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Control of a Double -Effect Evaporator using Neural Network Model Predictive Controller

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ABSTRACT

The dynamic models describing Multiple Effect Evaporator are nonlinear ODE's and it makes the performance of conventional PID controller deteriorates. Present work is about the Advanced controller i.e., The Neural network based model predictive controller are designed to control the concentration of the Double Effect Evaporator. The simulation study has been done using MATLAB & SIMULINK. The overshoot value and settling time are used to evaluate the performance of advanced control strategy. The simulation results show that the Neural networks Model predictive controller has a superior performance than conventional PID controller.

Keywords - Dynamic model, Evaporator, MATLAB Simulation, NN predictive controller, and Superior performance.

I INTRODUCTION

Evaporation is a process of removing water or other liquids from a solution and thereby concentrating it. The time required for concentrating a solution can be shortened by exposing the solution to a greater surface area which in turn would result in a longer residence time or by heating the solution to a higher temperature. But exposing the solution to higher temperatures and increasing the residence time results in the thermal degradation of many solutions, so in order to minimize this, the temperature as well as the residence time has to be minimized. This need has resulted in the development of many different types of evaporators.

The multiple effect evaporation system is formed a sequence of single effect evaporators, where the vapour formed in one effect is used in the next effect. The vapour reuse in the multiple effect system allows reduction of the salt and the temperature to low values and prevents rejection of large amount of energy to the surrounding, which was the main drawback of the single effect system. In addition to the desalination industry, the main bulk of the multiple effect evaporation processes is found in the food, pulp and paper, petroleum, and petrochemical industries.

H. Andre. and R.A. Ritter, (2003) presented the study work on the modelling and control of an industrial multiple-effect evaporator system used for black liquor recovery. They developed model with combination of phenomenological and empirical (neural networks) approaches, based on industrial data. An advanced model-predictive control strategy, allowing for manipulated variable constraints, compares favourably with a classical PID based scheme.

C. H. Runyon,. et al., (2010) presented the nonlinear dynamic behaviour of a double effect evaporator system. The governing equations are solved using Advanced Continuous Simulation Language (ACSL). Simulations are performed for a commercial double effect tomato paste evaporator using two possible control configurations. Experimental measurements are obtained for a commercial double fleet evaporator. Simulation results of product solids concentration are compared with experimental measurements in response to varying feed solids concentration.

Dwi Argo Bambang, et al (2013) presented a novel technique to improve the performance of Proportional+Integral+Differential (PID) control to reduce the speed of the steam flow rate and search optimal points in the evaporation process of Multiple Effect Evaporator (MEE).

J.C. Atuonwu et al., (2009) presented a recurrent neural network-based nonlinear model predictive control (NMPC) scheme in parallel with PI control loops. It is developed for a simulation model of an industrial-scale five-stage evaporator. Input-output data from system identification experiments are used in training the network using the Levenberg-Marquardt algorithm. The same optimization algorithm is used in predictive control of the plant. The scheme is tested with set-point tracking and disturbance rejection problems on the plant, while control performance is compared with that of PI controllers, a simplified mechanistic model-based NMPC developed in previous work and a linear model predictive controller (LMPC). Results show significant improvements in control performance by the new parallel NMPC-PI control scheme.

Praveen Yadav, Amiya K Jana(2010) presenteda detailed study on a commercial double-effect tomato paste evaporation system. The modeling equations formulated for process simulation belong to backward feeding arrangement.

In the present work, the design and evaluation of neural networks based predictive controller has been done for multiple-effect (i.e., double effect) evaporator system.

II MODELING OF THE DOUBLE EFFECT EVAPORATOR SYSTEM

The assumptions involved in the formulation of model are listed as : i) Negligible heat losses to the surroundings, ii) Constant liquid holdup and negligible vapour holdups iii)Total temperature around the system is constant and iv)No boiling point elevation of the solution.

The double-effect evaporator system is shown in Figure 1. The two effects are numbered from left to right as Tank1 and Tank 2, the raw feed having flow rate F, concentration X_f, enters Tank 2.The mass hold ups in the tanks are M_1 and M_2 . $V_1$and V_2 are vapour flow rates from the overhead of two Tanks. $P_1$and P_2 are the product flow rates from the two effects with product concentrations, as X_p and X_2.

The unsteady- state solid component balance equations for two tank evaporator system is written as,

$$M_1 \frac{dx_p}{dt} = P_2 X_2 - P_1 X_p \quad (1)$$

$$M_2 \frac{dx_2}{dt} = FX_f - P_2 X_2 \quad (2)$$

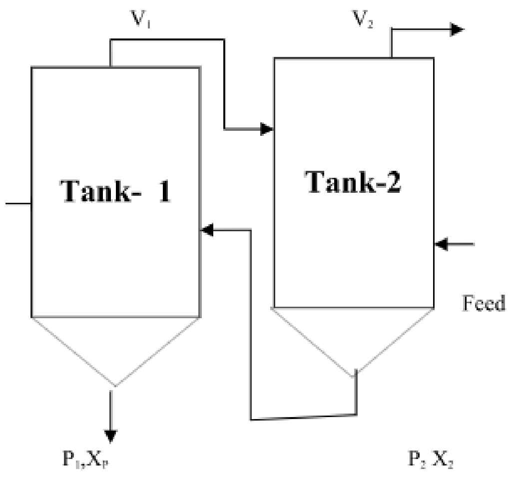

Figure 1. Double Effect evaporator process

Table 1 Operating conditions of Double Effect Evaporator

Term	**Abbreviation**	**Value**	**Units**
Tank1 mass holdup	M_1	2268	Kg
Tank2 mass holdup	M_2	2268	Kg
Input feed flow rate	F	26103	Kg/hr
Tank 1 liquid product flow rate	P_1	5006	Kg/hr
Tank 2 liquid flow rate	P_2	14887	Kg/hr
Vapour flow rate from Tank 1	V_1	9932	Kg/hr
Vapour flow rate from Tank 2	V_2	11165	Kg/hr
Feed composition	X_f	0.05	Kg/kg
Tank 1 composition	X_p	0.2607	Kg/kg
Tank 2 composition	X_2	0.0874	Kg/kg

The typical operating conditions of Double-Effect Evaporator are given in Table 1.

III DESIGN OF A NEURAL NETWORKS MODEL PREDICTIVE CONTROLLER

There are typically two steps involved when using neural networks for control: 1. System identification 2. Controller design. In the system identification stage, develop a neural network model of the plant that needs to be controlled. In the controller design stage, use the neural network plant model to design (or train) the controller.

The model predictive control method is based on the receding horizon technique. 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 over the specified horizon

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 + \rho \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2 \qquad (3)$$

Where N_1, N_2, and N_u 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 y_m is the network model response. ρ value determines the contribution that the sum of the squares of the control increments has on the performance index.

The neural networks model of double effect evaporator is shown in Figure 2. The neural networks architecture for training is given in Figure 3 and the optimum number of neurons in hidden layer is obtained as 13. Figure 4 gives the model predictive controller parameters.

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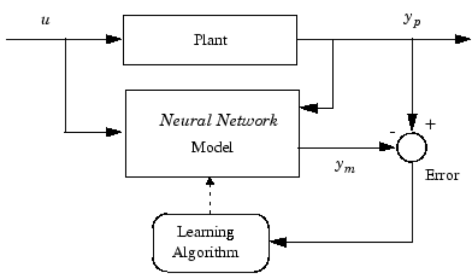

Figure 2.. Neural Network model of a process

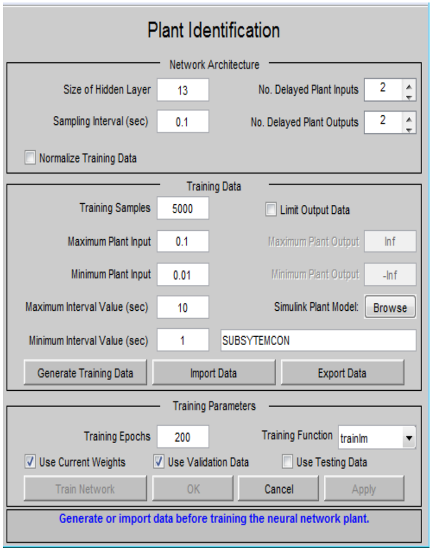

Figure 3. Plant identification of Neural Network model predictive controller

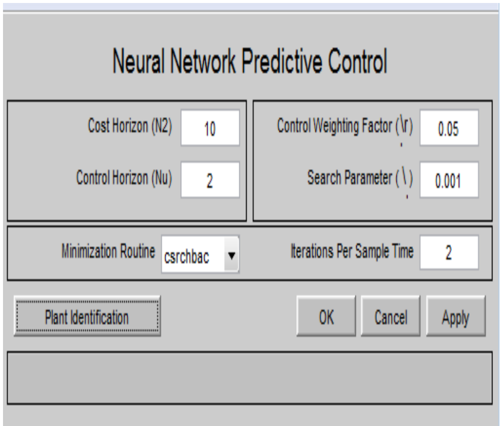

Figure 4. The Neural network model predictive controller

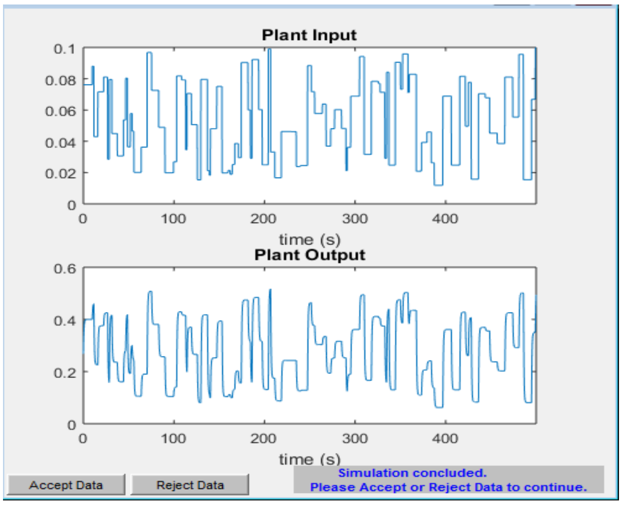

Figure 5. Plant data generation of the Neural Network training

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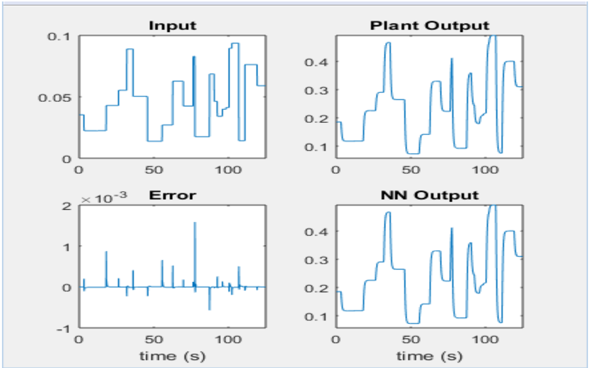

Figure 6.. Training error of Neural Networks

The PRBS data generation plot of double effect evaporator is provided in Figure 5. The training error plots are given in Figure 6.

IV RESULTS AND DISCUSSION

The Closed loop Simulation diagrams for PID and NNMPC are given in Figure 5, Figure 6 and Figure 7

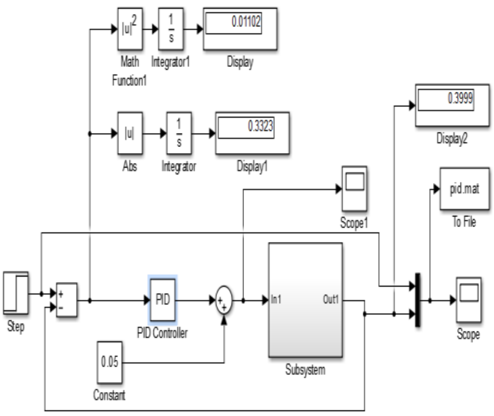

Figure 7. Closed loop SIMULINK program of PID controller

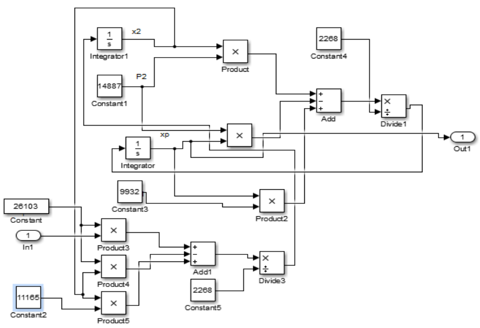

Figure 8. Subsystem model for double - effect evaporator (Eqs.1&2)

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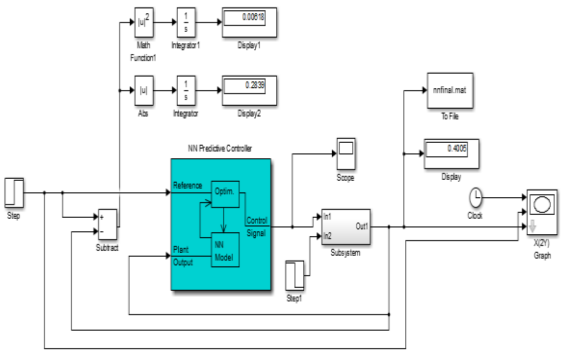

Figure 10. Closed loop SIMULINK program of Neural Network Model predictive Controller

The control objective is to keep the various performance specifications such as rise time, settling time, maximum overshoot, steady state error, IAE and ISE less within desirable limits.

Servo problem

The series of step changes in set point studied are 0.26 to 0.35 &0.26 to 0.20.The closed loop response of Neural networks Model predictive controllers(NNMPC) and PID controller for above set point changes shown in Figure 11 and Figure 13. From these results, NNMPC controller is found to be the faster than PID controller. The corresponding actions are plotted in Figure 12 and Figure 14

The PID Controller parameters obtained from the IMC method are

K_c = 0.14,

τ_i = 0.38hr   and

τ_d = 0.09hr

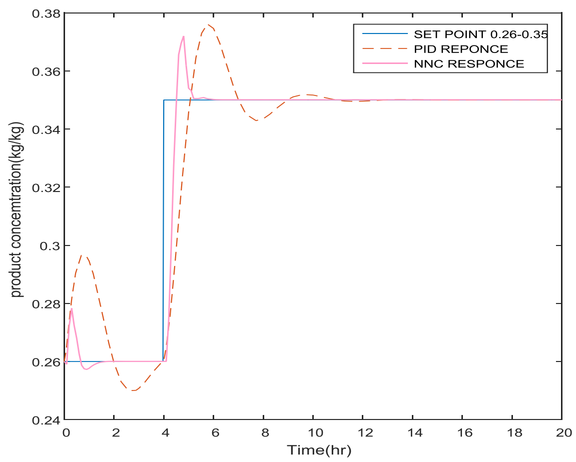

Figure 11. Closed loop response of NNMPC and PID controllers for set point change of 0.26 to 0.35 for product concentration.

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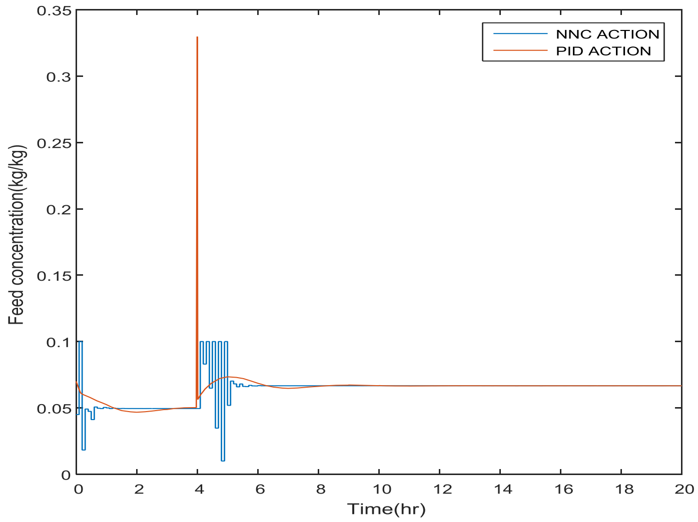

Figure 12. Control action of NNMPC and PID controllers for responses shown in Figure 11.

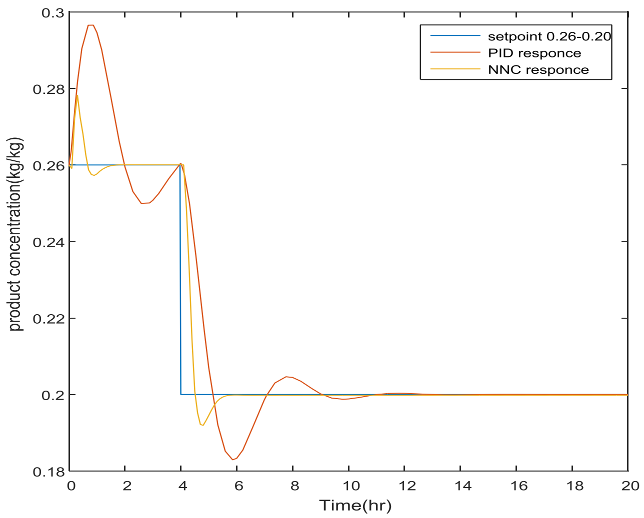

Figure 13. Closed loop response of NNMPC and PID controllers for set point change from 0.26 to 0.20 for product concentration.

Regulatory problem

The regulatory problem is studied by giving the disturbance in the feed flow rate. The step disturbance is given from 26103 to 28712 kg/hr. The Closed loop response of NNMPC and PID controllers is shown in Figure 14. The corresponding control actions are plotted in Figure 15. These results shows that Neural Network MPC Controller is found to be superior to the conventional PID controller for load changes of the MEE with lower maximum deviations and lower settling time.

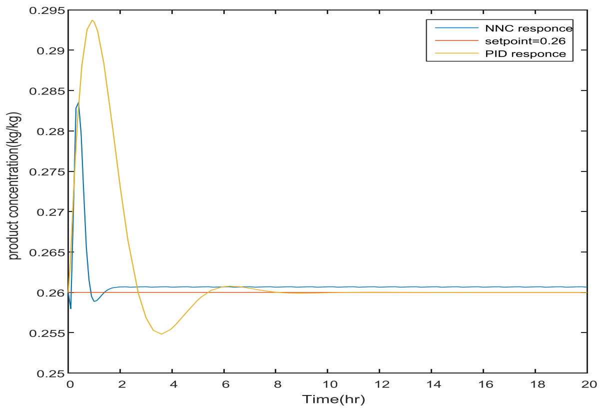

Figure 14. Closed loop responses of NNMPC and PID controller s for the load change from 26103 to 28712 kg/hr.

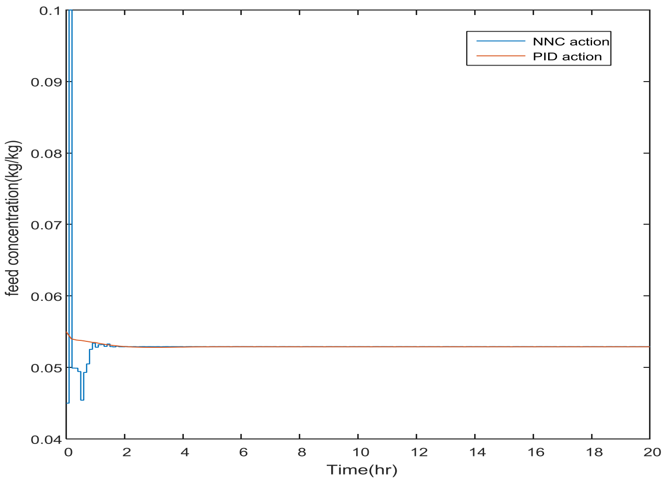

Figure 15. Control action of NNMPC and PID controller for regulatory responses shown in Figure 14

V CONCLUSIONS

Based on simulation results, the following conclusions are made: The closed loop responses of both the advanced Neural Networks model Predictive controller and conventional PID controller have been compared for set point changes and in the presence of disturbances. It has been observed that the present Neural Networks Model Predictive Controller gives lesser overshoot and lower settling time than that of PID controller. Thus, NNMPC is found to be better than PID controller. However, NNMPC shows oscillatory control actions which can be overcome with modified NNMPC.

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REFERENCES

[1]. H. Andre and R.A. Ritter, Dynamic Response of a Double Effect Evaporator, Can. J. Chem. Eng. **46**, 2010, 259–264

[2]. J. C. Atuonwu., Cao. Y, Rangaiah. G.P. and Tadé, M.O. Nonlinear model predictive control of a multistage evaporator system using recurrent neural networks, Proceedings, IEEE Conference on Industrial Electronics and Applications, Xian, China, 2009,1662-1667

[3]. Dwi Agro Bambang, Yusuf Hendrawn, Dimas Firmanda Al Rizza,Anung Nugroho Jaya Laksono Optimization of PID controller parameters on flow rate control system using particle Multiple Effect Evaporator particle swarm optimization (2013)

[4]. Praveen Yadav and Jana, Amiya K. Simulation and Control of a Commercial Double Effect Evaporator: Tomato Juice, Chemical Product and Process Modeling: 2010,Vol. 5: Iss. 1, Article 6.

[5]. C.H. Runyon, T.R.Rumsey & K. L. McCarty *Dynamic simulation of Nonlinear Model of a Double effect evaporator* (*U*niversity of California , Davis, USA.)