Neurocomputing 194 (2016) 135–150

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Multivariable control of a debutanizer column using equation based artificial neural network model inverse control strategies

Nasser Mohamed Ramli [a,b], Mohd Azlan Hussain [b,c,*], Badrul Mohamed Jan [b]

[a] Department of Chemical Engineering, Universiti Teknologi PETRONAS, 32610 Bandar Seri Iskandar, Perak, Malaysia
[b] Department of Chemical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia
[c] UMPDEC, University of Malaya, Malaysia

ARTICLE INFO

Article history:
Received 2 September 2015
Received in revised form
29 January 2016
Accepted 14 February 2016
Communicated by J. Zhang
Available online 22 February 2016

Keywords:
Debutanizer column
Neural network
Equation based
Multivariable control

ABSTRACT

The debutanizer column is an important unit operation in petroleum refining industries as it is the main column to produce liquefied petroleum gas as its top product and light naphtha as its bottom product. This system is difficult to handle from a control standpoint due to its nonlinear behavior, multivariable interaction and existence of numerous constraints on both its manipulated and state variable. Neural network techniques have been increasingly used for a wide variety of applications where statistical methods have been traditionally employed. In this work we propose to use an equation based MIMO (Multi Input Multi Output) neural network based multivariable control strategy to control the top and bottom temperatures of the column simultaneously, while manipulating the reflux and reboiler flow rates respectively. This equation based neural network model represented by a multivariable equation, instead of the normal black box structure, has the advantage of being robust in nature while being easier to interpret in terms of its input output variables. It is implemented for set point changes and disturbance changes and the results show that the neural network based model method in the direct inverse and internal model approach performs better than the conventional PID method in both cases.

1. Introduction

Debutanizer column operation is based on a multi-component, multivariable control strategy which is highly non-linear in nature involving nonlinear dynamics. The column is widely used in process plants and it constitutes a very difficult control problem. The product composition can normally be controlled by two variables, the product split and reflux ratio [1] as the two manipulated variables. However controlling these top and bottom compositions require a number of complex instrumentation which are due to the interactions of the these composition loops which face dynamic stability problems. Its control requires an on-line measurement performance variable directly related to composition, which is normally temperature. Although, temperature-composition relationship is a function of column pressure control, controlling the top and bottom temperatures of the column seems to give tight control on product composition despite wide variations in other factors such as the internal reflux ratio [1].

However, application of composition control at both ends of a debutanizer column has shown very little success [1]. The difficulty arises since the two individual control loops tend to interact where the top loop controls the heavy key in the overhead stream while the bottom loop controls the light key in the bottom stream. Slight disturbances in the system can cause the light key concentration in the bottom stream to increase while the lower loop may change the concentration through addition of heat in the reboiler system.

At the same time, laboratory measurement procedures for composition measurement are also slow, tedious and time consuming. Therefore, inferential model using linear regression usually encounters co-linearity problem, which adversely affects long-term prediction performance since the outputs of the debutanizer column usually depend on the feed composition which also cannot be determined online.

To circumvent some of these problems, the use of software based sensors and controllers incorporating neural network models is proposed in this work. This neural network based system is developed to simultaneously control the top and bottom temperature while at the same time regulating the compositions in a multi-input multi output approach. Since in the real industry large historical data are available, the use of neural network is also appropriate and economical as compared to hardware based

* Corresponding author at: Department of Chemical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia.
Tel.: +60 3 79675214; fax: +60 3 79675319.
E-mail addresses: nasser_mr@siswa.um.edu.my (N.M. Ramli), mohd_azlan@um.edu.my (M.A. Hussain), badrules@um.edu.my (B.M. Jan).

http://dx.doi.org/10.1016/j.neucom.2016.02.026
0925-2312/

instruments. It will also help improve product quality monitoring of the system by predicting the top and bottom compositions and temperatures simultaneously with high accuracy [2]. The software based are also cheap compared to hardware sensors and can be easily integrated on existing hardware controllers in the industry.

Previously some work utilizing neural network as a controller have been done which include robust stability analysis with harmonic balance for a multivariable non-linear plant using the neural network controller under generic Lur'e configuration [3]. The neural network controller was applied to describe the sinusoidal input while the linearized model has been derived to represent the nonlinear plant dynamics. The work was applied to a multivariable binary distillation column under feedback neurocontrol and it illustrates the use of a robustness approach to predict the presence of limit cycles subject to restriction of the describing function. In another work, the use of adaptive neural network for composition prediction which was used to control both the composition and inventory for a continuous ethanol-water pilot plant based distillation column has also been proposed [4]. A principal component analysis based algorithm was applied to select the input vectors for the soft sensor. The proposed control scheme offers high speed of change which is due to the set point changes with stationary error for composition and inventory control.

A multi-loop nonlinear model control strategy has also been proposed for a distillation column using an ARX-NN (Autoregressive Neural Network) cascaded structure incorporated into the PLS (Partial Least Square) inner model [5]. An optimization procedure is provided to identify the set parameter of the ARX-NN PLS in order to minimize the plant model mismatch. The approach was used to demonstrate the control effectiveness for setpoint tracking and disturbance rejection. Neural network has also been applied to handle the nonlinear dynamics of a hydrolyzer [6]. A mathematical model was used to simulate the dynamic response of the temperatures when the controller was applied to the system. Two control strategies implemented include the direct inverse control and internal model control and evaluated for setpoint tracking and disturbances studies. The IMC (Internal Model Control) was found to perform best for temperature control during setpoint and disturbance tests and found to be more stable than the conventional controllers.

In a novel implementation of a neural network inverse model based control method on an experimental system, a partially simulated reactor was used to test the neural network based algorithms [7]. The implementation involves the control of the reactor temperature in the face of set point changes and load disturbances which gave acceptable results as compared to the conventional controller. Neural networks for gain prediction within a nonlinear and multivariable system with constraints have also been developed [8]. This strategy was implemented on a lab-scale, non ideal system for a methanol–water distillation column using servo, regulatory and constrained control. The experimental results applied a Generic Model Controller using the neural network as the steady-state model inverse that was developed earlier. A comparative study of these neural network model-based controllers with other advanced controllers such as the dynamic matrix control showed better performance of the proposed controller.

A neural network controller design based on the process inverse dynamic modeling was also applied for product composition control of a distillation plant. The algorithm was applied to obtain the dynamic nonlinear relationship between product composition and reflux flow rate [9]. Neural networks model has also been used as the steady state inverse of a process which is then coupled with a simple reference system synthesis to generate a multivariable controller [10]. The control strategy was applied for controlling a distillation column in the lab and for an industrial-scale high-purity column. An efficient training algorithm based on a nonlinear least-squares technique was used to train the networks. The neural network model based controllers showed better performances for both setpoint and disturbance changes over the conventional feedback controllers.

The various works presented so far on the use of neural network models and controllers involve the use of black box models. This is non-versatile and non-robust in nature as well as being difficult to see the correlations between the inputs and outputs to the system, which are important factors for practitioners in many cases. In this work, which lies one of its main novelty and contribution, we have proposed using an equation based inverse neural network models in a MIMO system to control the top and bottom temperature of the debutanizer column simultaneously using the DIC (Direct Inverse Control) and IMC approach. Neural network equation based models have also been used to estimate the compositions in the column. The other contribution of this work is that it utilize a mixture of online close loop and open loop data for data available online and simulation data for data which are not available online, for training the neural network models. The simulation data was validated with the actual loop output to ascertain its accuracy.

The paper is organized in several sections. Section 2 describes the column and plant in detail while Section 3 outlines the hybrid modeling of the distillation column. Section 4 discusses the methodology for the hybrid model. Finally Section 5 covers the overall analysis results using the hybrid model for composition and temperature while section 6 covers the conclusion.

2. Plant and debutanizer column description

The plant under study in this paper is a crude oil processing unit to produce high value petroleum products for domestic and export markets as seen in Fig. 1. The plant consists of a refinery process and involves condensate fractionation and reforming of aromatics. The products are petroleum fractions, liquefied petroleum gas, naphtha and low sulfur waxy residue while the feed stock of the refinery is crude oil. There are two main process units for the refinery, which are the CDU (Crude Distillation Unit) and the CRU (Catalytic Reforming Unit) while the Crude Oil Terminal provides the crude oil feed stock. Heat exchangers are used to preheat the crude oil from 190 °C to 210 °C. The preheated stream is then further heated in a furnace with a temperature range of about 340 °C to 342 °C. The crude is then routed to the CDU. The crude oil is split into a number of fractions, which includes the heavy straight run naphtha as overhead vapor, untreated kerosene, straight run kerosene and straight run diesel. From the crude tower, there are three branches of cut streams, which are drawn to a stripper column that consists of naphtha stripper, kerosene stripper and diesel stripper.

The hydrogen from the reformer is mixed with the feed of the HSRN (Heavy Straight Run Naphtha) from the CDU and is then heated up to the reaction temperature prior to being fed into a pretreater catalytic reactor. The reactions consist of desulfurisation and denitrification, which protect the reformer catalyst from poisoning. The product from the reactor is then sent to the pretreater stripper. The feed to the reforming unit includes the bottom product of the stripper. The treated naphtha is heated to the reaction temperature and is then fed to the reforming reactors. Effluent from the reactor is cooled and collected in a reformer separator. One part of the gas is sent to an absorber while the other is recycled to the reactor feed stream. In the absorber, hydrogen gas is purged and recycled to the pretreater heater. The raw naphtha feed consists of hydrogen make-up gas while the liquid phase is drawn off and fed