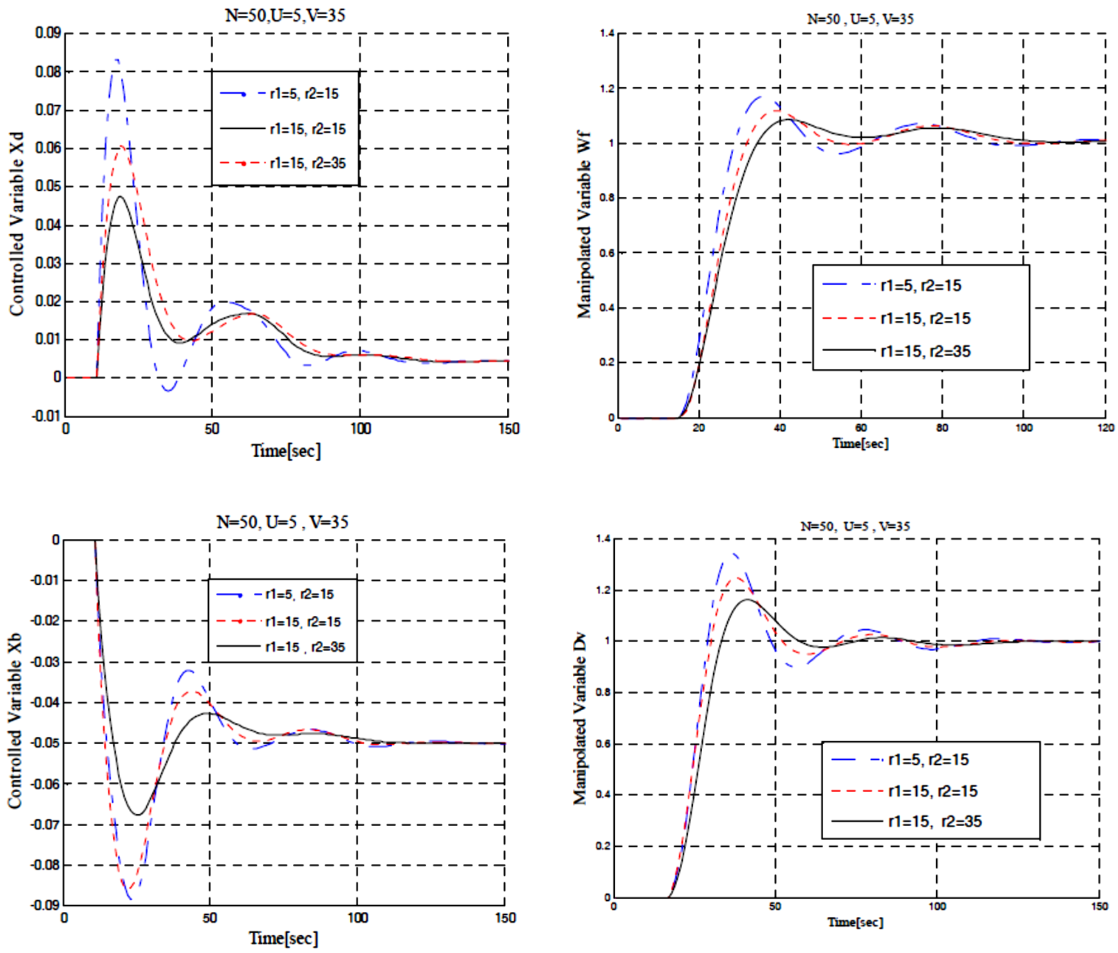


Figure 3: Effects of Input Weights (r1, r2)

Effects of Control Weights

The purpose of the simulation analysis is to observe the effect of the control weights (q1, q2) on the performance of closed-loop systems. This was performed on the MIMO (2x2) with dead-time process. Figure (4) shows that, a larger control weight results in a faster but oscillatory response. Further increasing of q can lead to an undesirable unstable response. However, a smaller control weight gives a better and slower response. Further decreasing of q does not affect the performance much.

In summary, the examples in Figures (1 - 4) show the control action is more aggressive, and the system response is faster and less robust as: (1) the prediction horizon V is decreased, (2) the control horizon U is increased and (3) the control weight or move suppression coefficient r is decreased. The response is clearly most sensitive to the choice of the move suppression coefficient r. The effects of V and U are significant only when the move suppression coefficient r is zero. The output weights q, was equal to one i.e. $q = 1$.

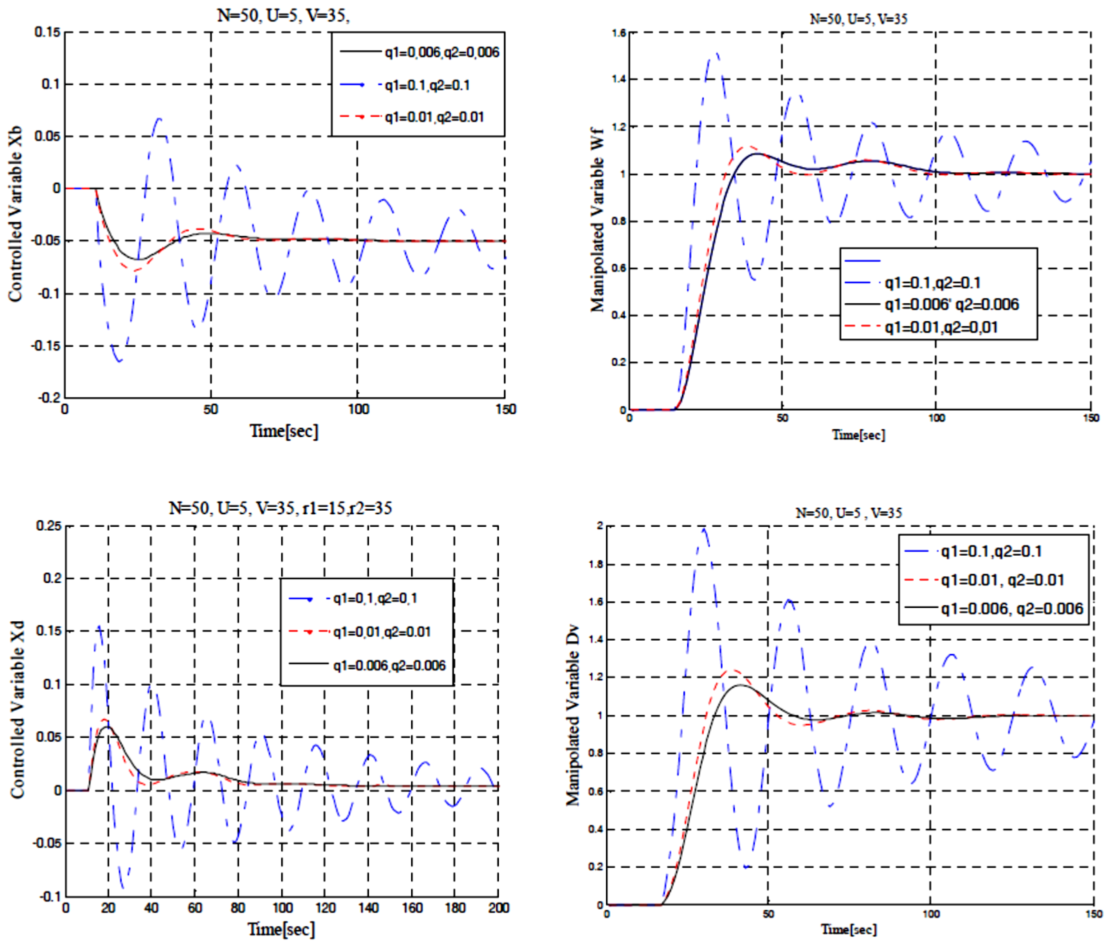


Figure 4: Effects of Control Weights (q1, q2)

SECOND CASE-STUDY: HEAT EXCHANGER NETWORK

Heat exchangers are devices providing heat transfer between two fluids at different temperatures. These devices are widely used in industry especially in chemical processing, oil refining, and power production. However, control of heat exchangers is a complex part of the whole process design and control. Nevertheless, many researchers have conducted a research in the design of a flexible and controllable heat exchanger network, Such as flexible low-level control [3, 16], distributed control system [17]. The basic objective of the considered shell-and-tube heat exchanger in this study is to exchange heat between streams in order to recover and integrate energy from process to process; one hotter and the other cooler. This study became an important in industries process because of the high cost on operating utilities (external sources of heat) and also environmental issues [17, 18]. These heat exchangers are governed by the steady-state characteristics:

$$Q = UA(T^{out} - T^{in}) \tag{3}$$

$$Q_h = w_h c_h (T_h^{out} - T_h^{in}) \tag{4}$$

$$Q_c = w_c c_c (T_c^{out} - T_c^{in}) \tag{5}$$

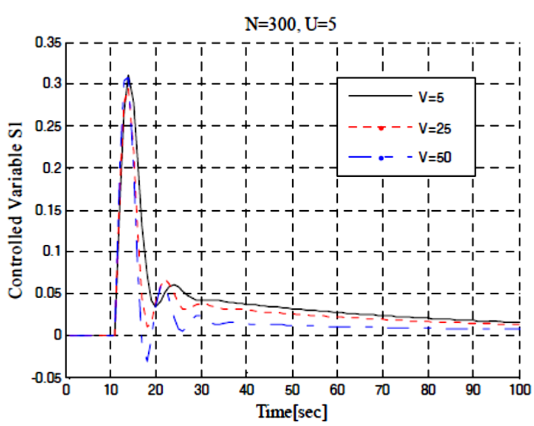
Where w is the stream flow rate, c is the stream heat capacity, T^{in} is the stream inlet temperature, T^{out} is the stream outlet temperature, U is the overall heat transfer coefficient and A is the heat exchanger area. The equation (3) represents the energy balance in the heat exchanger, which reflects the heat transferred, while the equations (4) and (5) refer to the balance of the inlet streams.

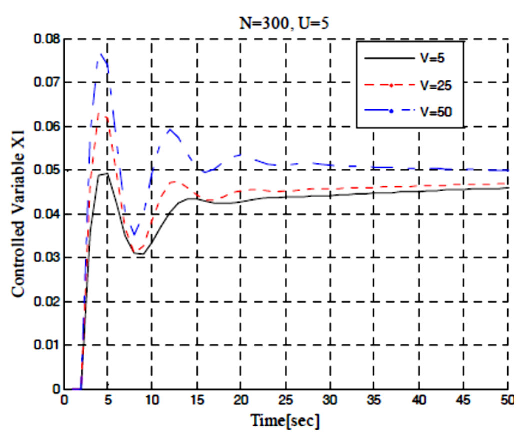
A heat exchanger's total flow rate or bypass ratio is manipulated by the controller to change the outlet temperature of the heat exchange i.e., vary the amount of heat exchanged between the inlet cold and hot streams. A linear model of the heat exchanger network is considering only four-input and four-output system which can be expressed as follows [3].

$$\begin{bmatrix} y_1(s) \\ y_2(s) \\ y_3(s) \\ y_4(s) \end{bmatrix} = \begin{bmatrix} 17.3\dfrac{e^{-4.8s}}{23.8s+1} & 20.6\dfrac{e^{-61.3s}}{38.8s+1} & 19.9\dfrac{e^{-28.9s}}{25.4s+1} & 0 \\ 0 & 4.6\dfrac{e^{-50.4s}}{48.4s+1} & 0 & 79.1\dfrac{31.4s+0.8}{31.4s+1} \\ 0 & 24.4\dfrac{48.2s^2+4.0s+0.05}{48.2s^2+3.9s+0.06} & 0 & -8.4\dfrac{e^{-18.79s}}{27.9s+1} \\ 0 & 16.9\dfrac{e^{-24.7s}}{39.5s+1} & -39.2\dfrac{22.8s+0.8}{22.8s+1} & 0 \end{bmatrix} \begin{bmatrix} u_1(s) \\ u_2(s) \\ u_3(s) \\ u_4(s) \end{bmatrix}$$

Effect of Prediction Horizon

In this work, a simulation experiment was performed using three different values of V (i.e. V=5, V=25, V=50). Figure (5) shows the effects of the prediction horizon on the MIMO (4x4) system. In the figure, it is clear that the control action is more aggressive, and the system response is faster as the prediction horizon V is decreased.





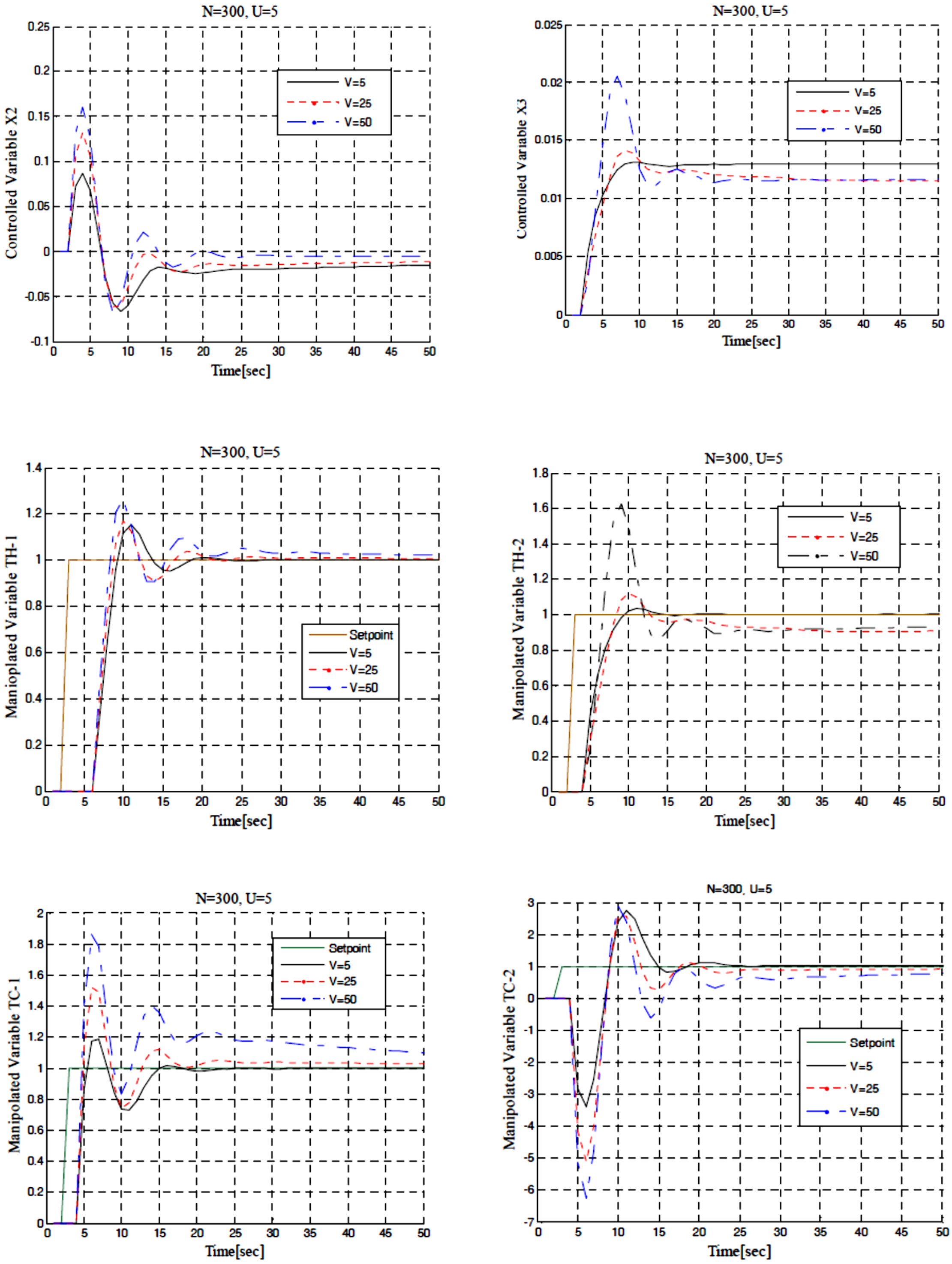
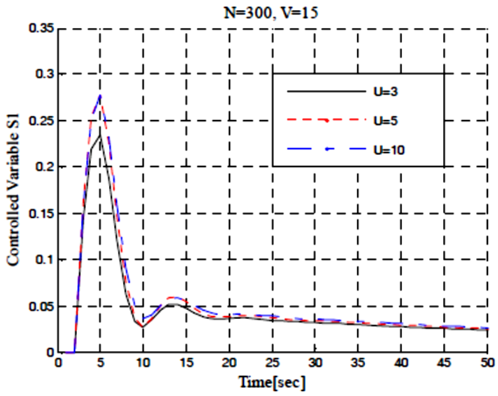
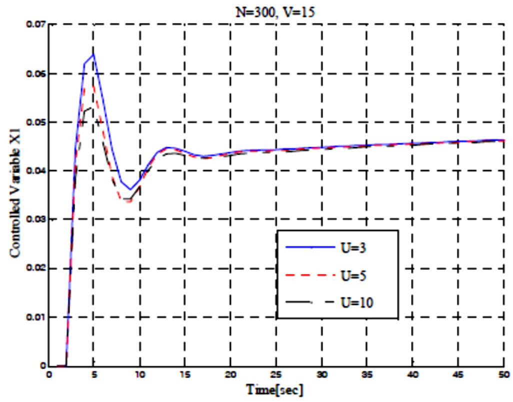


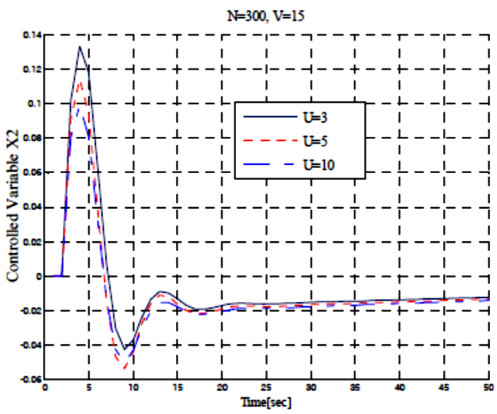
Figure 5: Effect of Prediction Horizon (V)

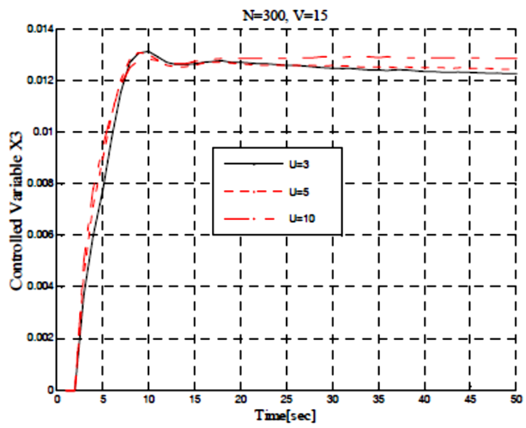
Effect of Control Horizon

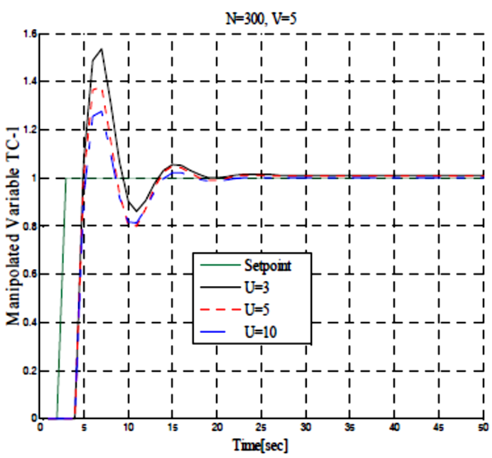
Three different values of U (i.e. U=3, U=5, U=10) are performed in a simulation to recognize the effect of the control horizon (U) on the performance of closed-loop systems. Figure (6) shows the effects of the control horizon (U) on the MIMO (4x4) system. In this figure the control action is more aggressive, and the system response is faster as the control horizon U is increased. Other results show that the rising of the control horizon from 3 to 10 does not alter the performance substantially. The only noticed effect is a slight increase in overshoot for a larger control horizon and this is due to the additional degree of freedom from a larger control horizon. This allows more aggressive initial moves that are later compensated by the extra moves available.

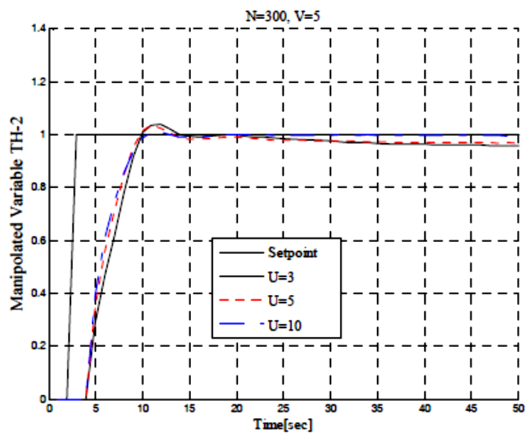












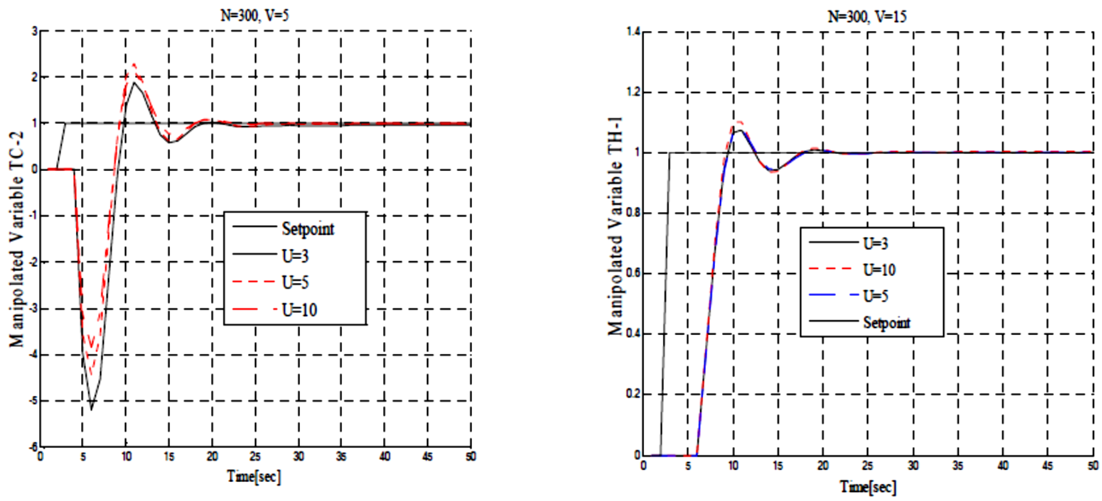


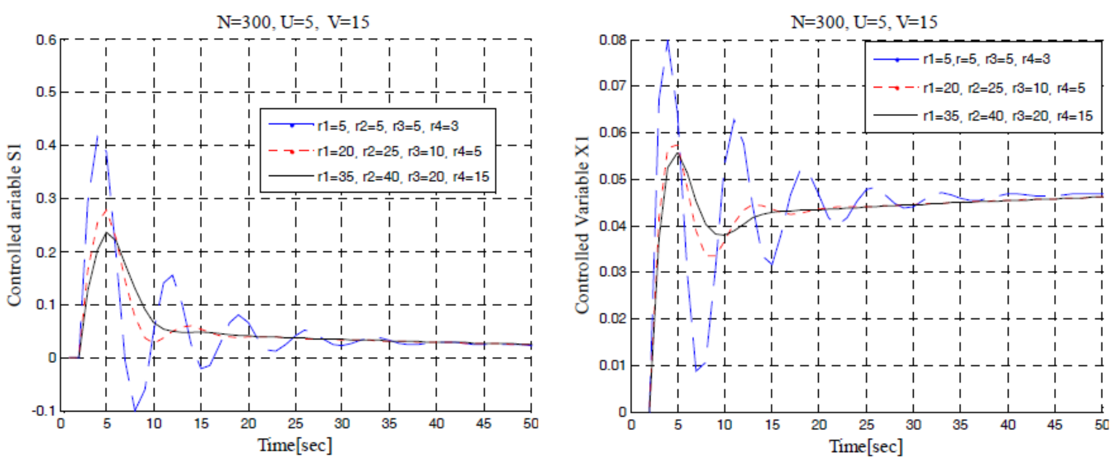
Figure 6: Effect of Control Horizon (U)

Effects of Input Weights

A simulation experiment was performed by considering three different set values of

(r), $[r_1 \quad r_2 \;\; r_3 \quad r_4] = \begin{bmatrix} 5 & 5 & 5 & 3 \\ 20 & 25 & 10 & 5 \\ 35 & 40 & 20 & 15 \end{bmatrix}$ to see the effect of the input weights on the performance of closed loop systems.

Figure (7) shows the effects of the input weights (r1, r2, r3 and r4) on the MIMO (4x4) system.



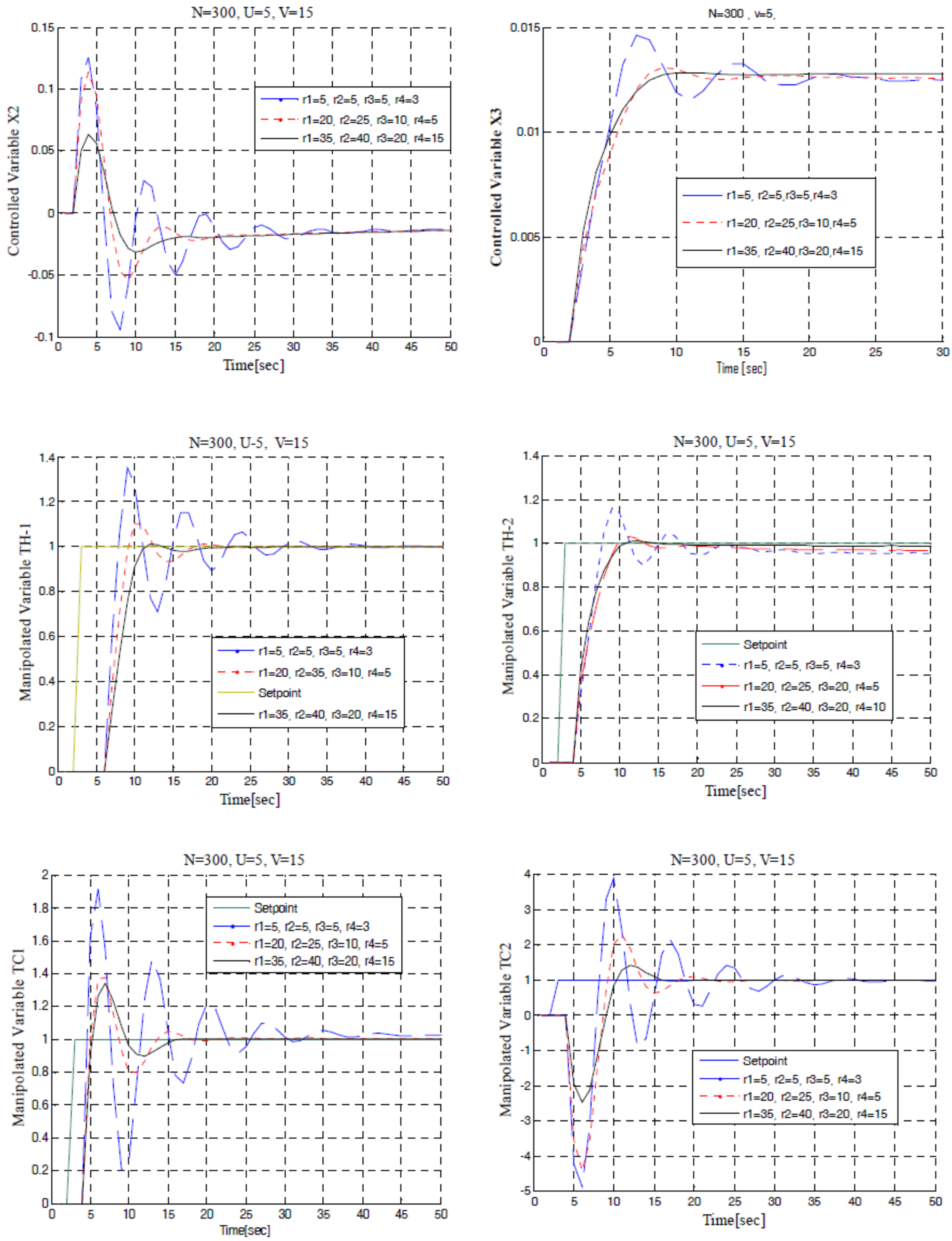


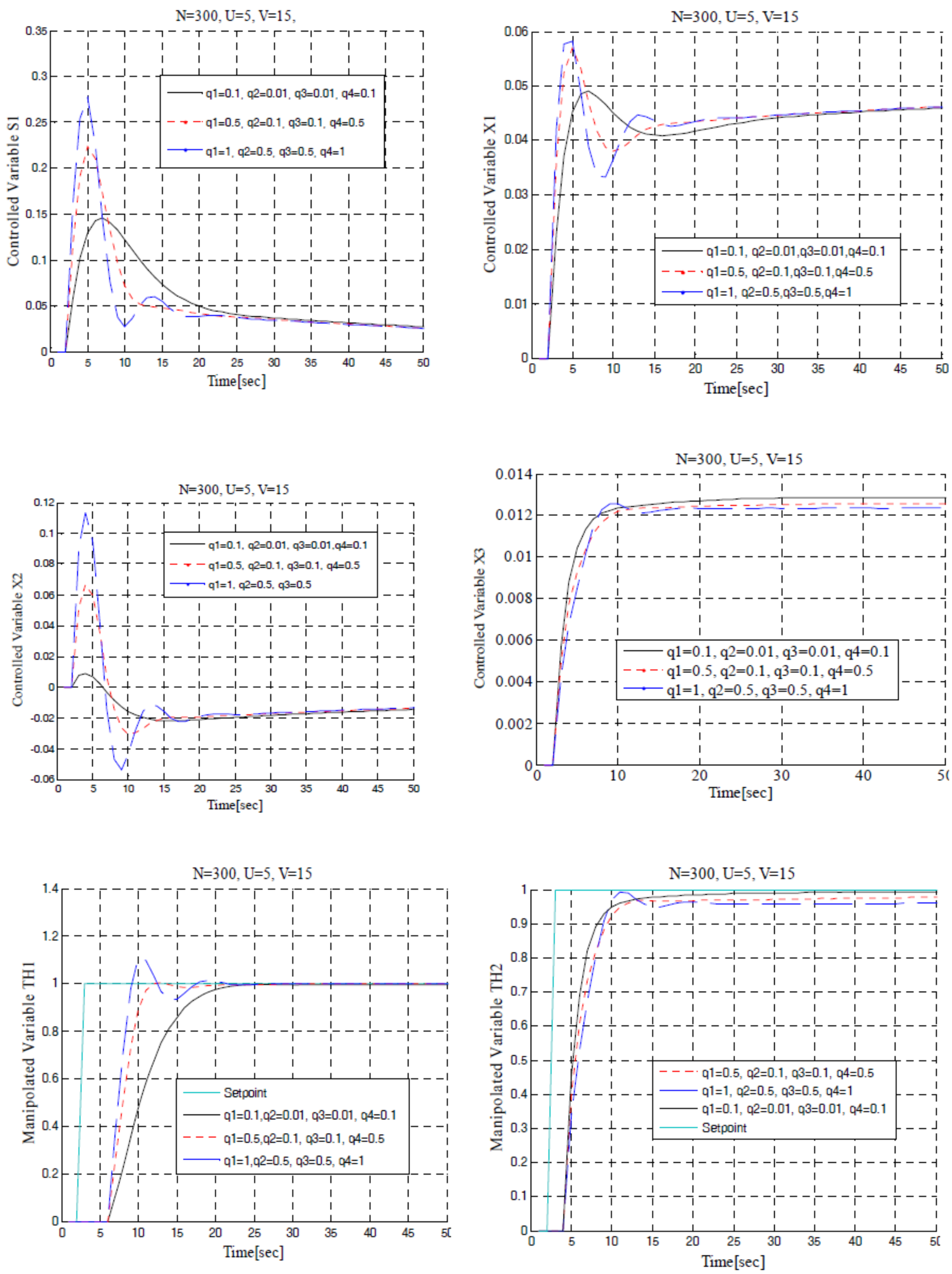
Figure 7: Effects of Input Weights (r1, r2, r3 and r4)

Figure (7) shows that, a larger move suppression coefficient makes a slower response. Further increasing r can lead to an undesirable slow response.

Effects of Control Weights

As it can be seen in Figure (8) that, a larger control weight results in a faster but oscillatory response. Further increasing of q can lead to an undesirable unstable response.

But a smaller control weight gives a better and slower response. Further decreasing q does not affect the performance much. Figure (8) shows the effects of the input weights (q1, q2, q3 and q4) on the MIMO (4x4) system.



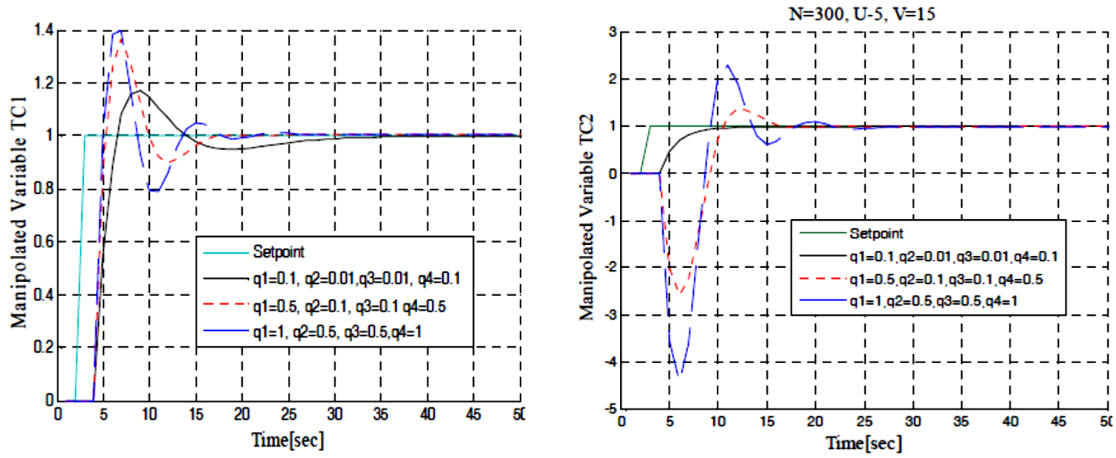


Figure 8: Effects of Control Weights (q1, q2, q3 and q4)

DISCUSSIONS

It can be seen from Figures (1) and (2) that the QDMC algorithm control action is more aggressive, and a faster closed-loop system response for each application (i.e. distillation column [2] and the heat exchanger network (HEN) [3]) is obtained as the prediction horizon V is decreased.

It can also be seen from Figures (2) and (6) that increasing the control horizon U from 3 to 10 results in more oscillatory control actions and faster closed-loop system responses. However, a slight change in the system performances is maintained if the control horizon U is selected to be more than ten. This indicates that, the control horizon parameter does not have a big influence on the overall system performance.

Whereas, Figures (4) and (8) demonstrate that, a smaller control weights (q) give a better and slower response. Increasing (q) results in a faster but oscillatory closed-loop system response, and undesirable unstable system performance may be obtained for a big value of (q) for each application.

Figures (3) and (7) show that a slow overall system response is yielded by gradually increasing the move suppression coefficient (r) for each application. However, a large choice of (r) will produce undesirable sluggish response. In addition, it can also be noticed from these figures, that the coefficient (r) is the most effective parameter and has a wide range of tuning, and hence, it can be considered as a primary tuning parameter.

CONCLUSIONS

The main objectives of this paper are to investigate the influence of the tuning parameters, (V, U, r and q) of the multivariable QDMC algorithm and to specify the most effective parameter that can further be used as a primary fine-tuning parameter.

In this context, in order to achieve these two objectives, the QDMC algorithm is applied to two different case-studies namely a (two by two) distillation column used by (Sridhar, R and Cooper, D) [2] and the (four by four) heat exchanger network (HEN) [1,3]. Based on the simulation experiments, it is clear that the closed-loop system is most sensitive to the choice of the move suppression coefficient (r) and suggested to have the first priority in the tuning procedure.

However, in this work only square (nxn) case-studies were considered. Therefore, an extended research which includes (nxm) systems can be made in order to generalize the assessment.

Certainly, this work gives a valuable opportunity to modify a new strategy for fine tuning the QDMC algorithm to optimize the closed-loop system performance.

ACKNOWLEDGEMENT

The authors are indebted to Professor Amir Hussain of the University of Stirling, Stirling, (UK) for highly stimulating discussion and insightful comments and suggestions.

REFERENCES

[1] Milaud, M., and Zayed, A., "A new Multivariable MBPC Controller," STA, IAA-3022, pp. 811-819, Tunisia, 2012.

[2] Sridhar, R., and Cooper, D. J., "A novel Tuning Strategy for Multivariable Model Predictive Control," ISA transactions, Vol. 36(4), pp. 273-280, 1998.

[3] Giovanini, L. L., and Marchetti, J. L., "Low-Level Flexible-Structure Control Applied to Heat Exchanger Networks," Computers and Chemical Engineering, Vol. 27, pp. 1129-1142, 2003.

[4] Seborg, D. E., Edgar, T. F., Mellichamp, D. A., Process Dynamics and Control. John Wiley, New York, 1989.

[5] Callaghan, P. J.; Lee, P. L. "An Experimental Investigation of Predictive Controller Design by Principal Component Analysis," Chem. Eng. Res. Des.1988, 66, 345.

[6] Zayed, A., Hussain, A., Smith, L., "A New Multivariable Generalized Minimum-Variance Stochastic Self-tuning with Pole-zero Placement," International Journal of Control and Intelligent Systems, 32 (1) 35-44, 2004.

[7] Maciejowski, J., "Predictive Control with Constraints," Prentice Hall, England, 2002.

[8] Qin, S., and Badgwell, T., "A Survey of Industrial Model Predictive Control Technology," Control Engineering Practice, Vol.11 (7), pp. 733-764, 2003.

[9] Garcia, C. E., Prett, D. M., Morari, M., "Model Predictive Control: Theory and Practice – A Survey," Automatica, Vol. 25 (3), pp. 335-348, 1989.

[10] Cutler, C. R., and Ramaker, B. L., "Dynamic Matrix Control- A Computer Control Algorithm," in AICHE National Meeting, Houston, TX, 1979.

[11] Garcia, C. E., and Morari, M., "Internal Model Control. A Unifying Review and Some New Results," Ind. Eng. Chem. Process Des. Dev., vol. 21, pp. 308, 1982.

[12] Richalet, J., "Industrial Applications of Model Based Predictive Control," Automatica, vol. 29 (5), pp. 1251-1274, 1993.

[13] Clarke, D. W., and Scattolini, R., "Constrained Receding Horizon Predictive Control," IEE Proc., vol. 138(4), pp. 347, 1991.

[14] Huyck, B., De Brabanter, J., De Moor, B., Van Impe, J. F., Logist, F., "Online Model Predictive Control of Industrial Processes Using Low Level Control Hardware: A Pilot-scale Distillation Column Case Study," Control Engineering Practice, vol. 28, pp. 34-48, 2014.

[15] Mathur, U., Rounding, R. D., Webb, D. R., Conroy, R., "Use Model Predictive Control to Improve Distillation Operations," Chemical Engineering Progress, Vol. 104, no. 1, pp. 35-41, 2008.

[16] Aguilera, N., and Marchetti, J. L., "Optimizing and Controlling the Operation of Heat Exchanger Networks," American Institute of Chemical Engineers Journal, Vol. 44(5), pp. 1090-1104, 1998.

[17] Aguilera, N., and Marchetti, J. L., "Optimizing and Controlling the Operation of Heat Exchanger Networks," American Institute of Chemical Engineers Journal, Vol. 44(5), pp. 1090-1104, 998.

[18] Gonzales, A.H., Odloak, D., Marchetti, J. L., "Predictive Control Applied to Heat-Exchanger Networks," Chemical Engineering and Processing. Vol. 45 (Aug), 2006.