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Linear and Non-linear Multi-Input Multi-Output Model Predictive Control of Continuous Stirred Tank Reactor

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Abstract

In this article, multi-input multi-output (MIMO) linear model predictive controller (LMPC) based on state space model and nonlinear model predictive controller based on neural network (NNMPC) are applied on a continuous stirred tank reactor (CSTR). The idea is to have a good control system that will be able to give optimal performance, reject high load disturbance, and track set point change. In order to study the performance of the two model predictive controllers, MIMO Proportional-Integral-Derivative controller (PID) strategy is used as benchmark. The LMPC, NNMPC, and PID strategies are used for controlling the residual concentration (C_A) and reactor temperature (T). NNMPC control shows a superior performance over the LMPC and PID controllers by presenting a smaller overshoot and shorter settling time.

Keywords: Linear Model, Model Predictive Control, Neural Network, Continuous Stirred Tank Reactor.

السيطرة التنبؤية النموذجية متعددة المدخلات والمخرجات الخطية وغير الخطية للمفاعل ذو الخلط المستمر

الخلاصة

في هذه المقالة ، متعدد المدخلات والمخرجات للمسيطر من نوع النموذج التنبؤي الخطي (LMPC) والمعتمد على نموذج فضاء الحالة والمسيطر من نوع النموذج التنبؤي غير الخطي والمعتمد على نوذج الشبكة العصبية (NNMPC) تم تطبيقهما على المفاعل ذو الخلط المستمر . الفكرة من البحث هو للحصول على نظام سيطرة جيد قادر على اعطاء افضل اداء ، رفض اضطراب عالي لمتغيرات الحمل ، ويستطيع تتبع مجموعة من القيم المرغوب فيها. لغرض دراسة ادائية انظمة السيطرة التنبؤية فان متعدد المدخلات والمخرجات للمسيطر ذو التغذية المرتدة من نوع (PID) تم استخدامه كمقارن . كل انواع المسيطرات المستخدمة في هذا البحث استخدمت للسيطرة على تركيز المادة المتبقية للمادة المتفاعلة ودرجة حرارة المفاعل . ان المسيطر من نوع النموذج التنبؤي غير الخطي يظهر تفوق في الاداء على المسيطر من نوع النموذج التنبؤي الخطي ومسيطر التغذية المرتدة من خلال تقديم اصغر قيمة لتجاوز الحد واقصر وقت لزمن الاستقرار .

الكلمات الدالة: النموذج الخطي ، سيطرة النموذج التنبؤي ، الشبكة العصبية ، المفاعل ذو الخلط المستمر

Introduction

In any manufacturing process, where there is a chemical change taking place, a chemical reactor is at the heart of the plant. Depending on mode of operation, reactors are classified as batch-wise or continuous. In batch-wise mode, reactants are charged at the beginning of the reaction and products are removed at the end of the reaction. In continuous stirred tank reactor (CSTR), reactants are continuously charged and products are continuously removed.

Thermodynamic systems, and among them chemical reaction systems, are usually nonlinear dynamical systems. They can therefore have a complex behavior and be difficult to analyze and control. Stirring tank reactor exhibits nonlinear operations where reaction is exothermic. Thus, performance prediction becomes more difficult with high degree of nonlinearity.

Therefore, and with the advent of high-speed computer systems in addition to giant programs such as (MATLAB, SIMULINK, LABVIEW… etc), there is more increase interest in the study for these types of systems.

Process control has become an integral part of process plants. An automatic controller must be able to facilitate the plant operation over a wide range of operating conditions. The proportional-integral (PI) or proportional-integral-derivative (PID) controllers are commonly used in many industrial control systems. These controllers are tuned with different tuning techniques to deliver satisfactory plant performance. However, specific control problems associated with the plant operations severely limit the performance of conventional controllers. The increasing complexity of plant operations together with tougher environmental regulations, rigorous safety codes and rapidly changing economic situations demand the need for more sophisticated process controllers [1].

Model Predictive Control (MPC) is an important advanced control technique which can be used for difficult multivariable control problems [2].

The term MPC describes a class of computer control algorithms that control the future behavior of the plant through the use of an explicit process model. At each control interval the MPC algorithm computes an open loop sequence of manipulated variable adjustments in order to optimize future plant behavior. The first input in the optimal sequence is injected into the plant, and the entire optimization is repeated at subsequent control intervals [3].

Model predictive control (MPC) has become a first choice of control strategy in industry because it is intuitive and can explicitly handle multivariable systems with constraints. The basic control strategy in MPC is the selection of a set of future control moves (control horizon) and minimizes a cost function based on the desired output trajectory over a prediction horizon with a chosen length. This requires a reasonably accurate internal model that captures the essential on linearities of the process under control and predicts the dynamic behavior [4].

In this search, the continuous stirred tank reactor (CSTR) was controlled by using three different controller types which are: linear, nonlinear model predictive controller, and the conventional feedback controller which used as a comparable. The steady state calculations, dynamic behavior, and controllers programs was developed by several SIMULINK models.

In the next section, the mathematical model of CSTR is described. The feedback and model predictive controller are explained in sections three and four. In the section five, the SIMULINK environment is described. Finally, the results are discussed in section six.

CSTR Mathematical Model

The first step in the studying of the dynamic behavior and control of CSTR is to develop a mathematical model depending on mass and energy balances that can be considered the gate for all works.

Suppose first order irreversible exothermic reaction (A → B) in a Continuous Stirred Tank Reactor as shown in Figure (1). The heat generated by the reaction is removed using a cooling jacket surrounding the reactor. Perfectly mixing is assumed in CSTR and the change in volume due to reaction is negligible. The jacket water is assumed to be perfectly mixed, the mass of the metal walls is considered negligible, and constant hold up of the water in the jacket.

The reactor mass and energy equations are:

Over all Mass Balance

$$\frac{dV}{dt} = F_{in} - F_{out} \qquad \dots (1)$$

(Since the volume of the reactor is constant), therefore:

$$F_{in} = F_{out} = F \qquad \dots (2)$$

Component (A) Mass Balance

$$\frac{dVC_A}{dt} = F_{in}C_{AO} - F_{out}C_A - VC_AK_Oe^{(-E/RT)} \quad \dots (3)$$

Since (V) is constant and from equation (2), equation (3) becomes:

$$\frac{dC_A}{dt} = \frac{F}{V}C_{AO} - \frac{F}{V}C_A - C_AK_Oe^{(-E/RT)} \quad \dots (4)$$

Heat Balance

$$\rho\frac{dVCpT}{dt} = \rho CpF_{in}T_{in} - \rho CpF_{out}T - H_rVC_AK_Oe^{(-E/RT)} - UA(T - T_C) \quad \dots (5)$$

Since (V) is constant, the specific heat (Cp) is not function of Temperature, and from equation (2), equation (5) becomes:

$$\frac{dT}{dt} = \frac{F}{V}T_{in} - \frac{F}{V}T - \frac{H_rC_AK_Oe^{(-E/RT)}}{\rho Cp} - \frac{UA}{\rho CpV}(T - T_C) \quad \dots (6)$$

Energy Balance on the Jacket

$$\rho_CV_CCp_C\frac{dT_C}{dt} = F_CCp_C\rho_C(T_{Cin-}T_C) + UA(T - T_C) \quad \dots (7)$$

After simplification, equation (7) becomes:

$$\frac{dT_C}{dt} = \frac{F_C}{V_C}(T_{Cin-}T_C) + \frac{UA}{\rho_CV_CCp_C}(T - T_C) \quad \dots (8)$$

The variables and nominal CSTR parameter values are shown in table (1).

Feedback Controller

Currently, the Proportional-Integral-Derivative (PID) algorithm is the most common control algorithm used in industry. Often, it is use to control processes that include heating and cooling systems, fluid level monitoring, and pressure control. In PID control, a process variable and a set point must be specific. The process variable is the system parameter determines to control, such as temperature, concentration and the set point is the desired value for the controlling parameters. The PID controller compares the controlled variable value with the set point value to compute the error.

$$\begin{aligned} &Error\ value\ (E) \\ &= Set\ point\ value \\ &- Controlled\ variable\ measuring\ value \end{aligned} \quad \dots (9)$$

Depending on error value, a PID controller determines a controller output value, such as the heater power or valve position. The controller applies the controller output value to the system (manipulated variable), which in turn drives the process variable toward the set point value.

The most important types of industrial feedback controllers include: on-off controller, proportional controller (P), Proportional-Integral Controller (PI), Proportional-Derivative Controller (PD), Proportional-Integral-Derivative Controller (PID).

For most processes, the PID controller is the best one of the above types since it compromises between the advantages and disadvantages of PI and PD controllers.

The PID controller action U (t) can be expressed as [5]:

$$U(t) = K_c \left[E(t) + \frac{1}{\tau_i} \int_0^t E(t)dt + \tau_D \frac{dE(t)}{dt} \right] \quad \dots (10)$$

Where: K_c=proportional constant, τ_i= integral time constant, τ_D=derivative time constant, *E(t)* = the tracking error, *U(t)* = the controller action that will pass to the plant to adjust the appropriate manipulated variable.

Model Predictive controller (MPC)

Model predictive control (MPC) refers to a wide class of control algorithms that use an explicit process model to predict the behavior of a plant.

Model predictive control was conceived in the 1970s primarily by industry. Its popularity steadily increased throughout 1980s. At present, there is little doubt that it is the most widely used multivariable control algorithm in the chemical process industries and in other areas. While MPC is suitable for almost any kind of problem, it displays its main strength when applied to problems with [6]:

1- A large number of manipulated and controlled variables.
2- Constraints imposed on both the manipulated and controlled variables.
3- Changing control objectives and/or equipment (sensor/actuator) failure.
4- Time delays.

Over 30 years, there are a wide variety of MPC algorithms have been developed. The fundamental framework of MPC algorithms is common for any kind of MPC schemes. The main differences in many MPC algorithms are the types models used to represent the plant dynamics and the cost function to be minimized. The basic elements of MPC are illustrated in Figure (2) and can be defined as follows [7]:

An appropriate model is used to predict the output behavior of a plant over a future time interval or normally known as the prediction horizon (P). For a discrete time model this means it predicts the plant output from $\hat{y}(k+1)$ to $\hat{y}(k+p)$ based on all actual past control inputs u(k),u(k-1),...,u(k-j) and the available current information y(k).

A sequence of control actions adjustments (Δu(k|k-1)… Δu(k+m|k-1))

Tikrit Journal of Engineering Sciences/Vol.19/No.3/September 2012, (41-57)

to be implemented over a specified future time interval, which is known as the control horizon (m) is calculated by minimizing some specified objectives such as the deviation of predicted output from set point over the prediction horizon and the size of control action adjustments in driving the process output to target plus some operating constraints. However, only the first move of computed control action sequence is implemented while the other moves are discarded. The entire process step is repeated at the subsequent sampling time.

A nominal MPC is impossible, or in other words that no model can constitute a perfect representation of the real plant. Thus, the prediction error, ε(k) between the plant measurement $y_m(k)$ and the model prediction $\hat{y}(k)$ will always occur. The ε(k) obtained is normally used to update the future prediction. Figure (3) illustrated the error feedback of MPC.

Recently, the MPC is actually a synonym to Linear Model Predictive Control (LMPC). Most of the MPC software available in the market nowadays used linear models even though most processes are nonlinear [8].

LMPC algorithms employ linear or linearized models to obtain the predictive response of the controlled process. There are many LMPC algorithms and all similar in the sense that they rely on process models to predict the behavior of the process over some future time interval, and the control calculations are based on these model predictions.

In this work, LMPC based on state space model is used. The general discrete time linear time invariant (LTI) state space based model predictive control used in the MATLAB toolbox is described as follows [9][10]:

The controller design is based on a model of the open loop process.

$$x(k+1) = Ax(k) + B_u u(k) + B_d d(k) + w(k) \quad \dots (11)$$

$$z(k) = Cx(k) \quad \dots (12)$$

$$y(k) = Cx(k) + v(k) \quad \dots (13)$$

Where: y(k) and z(k): are vectors with measured and noise free process variables.
x(k): is the vector with state variables.
u(k): is the vector with manipulated outputs.
d(k): is the vector with measurable disturbances.
w(k) and v(k): are noise vectors and assumed to be white noise sequences.
(A, B_u, B_d… etc): are constant matrices of appropriate size.

Integrators are introduced by using an extended state space model that uses the differentiated state vector Δx(k) = x(k) – x(k-1) and the controlled outputs z(k) of above model equations (11, 12, and 13). This gives:

$$\bar{x}(k+1) = \bar{A}\bar{x}(k) + \bar{B}_u \Delta u(k) + \bar{B}_d \Delta d(k) + \Delta\bar{w}(k) \quad \dots (14)$$

$$z(k) = \bar{C}\bar{x}(k) \quad \dots (15)$$

$$y(k) = Cx(k) + v(k) \quad \dots (16)$$

The state vector is estimated using a state observer. It is based on the model of eq. (14, 15, and 16). The observer is given by:

$$\varepsilon(k) = y(k) - \bar{C}\bar{x}(k|k-1) \quad \dots (17)$$

$$\hat{x}(k+1|k) = \bar{A}\hat{x}(k|k-1) + \bar{B}_u \Delta u(k) + \bar{B}_d \Delta d(k) + K\varepsilon(k) \quad \dots (18)$$

The observer (17, 18) provides the one step ahead prediction of the extended state vector. Further predictions are obtained by repeated use of equations (14, 15, and 16) with the assumption that $\Delta u(k) = 0$, $k > m$, $\Delta d(k) = 0$, $k > 1$, and $\varepsilon(k) = 0$, $k>1$.

Multiplication with $\bar{C}$ provides prediction of z, based on estimated state, actual measurements, and future manipulated output moves. The output vector is predicted p samples ahead (prediction horizon) and control actions are considered for m future samples, $m \leq p$ (control horizon).

Now, introduce:

$$U(k) = \begin{bmatrix} u(k) \\ \vdots \\ u(k+m-1) \end{bmatrix},$$

$$Z(k) = \begin{bmatrix} z(k) \\ \vdots \\ z(k+p-1) \end{bmatrix} \qquad \dots (19)$$

The predicted process variables over the prediction horizon are:

$$Z(k+1|k) = S^x \hat{x}(k|k-1) + S^u \Delta U(k) + S^d \Delta d(k) + S^e \varepsilon(k) \qquad \dots (20)$$

Where: S^x, S^u, S^d, S^e are constant matrices of appropriate size from ($\bar{A}, \bar{C}, \bar{B}_u$ ... etc).

The control error over the prediction horizon is the difference between predictions and the trajectory of future set points (y_r).

$$E(k+1) = Z(k+1|k) - y_r(k+1) \qquad \dots (21)$$

Each optimization problem is of the form:

$$min_{\Delta u(k)\dots\Delta u(k+m-1)} = \sum_{l=1}^{p} \left\| \Gamma_l^y([Z(k+l|k) - y_r(k+l)]) \right\|^2 + \sum_{l=1}^{m} \| \Gamma_l^u [\Delta U(k+l-1)] \|^2 \qquad \dots (22)$$

Where Γ_l^y and Γ_l^u are weighting matrices to penalize particular components of Z or U at certain future time intervals.

The main Steps for LMPC design in SIMULINK are described as follows:

1- Development of the Plant Model.
2- Introduce the steady state condition.
3- Linearize the plant model at current steady state condition.
4- Define of controlled, manipulated, and disturbance variables.
5- Define the model predictive control toolbox for the model.
6- Simulate the plant for change in set point or disturbance variable.

Although of LMPC is probably acceptable in more industrial process but it still undesirable when the process nonlinearities are strong, operates at multi set points, and the controller is use for large disturbances rejection. Therefore nonlinear model predictive controller NMPC is more applicable and desirable to the areas of these conditions.

Nonlinear Model Predictive Control refers to the MPC algorithm that employs a more accurate nonlinear model in doing prediction and optimization.

In NMPC, there are many different nonlinear models for system identification and control that depend on first-principle models or black–box model methods which are: Volterra models, Polynomial autoregressive moving average model, Hammerstein and Wiener type models, artificial neural networks, and others.

Neural networks have been applied successfully in the identification and control of dynamic systems. Neural network based model predictive controller (NNMPC) is one of the best types of nonlinear model predictive control [11].

When using NNMPC, Two steps are carried out which are: system identification and control design. In the system identification step, a neural network model of the plant is developed. In the control design stage, the neural network model is used to design (or train) the controller.

In this controller type a neural network model of the nonlinear plant is used to predict future plant performance and an optimization algorithm is used to select the control input that optimizes future performance.

The most common neural network model structure employed is multilayer perception (MLP).This structure consists of a number of highly interconnected processing unit called "neurons" which are interconnected by connection weights. Each unit typically receives signals from other units or from the external environment (bias, offset). A subgroup of neurons is called a layer in the neural network. The first layer is the input layer and the last layer is the output layer. The layers that are placed between the input and the output layers are called hidden layers. The neural network plant model trained off-line from a set of N real system outputs by minimizing an output error least-square (OLS) criterion (J):

$$min\ (J) = min \sum_{i=1}^{N} (y_{m\,i} - \hat{y}_i)^2 \quad ...(23)$$

Where: y_m : the plant measurement, $\hat{y}$: the model prediction.

Figures (4, 5) show the system identification and the structure of the neural network plant model.

The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion (I) over the specified horizon.

$$I = \sum_{j=N_1}^{N_2} (y_r(t+j) - \hat{y}(t+j)^2 + p \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2 \quad ...(24)$$

Where: N1, N2, and Nu are define the horizons over which the tracking error and the control increments are evaluated. The u' variable is the tentative control signal, y_r is the desired response, and $\hat{y}$ is the network model response. The p value determines the contribution that the sum of the squares of the control increments has on the performance index. The block diagram that illustrates the NNMPC process is shown in figure (6).

To have good representation of the model, two data sets were generated from the system to train the network, one data set for validation and another one testing. Uniform random input signals, which span the upper and lower limit of operating range, were used to excite the system. This was done to enable network learn the non-linear nature of the system.

In this study, the neural network considered as a multi layer perceptron (MLP) with a single hidden layer. The activation function used is non-linear tan sigmoid function in hidden layer and the linear function in the output layer, the optimum number of hidden layer neurons is (11), 10000 data were generated to train, validate and test the trained network.

Simulation

MATLAB (matrix laboratory) is a technical computing environment for high performance numeric computation and fourth-generation programming language.

SIMULINK (Simulation and Link) is an extension of MATLAB. It works with MATLAB to offer modeling, simulation, and analysis of dynamical systems under a graphical user interface (GUI) environment.

The Model Predictive Control and Neural Network Toolboxes are a collection of software built in MATLAB and SIMULINK blocks which help to design, analyze, and control of the linear and nonlinear processes.

The first design step in the control of the processes in SIMULINK is to implement the linear or nonlinear equations of the process model in a SIMULINK block model.

The nonlinear equations (4, 6, and 8) are implemented in a subsystem SIMULINK model named Continuous Stirred Tank Reactor as given in Figure (7).

The steady state calculations, dynamic behavior, PID, LMPC, and NNMPC controllers SIMULINK models are shown in figures (8, 9, 10, and 11) respectively.

Results and Discussion

Steady State Calculations

The steady state mass and heat calculations displayed that the equilibrium points for component (A) residual Concentration (C_A), reactor temperature (T), and coolant temperature (T_C) are:

$$C_{AS} = 0.0922 \text{ mol/l} \qquad T_S = 375.8 \text{ K}$$
$$T_{CS} = 336.2 \text{ K}$$

Close Loop Response

In the control design process, the manipulated variables must be choosing and by using relative gain array, it found that when the inlet flow rate (F) coupled with concentration (C_A) and coolant water flow rate (F_C) coupled with reactor temperature (T), the relative gain array is:

$$\mathrm{RGA} = \begin{array}{cc} \begin{array}{cc} F & F_C \end{array} & \\ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & \begin{array}{c} C_A \\ T \end{array} \end{array}$$

As show above, the best loops are obtained by pairing these variables.

In order to check the ability of the controller to reject the load disturbance, 10% step change in Feed Conc. C_{Ao} is applied.

The close loop responses for PID, LMPC, and NNMPC of component (A) residual concentration and reactor temperature for 10% step change in C_{Ao} are shown in figures (12, 13) respectively.

In figure (12), for PID, the response has overshooting with oscillation and didn't be able to reject the disturbance and return to its starting value. For the LMPC, the response is slow and settled through the simulation with long time but didn't return to its starting value. The NNMPC response has overshooting and long settled time but it is return to its starting value, the response characteristics (steady state error, Maximum percent overshoot, rise time, and settling time) of the concentration C_A response for the model predictive controller types are shown in table (2).

In figure (13), for PID the response has overshooting with large oscillation. For the LMPC, the response has overshooting. The PID and LMPC responses have long settled time but they are able to reject the disturbance and return to the starting value. The NNMPC response has overshooting but it is settled through small time and return to the starting value, the response characteristics of the rector temperature response for the model predictive controller types are shown in table (3).

The next test is to study the ability of the controllers to track set point change; set point was allowed to change in different values. The responses were shown in figures (14, 15).

As shown in figure (14), the response of PID controller has overshooting in first set points, its slow response with oscillation specially in first, second, and fifth set points, also its didn't settled through simulation time in all set points. For the LMPC, the response is slow and settled in second, third, and forth set points only. The response of NNMPC has overshooting in first set point only, its show perfect set point tracking.

In figure (15), the response of PID controller has overshooting with oscillation in all set points, also its slow response. For the LMPC, the response is settled in all set points with very small overshooting and show good set point tracking. The response of NNMPC shows perfect set point tracking.

Conclusions

In present work, the continuous stirred tank reactor was controlled by using linear model predictive controller (LMPC) based on state space model, nonlinear model predictive controller based on neural network (NNMPC), and conventional feedback (PID) controller which was used as benchmark. The results from NNMPC were found to be more accurate and suitable and give best responses than the LMPC and conventional (PID) controller. The results showed also the high ability of NNMPC to track set point change and reject load disturbance and settle through small period compared with the other controllers. The reason of this poor performance for LMPC and PID compared to high performance of the NNMPC can be adduced because of non-linearity of the continuous stirred tank reactor since NNMPC is able to take care of non-linearly aspect of the system.

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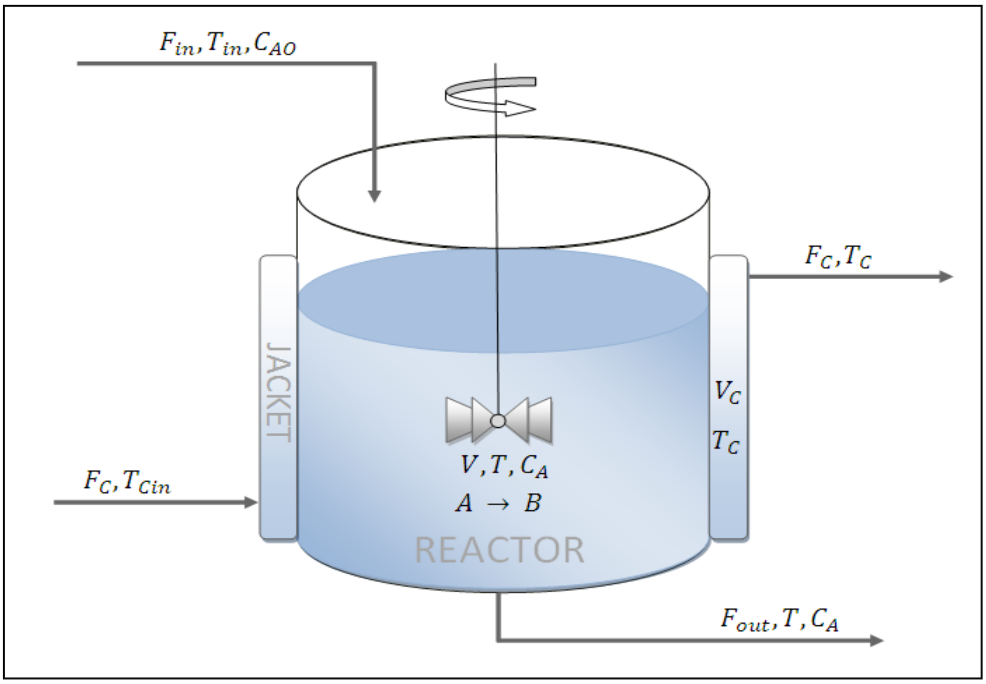


Figure (1): the Continuous Stirred Tank Reactor

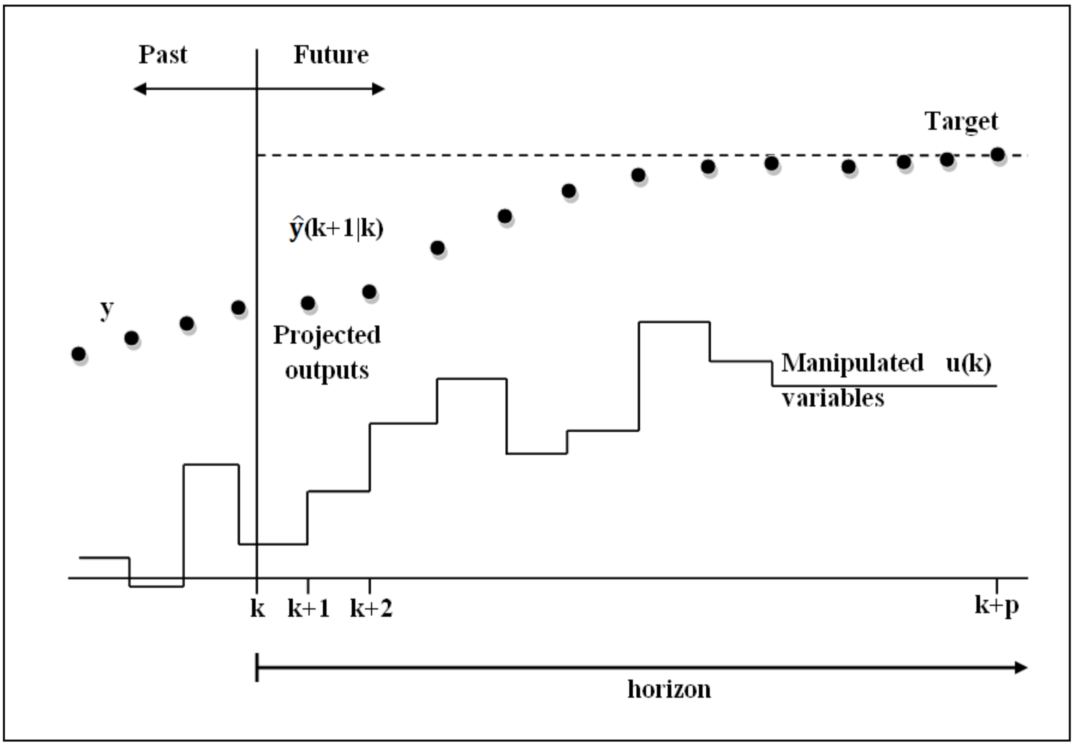


Figure (2): model predictive control strategy

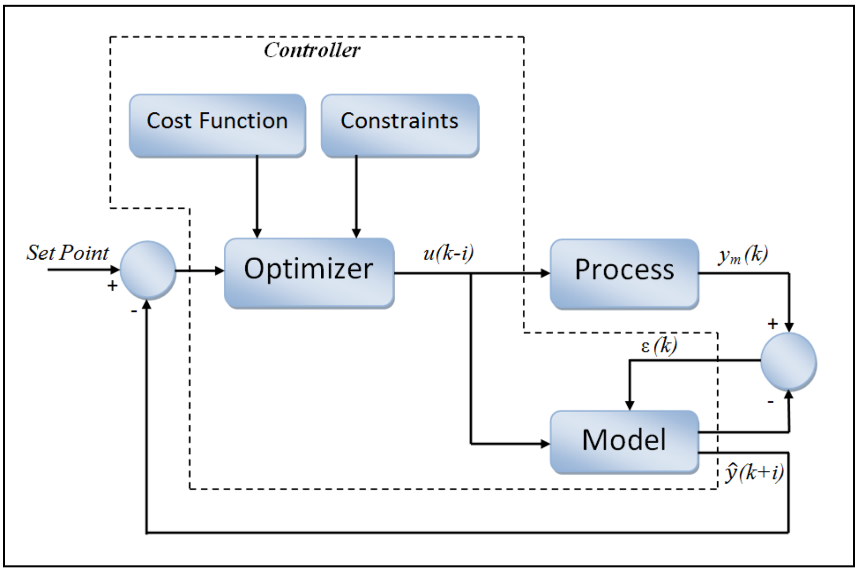


Figure (3): the model predictive control block diagram

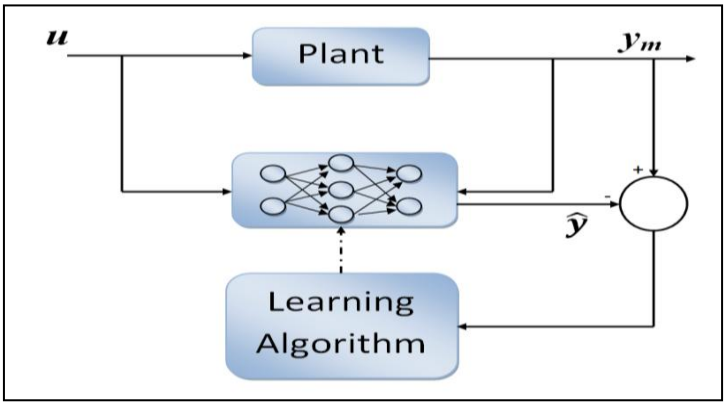


Figure (4): the neural network plant model identification

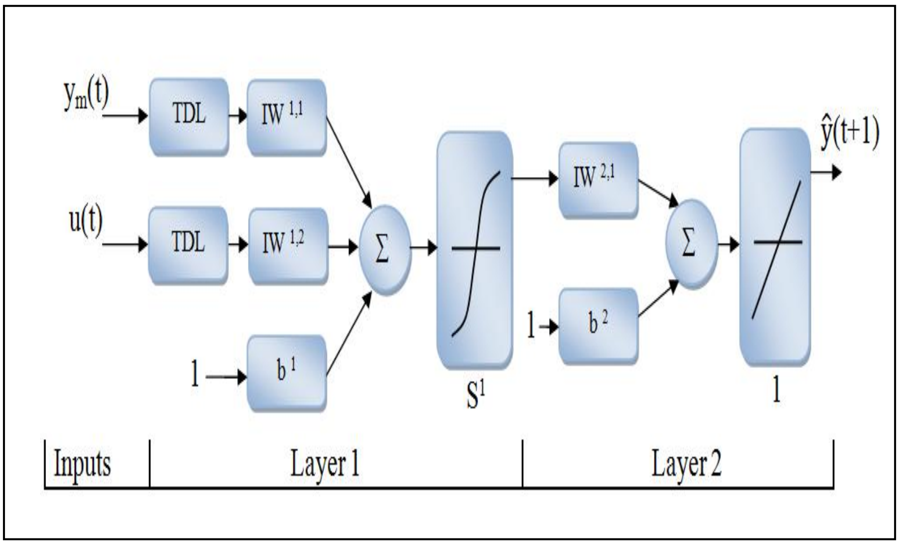
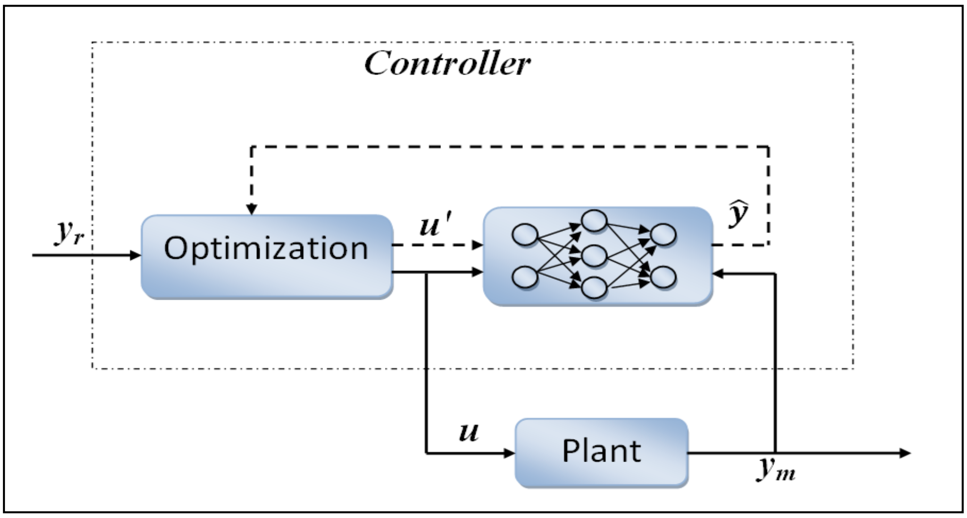


Figure (5): the neural network plant model Structure



Figure(6): the neural network model Predictive Controller

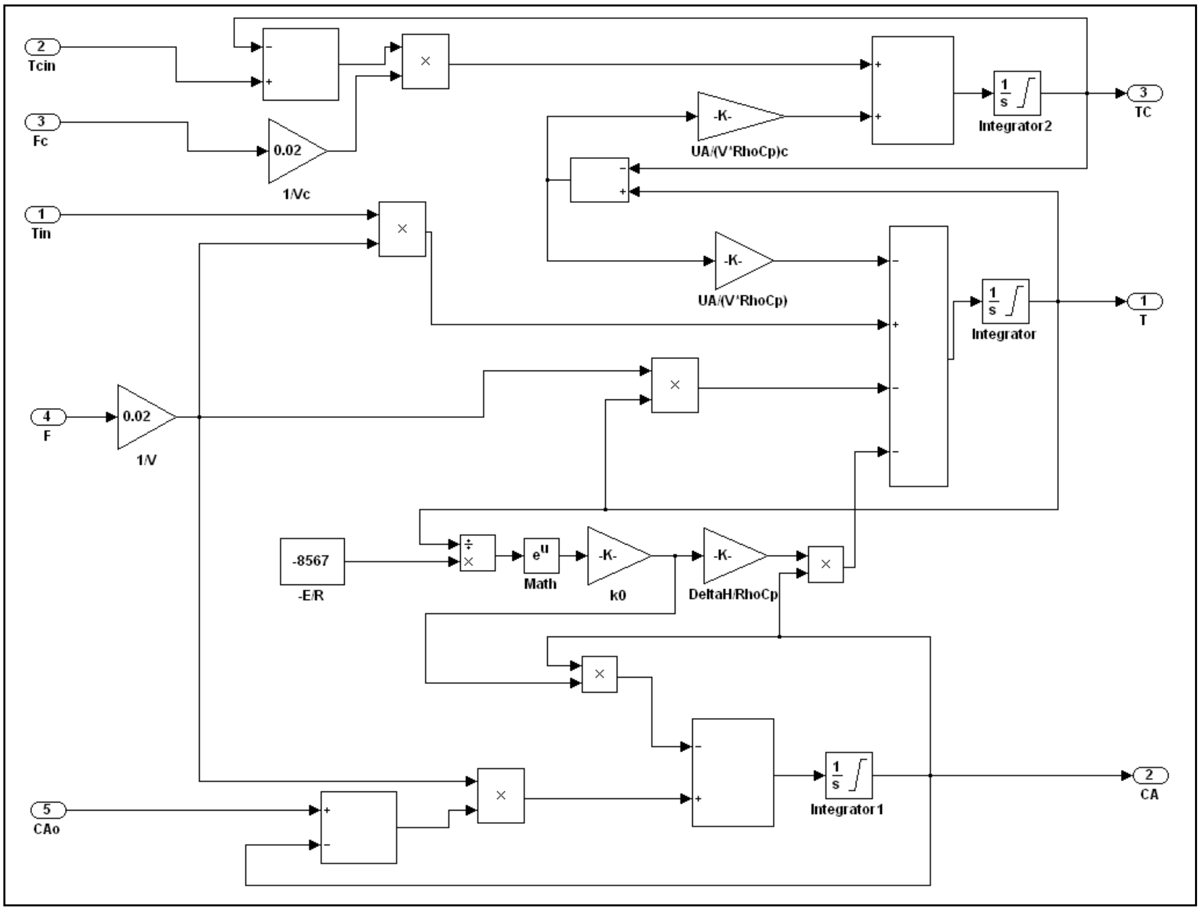
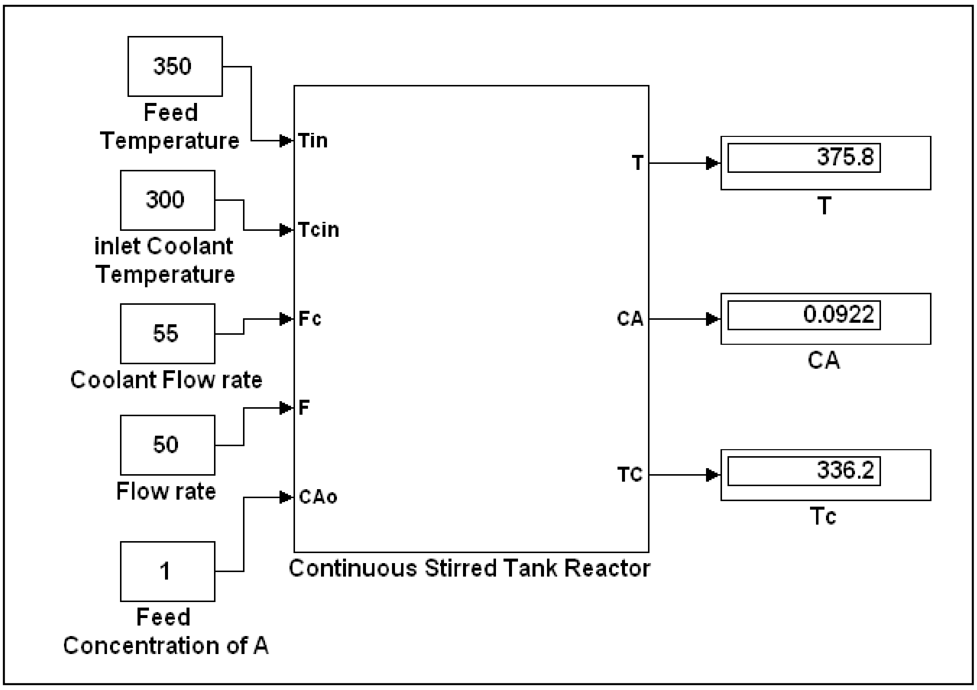
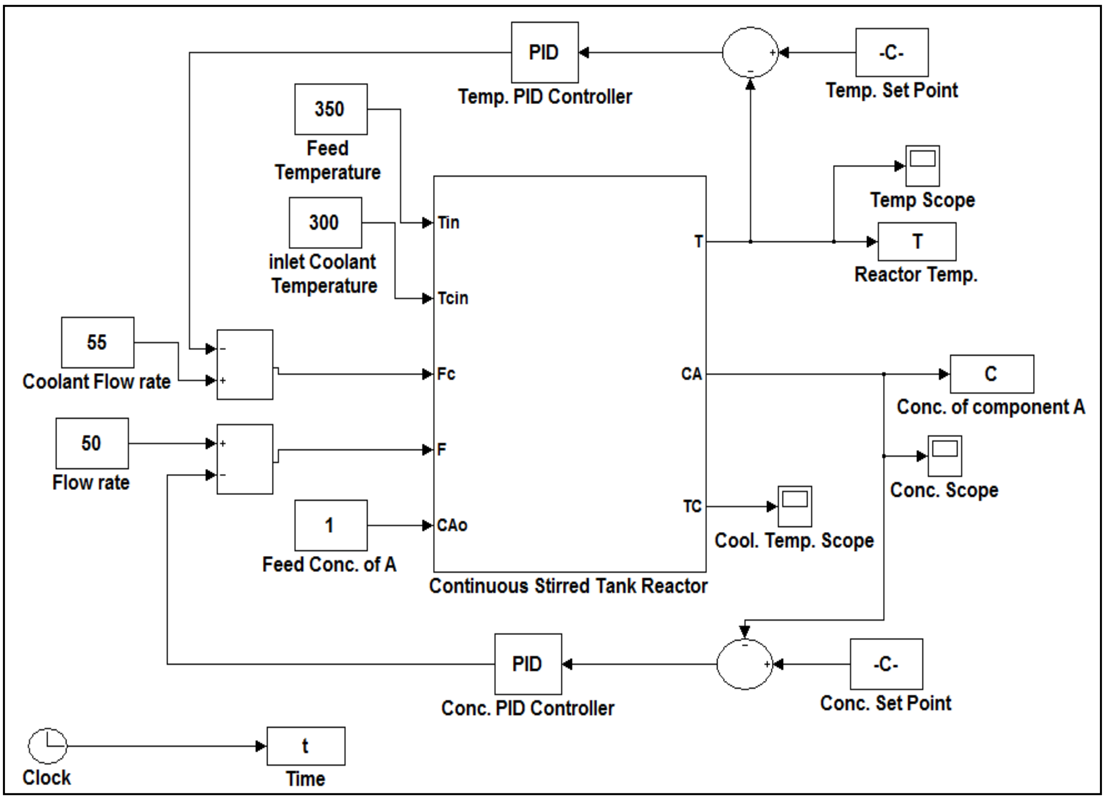


Figure (7): Nonlinear SIMULINK model of the CSTR



Figure(8): Steady State Calculation Model



Figure(9): Feedback PID Controller Model

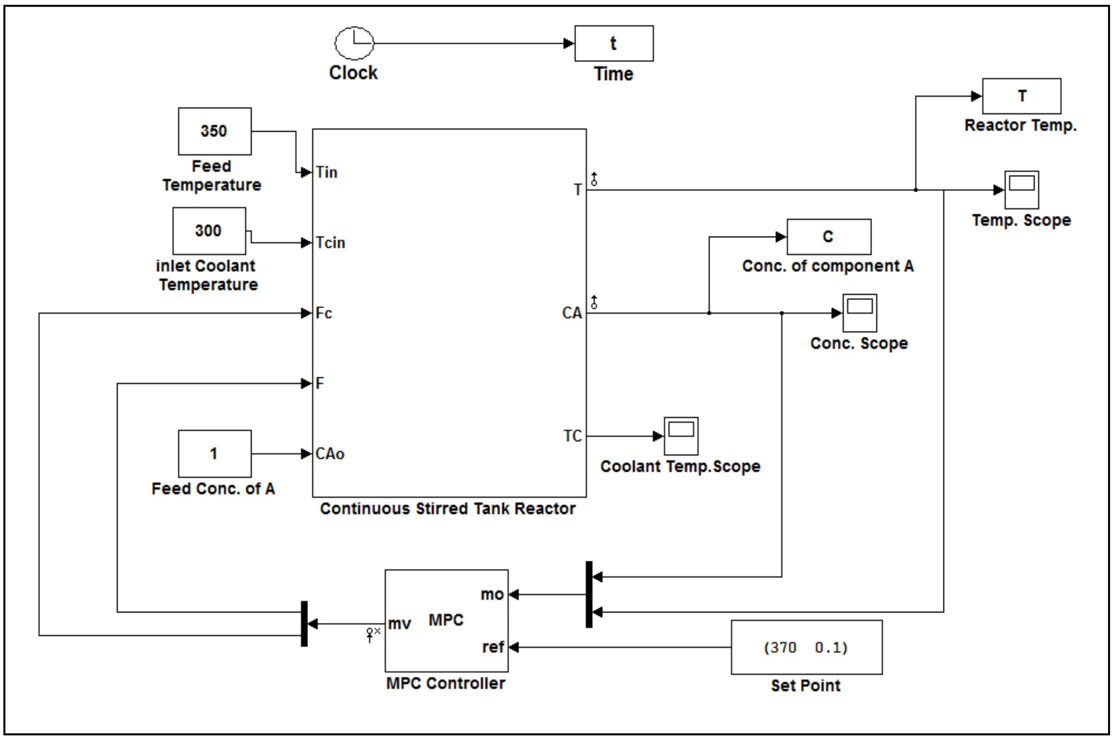


Figure (10): MPC Controller Model

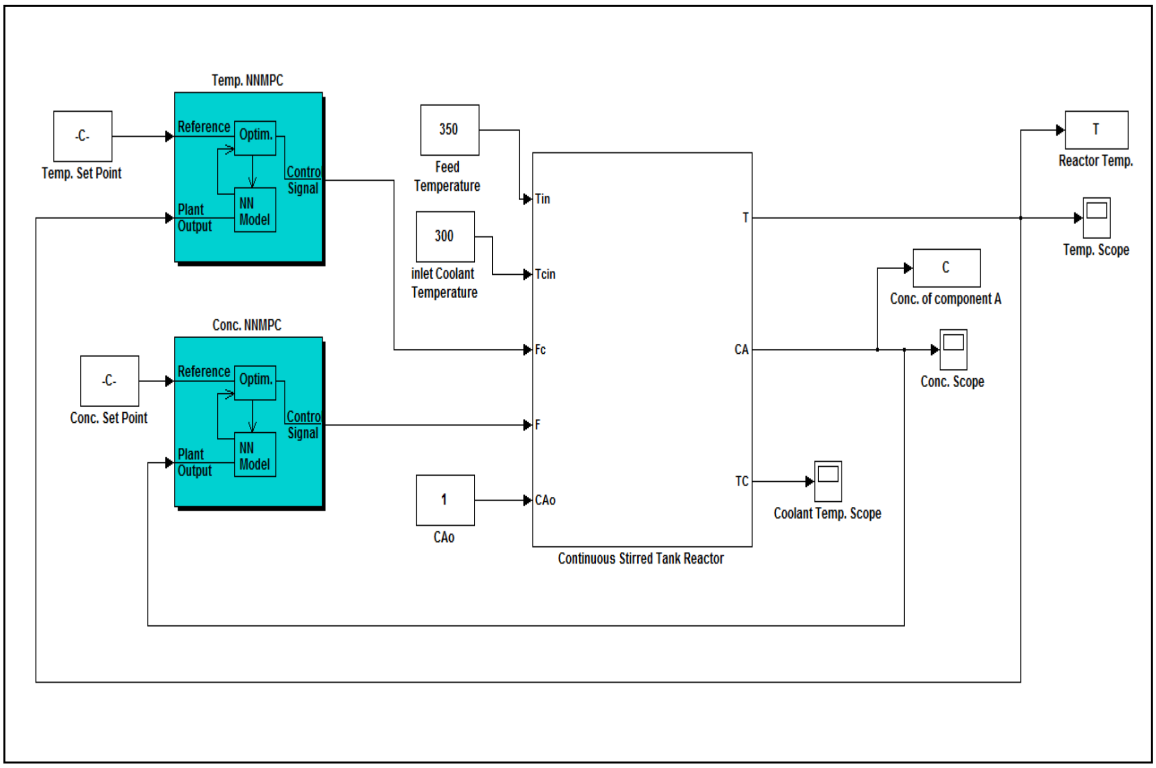
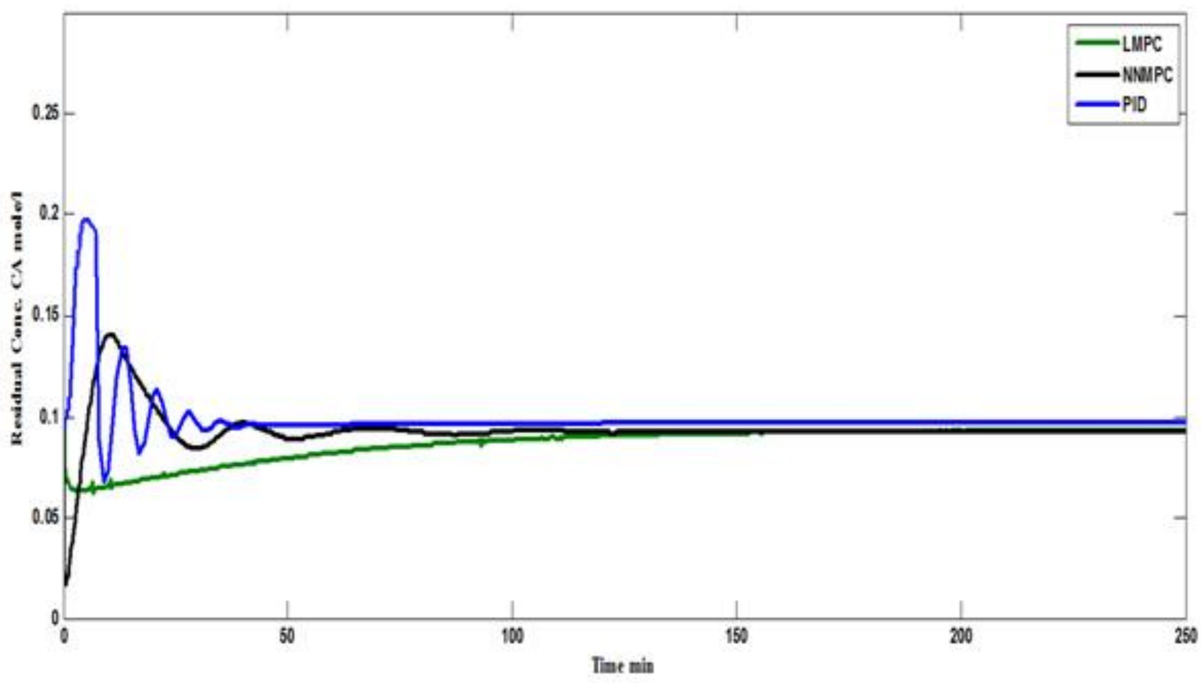


Figure (11): NNMPC Controller Model



Figure(12): close loop Concentration C_A response for 10% step change in C_{AO}

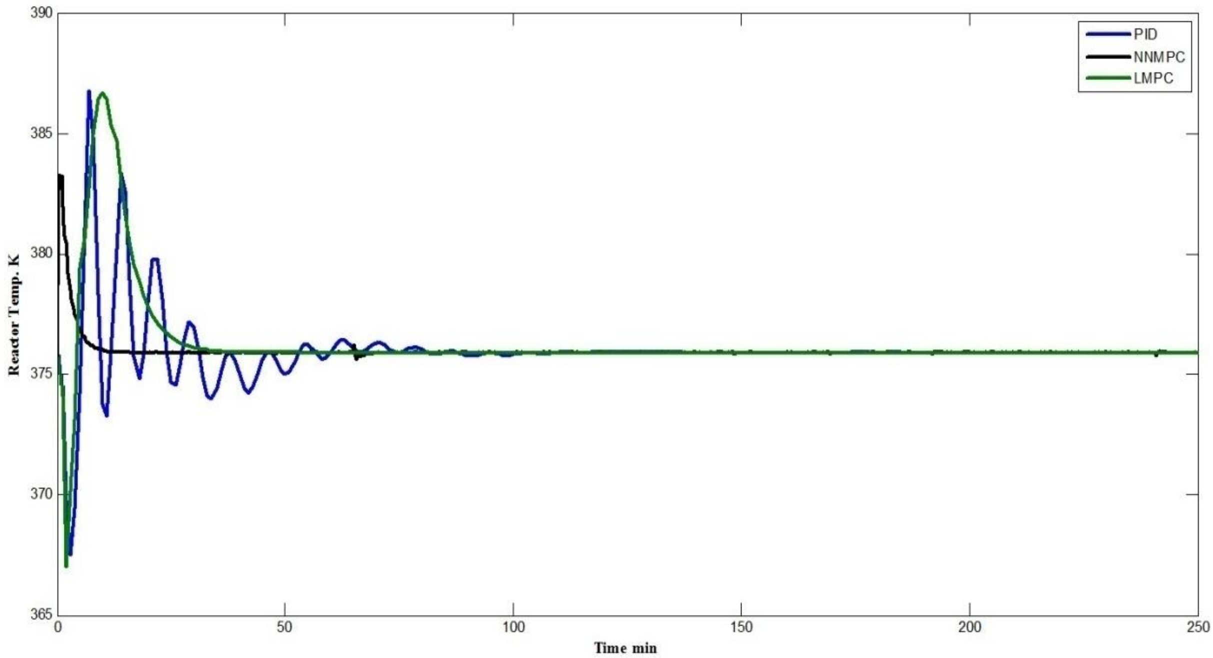


Figure (13): close loop reactor temperature (T) response for 10% step change in C_{AO}

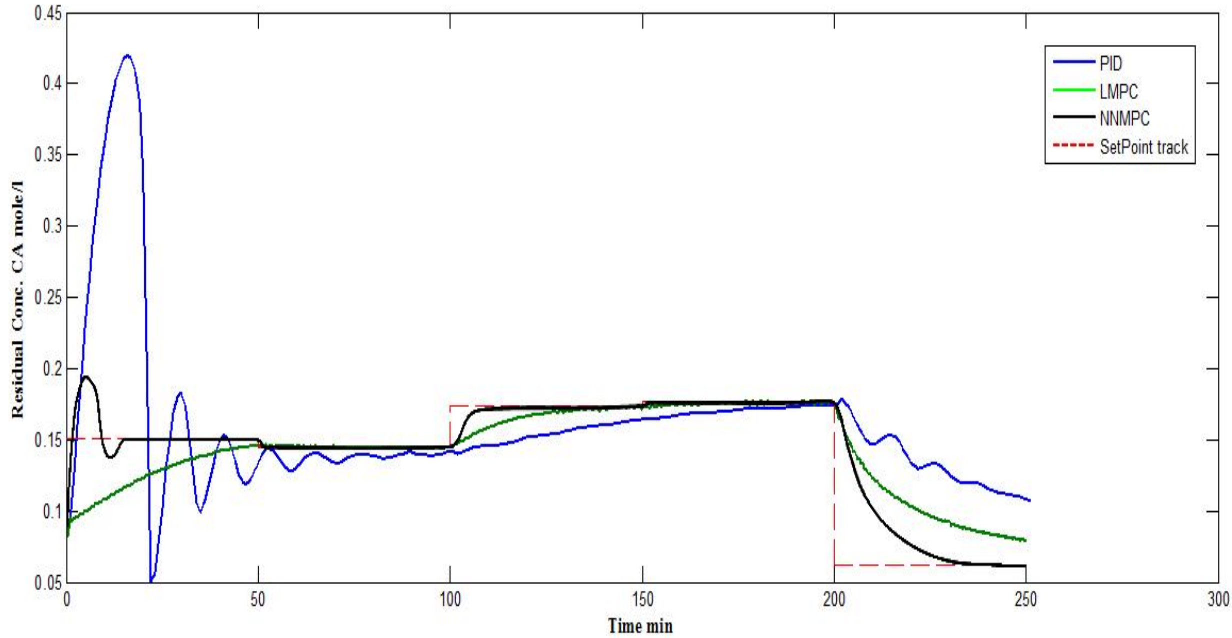
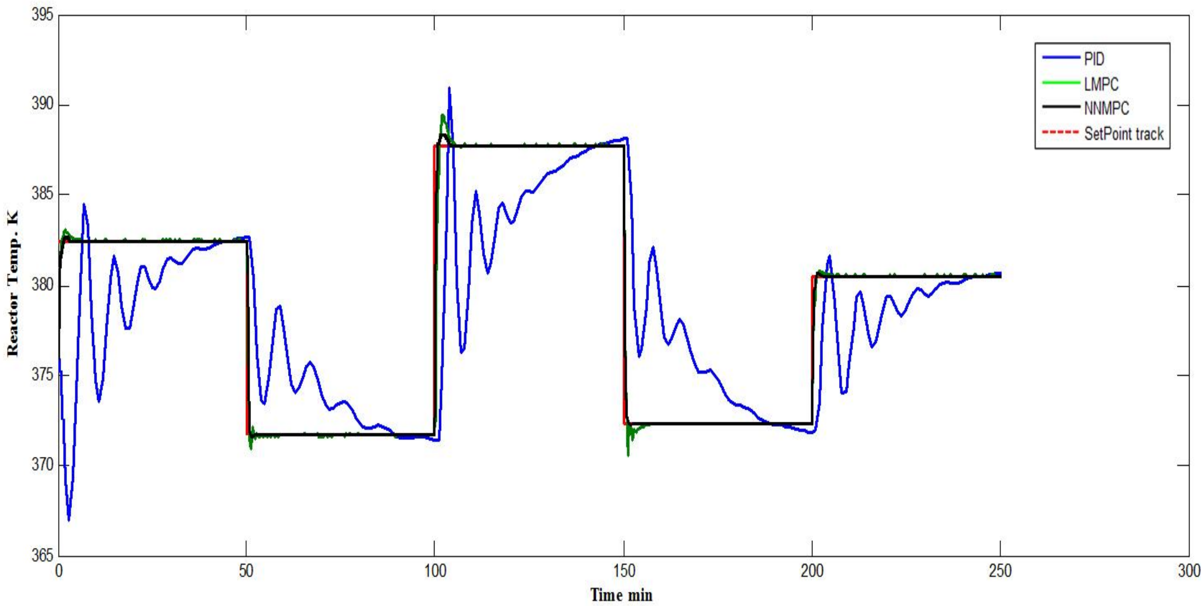


Figure (14): close loop Concentration C_A response for set point tracking



Figure(15): close loop reactor temperature (T) response for set point tracking

Table (1): The variables and nominal CSTR Parameter values

Variable	Description	Value
V	Reactor Volume (l)	50
F_{in}	Inlet volumetric flow rate to the reactor (l/min)	50
F_{out}	outlet volumetric flow rate from the reactor (l/min)	50
C_A	Concentration of component A in outlet Stream (mole/l)	-
C_{Ao}	Feed concentration of component A (mole/l)	1
K_O	Pre-exponential factor (1/min)	$7.8*10^{10}$
E	Activation energy in the Arrhenius equation (cal/mole)	E/R = 8567
R	Universal gas constant (cal/mole. K)	
ρ	Density of the inlet and outlet stream (g/l)	900
Cp	Heat Capacity of inlet and outlet stream (cal/g.K)	0.329
T	Temperature of the reactants in the reactor(K)	-
T_{in}	Inlet stream Temperature (K)	350
H_r	Heat of Reaction (cal/mole)	$-5*10^4$
UA	Heat Transfer Term (cal/min. K)	$5*10^4$
Tc	Temperature of the coolant water in the jacket(K)	-
ρ_c	Density of the coolant water in the jacket (g/l)	1000
Cp_c	Heat Capacity of the coolant water in the jacket (cal/g.K)	1
F_C	Inlet coolant water volumetric flow rate (l/min)	55
Vc	Jacket Volume (l)	50
Tc_{in}	Temperature of the inlet coolant water in the jacket(K)	300

Table (2): The response characteristics of the concentration (C_A) for 10% step change in C_{AO}

Controller Type	Error E	Maximum Percent Overshoot M_P	Rise Time t_r	Settling Time t_s
LMPC	0.0016	Very small	68.1379 min	194.3531 min
NNMPC	0	52.4946 %	6.2082 min	68.2649 min

Table (3): The response characteristics of the Reactor Temperature (T) for 10% step change in C_{AO}

Controller Type	Error E	Maximum Percent Overshoot M_P	Rise Time t_r	Settling Time t_s
LMPC	0	2.8872 %	9.1431 min	13.7118 min
NNMPC	0	2.0490 %	0.7836 min	1.1063 min