ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Special Issue 4, May 2014

State Estimation of Concentration in CSTR by Extended Kalman Filter

Ranojidoss R[1], Sandhya V.P[2], VamsiKrishnaMuvalla V[3]

PG Student, Dept. of Electronics and Instrumentation Engineering, Valliammai Engineering College, Chennai, India[1]

Assistant Professor, Dept. of Electronics and Instrumentation Engineering, Valliammai Engineering College, Chennai, India[2]

Assistant Professor, Dept. of Electronics and Instrumentation Engineering, Valliammai Engineering College, Chennai, India[3]

ABSTRACT*:* Extended Kalman filtering algorithm has been applied to various fields due to its capacity to handle nonlinear/non-Gaussian dynamic problems. The filter is very powerful in several aspects it supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modelled system is unknown. Firstly, prediction strategy is used, in which the datas required for filter get predicted. Afterward, correction of errors in predicted datas like instruments error, measurements error will be made. People can flexibly design the filter according to their idiographic requirements. We provide simulation results that show its efficiency and performance..

KEYWORDS: Kalman filter, Extended kalman filter, Process Error, Measurement error.

I. INTRODUCTION

In today's world the application in various fields of science requires prediction of the past, present, future states are necessary. So that proper input and control can be given to the system which we modeled will provide the optimized output. The state and parameter estimations are applied in the fields of rocket launching, tracking etc. The Kalman filter helps for the state estimation but it was applicable only to linear system. Systems will be non-linear in nature , practically the extended Kalman filter is preferable for these systems. This Extended Kalman filter can be used as alternation to kalman filter when the system is non-linear with Gaussian error.

II. STATE ESTIMATION IN CSTR

Here the system of estimation is CSTR (Continuous Stirrer Tank Reactor). The measuring device is a temperature sensor. The system error sources are the process noise/error. The measurement error sources we mention is instrumental noise / error. Extended controls are which controls the functions of CSTR. The observed measurement gives the present predicted state of the system. The Estimator role was played by EKF. The EKF comes under the unconstrained state estimation classification. It replaces the role of kalman filter in the non-linear system.

III. EXTENDED KALMAN FILTER

A kalman filter that linearizes about the current mean and covariance is referred to an Extended Kalman Filter (EKF) the nonlinear function around the current estimate can be linearized to compute the state estimate even in the face of nonlinear relationships. The EKF implements a kalman filter for a system dynamics that results from the linearization of the original nonlinear filter dynamics around the previous state estimates.

EKF state distribution is propagated analytically through 1st order linearization of nonlinear system due to which the mean and covariance value could be corrupted. It's a standard technique used in a number of nonlinear estimation and machine learning applications. The applications include estimation of the state of nonlinear dynamic system, estimation of parameters of nonlinear system.

A. *EKF algorithm*

Prediction Equations:

Predicted State Estimate:

$$\hat{x}_{k/k-1} = f\left(\hat{x}_{k/k-1}, u_k, 0\right) \qquad (1)$$

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Special Issue 4, May 2014

Predicted Estimate Covariance:

$$p_{k/k-1} = A_k p_{k/k-1} A_k^{T} + Q_k \quad (2)$$

The transition state matrices can be given by Jacobian matrix:

$$A_k = \frac{\partial f}{\partial x}[\hat{x}_{k-1/k-1}, U_k] \quad (3)$$

Correction Equations:

Measurement Residual:

$$\bar{Y}_k = Z_k + H\hat{x}_{k/k-1}] \quad (4)$$

Measurement Covariance:

$$S_k = Hp_{k/k-1}H^T + R_k \quad (5)$$

Kalman Gain:

$$K_k = p_{k/k-1}H^T S_k^{-1} \quad (6)$$

Updated State Estimate:

$$\hat{x}_{k/k-1} = \hat{x}_{k/k-1} + K_k \tilde{Y}_k \quad (7)$$

Updated Estimate Covariance:

$$p_{k/k} = (1 - K_k H)p_{k/k-1} \quad (8)$$

IV. LIMITATIONS OF EKF

Possibility of inconsistency in the values predicted due to under estimation of true covariance matrix. Error occurance possibility was more when the initial estimated state was not correct.

V. CONTINUOUS STIRRER TANK REACTOR

It’s a common ideal reactor for the perfect mixing of chemicals which are feed into it. For better operation of CSTR the designer must have the knowledge in dynamic characteristics of CSTR. The dynamic characteristics of CSTR will be explained by the mass balance equation, component balance equation, energy balance equation. Depending upon the operation required the equations are designed.

a. *Mass Balance Equation:*

Rate of change of Mass within system = Rate of mass flow in – Rate of mass flow out

$$\frac{dv}{dt} = F_{in}\rho_{in} - F_{out}\rho_{out} \quad (9)$$

Assuming the constant amount of mass in the CSTR and the density also.

$$F_{in}\rho_{in} - F_{out}\rho_{out} = 0 \quad (10)$$

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Special Issue 4, May 2014

$$F = F_{in} = F_{out} \qquad (11)$$

b. Component Balance Equation:

In component balance equation the changes in the each component reacting in the CSTR with respect to time can be calculated.

Rate of change in Component = Rate of flow of component A in - Rate of flow of component A out + Rate of formation of component A

$$\frac{dvC_A}{dx} = FC_{A_f} - FC_A - rv \qquad (12)$$

c. *Energy Balance Equation:*

The energy balance equation is explained by
Rate of change of Energy = Rate of energy flow in – Rate of energy flow out + Rate at which heat added due to reaction

$$\frac{d\left(v\rho C_p(T - T_{ref})\right)}{dt} = F\rho C_p(T_f - T_{ref}) - F\rho C_p(T - T_{ref}) + (-\Delta H)\, v_r - UA(T - T_i) \qquad (13)$$

The reaction in CSTR is assumed to be exothermic. A cooling coil is used to remove any heat generated by reaction. Fluid specific heat and density are assumed constant. The functions of concentration and temperature are represented below the function of coolant flow is represented byf_2.

$$f_1(C_A, T) = \frac{dC_A}{dx} = \frac{F}{v}(C_{A_f} - C_A) - r \qquad (14)$$

$$f_2(C_A, T) = \frac{dT}{dx} = \frac{F}{v}(T_f - T) + \left(\frac{-\Delta H}{\rho C_p}\right) r \frac{UA}{\rho C_P}(T - T_O) \qquad (15)$$

The above functions are represented in state representation by applying the Jacobian Equation. After substituting these functions the state of the system (CSTR) will be obtained from equation 17 and the concentration will be obtained by equation 18.

$$\dot{X} = AX + BU + W \qquad (16)$$

$$Y = CX + V \qquad (17)$$

VI. RESULTS

The simulations of true and estimated values of concentration and temperature when the coolant rate get varied where shown in Figure 2, 3, 4 the nominal value of concentration is 0.0989 mol/L and nominal value of temperature is 438.7763K, and for the coolant flow rate of 110 L/min the nominal value of temperature and concentration are 428.6877 K and 0.1672 mol/L respectively.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Special Issue 4, May 2014

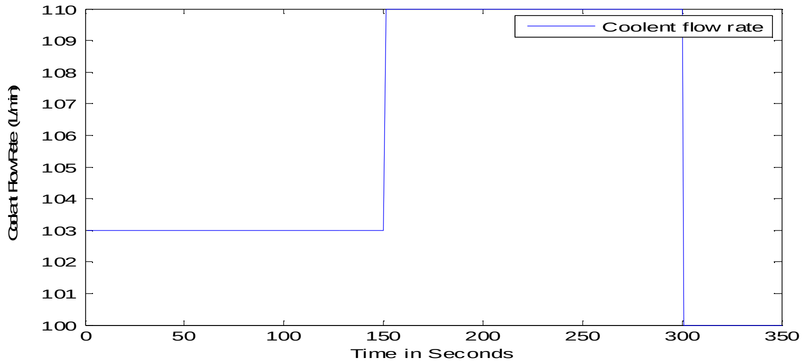

Fig. 1 coolant flow rate variation

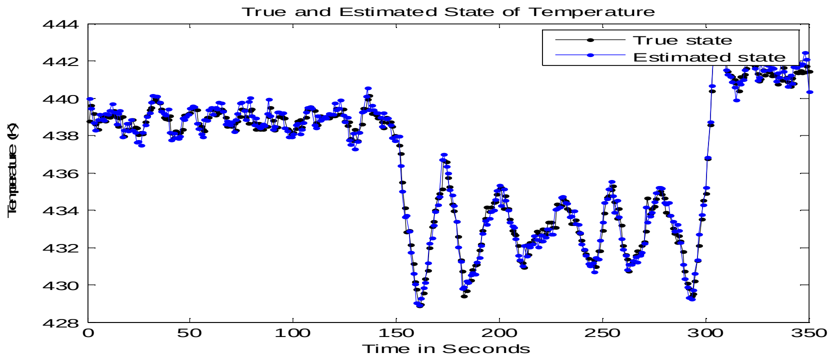

Fig. 2 change in temperature due to coolant flow rate

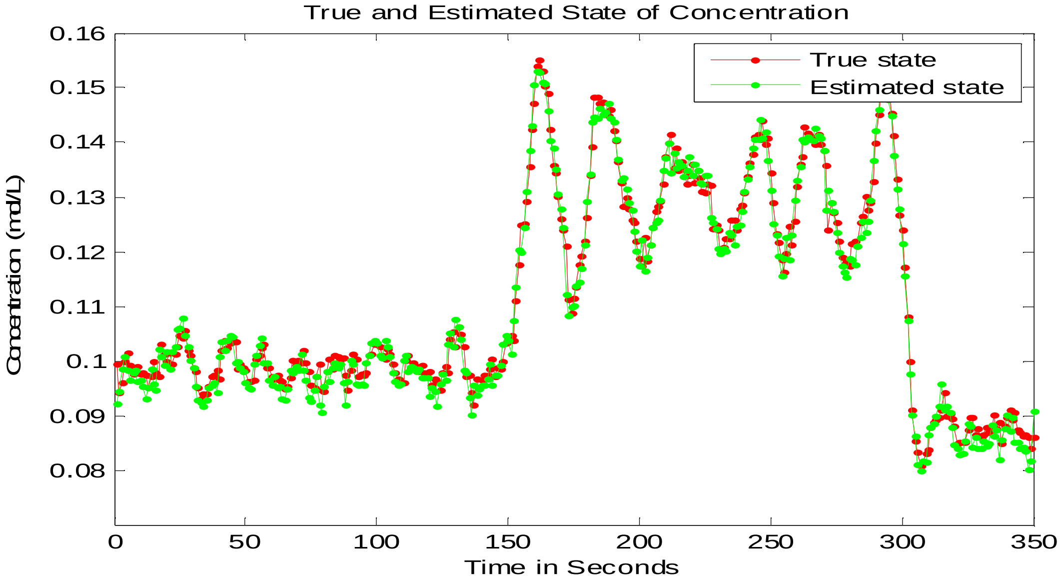

Fig. 3 change in concentration due to temperature variation.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Special Issue 4, May 2014

VII. CONCLUSION

In this paper Extended kalman filter was giving better performance for non-linear system. It estimates the concentration of CSTR in order to provide the optimized inputs. In order to gain more accuracy the Unscented Kalman Filter [UKF] can be adopted for the sensitive systems.

REFERENCES

[1] N.J.Gordon, D.J.Salmond, A.F.M. Smith, "Novel approach to nonlinear/non-Gaussian Bayesian state estimation", IEEE proceedings-F, vol.140, no.2, 1993, pp.107-113.
[2] Y.M.Liang, H.W. Luo, X.X.Zhao, H.B. Zhang, C.G.Y."Nonlinear Channel Estimation Based on Particle Filtering for MIMO-OFDM System", process of International Conference on Communications Circuits and System, Vol.1.June,2006, pp.347-351.
[3] Kim-Hung Li,"Pool size Selection Sampling/Importance Sampling Algorithm", Statistica sinica, vol.17, pp.895-907, 2007.
[4] Bart Vandewoestyne, Ronald Cools, "Quasi-Random Sampling Importance Resampling and its convergence" IUAP DYSCO study of day, 22th November 2001.
[5] A.V. Shenoy, J. Prakash, V.Prasad, S.L.Shah, K.B. McAuley, "Particle issues in State Estimation using particle filters: Case Studies with polymer reactors", Elsevier Journal of process control, 2012.
[6] M. Kodabandeh, H. Bolandi, "Model Predictive control with State Estimation and Adaption Mechanism for a Continuous Stirred Tank Reactor", International Conference on Control, Automation and Systems, vol.12, pp.1466-1471, October 2001.
[7] K.Srinivasan, J.Prakash, "Nonlinear State Estimation for Continuous Stirred Tank Reactor using Neural network State Filter", India Conference, Annual IEEE, pp.1-4, September 2006.