NARX NETWORK BASED DATA-DRIVEN ALGORITHM FOR DETECTION OF TRAY FAULTS IN NONLINEAR DYNAMIC DISTILLATION COLUMN

Syed Ali Ammar Taqvi[a,b], Haslinda Zabiri[b*], Lemma Dendena Tufa[c], Fahim Uddin[a], Syeda Anmol Fatima[b], Abdulhalim Shah Maulud[b]

[a]NED University of Engineering and Technology Karachi, Pakistan
[b]Chemical Engineering Department, Universiti Teknologi PETRONAS, 32610, Perak, Malaysia
[c]School of Chemical and Bioengineering, Addis Ababa Institute of Technology, King George VI St Addis Ababa 1000, Addis Ababa, Ethiopia

Graphical abstract
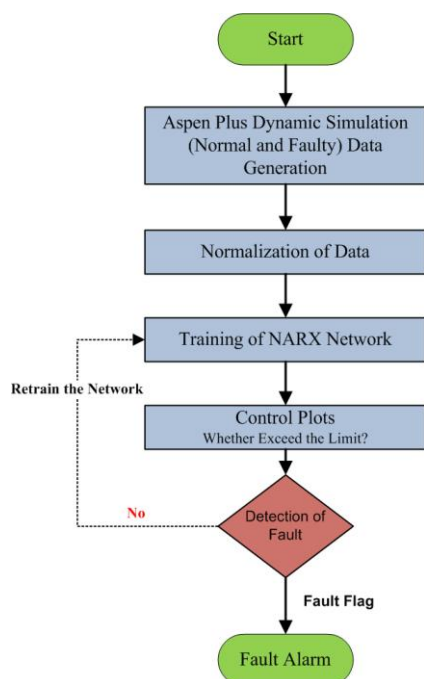
Abstract

Efficient monitoring of highly complex process industries is essential for better management, safer operations and high-quality production. Timely detection of various faults helps to improve the performance of the complex industries, prevent various unfavorable consequences and reduce the maintenance cost. Fault Detection and Diagnosis (FDD) for process monitoring and control has been an active field of research for the past two decades. Distillation columns are inherently nonlinear, and thus to have an accurate and robust performance, the fault detection methods should be based on nonlinear dynamic methods. The paper presents a robust data-driven fault detection approach for realistic tray upsets in the distillation column. The detection of tray faults in the distillation column is conducted by Nonlinear AutoRegressive with eXogenous Input (NARX) network with Tapped Delay Lines (TDL). Aspen Plus® Dynamic simulation has been used to generate normal and faulty datasets. The study shows that the proposed method can be used for the detection of tray faults in distillation column for dynamic process monitoring. The performance of the proposed method has been evaluated by the Missed Detection Rate (MDR) and the Detection Delay (DD).

Keywords: NARX network, data driven, fault detection, distillation column, Aspen Plus

Abstrak

Pemantauan cekap industri proses yang sangat kompleks adalah penting untuk pengurusan yang lebih baik, operasi yang lebih selamat dan pengeluaran berkualiti tinggi. Pengesanan pelbagai kesalahan pada masa yang tepat membantu meningkatkan prestasi industri yang kompleks, mencegah pelbagai masalah dan mengurangkan kos penyelenggaraan. Pengesanan dan Diagnosis Kesalahan (FDD) untuk pemantauan dan kawalan proses telah menjadi bidang penyelidikan yang aktif dalam dua dekad lalu. Kolom distilasi adalah tidak linear, oleh itu kaedah pengesanan kesalahan yang tepat dan mantap harus berdasarkan kaedah dinamik tidak linear. Dokumen ini membentangkan tentang sistem pengesanan kesalahan yang didorong data kukuh, untuk kesilapan dulang dalam kolom distilasi. Pengesanan kesilapan dulang dalam kolom distilasi dijalankan oleh Rangkaian Nonlinear AutoRegressive dengan rangkaian Input (NARX) dengan Talian Kelewatan

Disalurkan (TDL). Simulasi dinamik Aspen Plus® telah digunakan untuk menghasilkan dataset normal dan rosak. Kajian menunjukkan bahawa kaedah yang dicadangkan boleh digunakan untuk mengesan kesilapan dulang dalam kolom distilasi untuk pemantauan proses dinamik. Prestasi kaedah yang dicadangkan telah dinilai oleh Kadar Pengesan Terlepas (MDR) dan Kelewatan Pengesanan (DD).

Kata kunci: Rangkaian NARX, didorong data, pengesanan kesalahan, lajur penyulingan, Aspen Plus

1.0 INTRODUCTION

The industrial systems and technical processes are gradually becoming more complex [1-3]. They incorporate various subsystems from different energy domains which are equipped with actuators, sensors, digital circuits, and software. The safety, maintainability, and reliability are essential to protect these engineering systems due to increased safety requirements and quality assurance. A supervisory control system is needed which can immediately detect the abnormal behavior of the system, isolate the root cause of the faults and generate alarms to initiate appropriate action in time [4]. This will allow taking various decisions such as to continue the operation if the abnormal dynamic behavior is still within the acceptable threshold limit.

Distillation column is a multivariable system and holds a substantial part of the refinery and other chemical process industries [5, 6]. The change in reboiler steam pressure, tray efficiency, feed composition, or overall pressure and temperature of distillation column may significantly affect the overall performance of the column [7, 8]. It is reported that significant financial losses are incurred when a high-throughput plant is shut down or partially operated. These losses may be direct costs, such as repair and dismantling expenses, or indirect costs of production losses [9]. Some of the abnormal behaviors have multiple causes, for example, foaming may be caused by plugging and/or tray damage. Flow changes, pressure fluctuations, and tray damage cause similar issues of column stability. However, identification of the root causes of the column instabilities is essential as different solutions may have different complexities and costs. Instrumentation and control remedies are suggested for the restoration of column stability and diagnosis of the root cause. Very less attention has been given to detect the tray damages in the distillation column. However, the savings expected from a new control strategy may be lost because of the tray damage during start-up or shutdown.

Fault detection and diagnosis is an essential area for accident prevention in process industries to achieve most of the desired and challenging goals [10]. For a few decades, process industries have used fault detection and diagnosis extensively for efficient process monitoring where timely detection of the faults is vital for safety and profitability [7]. Fault detection is to evaluate whether the process is operating in the acceptable range, while fault diagnosis identifies the cause and characteristic of the fault [11]. Fault detection and diagnosis is divided into model-based, data-driven and knowledge-based methods [3, 12-14]. The model-based approach utilizes first-principle modeling for the development of rigorous models. These model-based approaches have been widely applied due to their reliability and robustness [15]. However, model-based approaches are difficult to implement due to the complexities and nonlinearities in the processes. On the other hand, there is a continuous development in the soft-computing techniques, information technology, advanced process control (APC), and data mining and analytics for process monitoring in the modern process industries. The data collection and processing of the complex industrial processes has also increased [16].

The data-driven approaches are based on process measurements. These approaches classify the faults by utilizing trained classifier based on normal and faulty data [17, 18]. The data-driven approaches are reliable for those complex processes which are either too complicated or uneconomical to develop an accurate mathematical model. Moreover, due to the nonlinearity and complexity in the modern process industry, there is a demand for data-based methods [14, 19]. Several methods have been adopted for the data-driven detection and diagnosis of abnormal behavior in process industries [12, 20]. Data-driven approaches consider fault detection and diagnosis as classification tasks [21]. This classification can be done by supervised or unsupervised learning methods, including Partial Least Square (PLS) [22], Principle Component Analysis (PCA) [23, 24], Artificial Neural Network (ANN) [25-27], Fisher Discriminant Analysis (FDA) [28], Bayesian Networks [29] and Support Vector Machine (SVM) [7].

The fault detection in distillation column is a challenging task due to complex interactions of faults and symptoms, high correlation between the measured variables and the nonlinear behavior [30]. Multilayer perceptron (MLP) type neural network has received considerable attention for fault detection [19, 31-33]. However, the conventional neural network-based methods are either complicated or applicable only to steady-state processes [34]. On

the other hand, nonlinear auto-regressive with exogenous inputs (NARX) based neural network structures are also used as they have the ability to capture the nonlinearity of the process accurately [35]. It has significant applications in simulation, monitoring, analysis, and control of various systems [36, 37].

The distillation columns are inherently nonlinear, it is expected that accurate and robust fault detection methods should be based on nonlinear dynamic methods. However, there is no significant work published on fault detection based on nonlinear dynamic methods for the detection of tray faults. Thus, there is a need to develop an accurate and robust fault algorithm based on the dynamic nonlinear model of the process under investigation.

The main contribution of this study is as follows:

1. A robust fault detection algorithm is proposed that is capable of accurate and rapid fault detection applicable to the nonlinear dynamic distillation column.
2. The tray faults have been simulated in Aspen Plus® and detected by using proposed NARX network-based data-driven fault detection framework.
3. The performance of the proposed fault detection algorithm has been evaluated using Missed Detection Rate (MDR) and Detection Delay (DD) used in various studies.

The paper is organized as follows: Section 2 presents an Aspen Plus® dynamic simulation of the ethanol-water distillation column which has been used for the generation of normal and faulty data. Section 3 discusses the methodology of NARX network-based fault detection. Section 4 comprises results and discussion. The contribution and conclusion have been presented in Section 5.

2.0 METHODOLOGY

2.1 Aspen Plus® Steady-state & Dynamic Simulation

The proposed fault detection framework based on NARX network utilizes a dynamic simulation of a binary distillation column for the generation of normal and faulty data. The distillation column located in Universiti Teknologi PETRONAS has been used for the development of steady-state and dynamic simulations. The column comprises ethanol-water mixture with the feed composition of 25% (molar) ethanol entering at 65°C at tray 9. The column comprises 17 stages including condenser and reboiler. The internal diameter and the height of the column are 0.15 m and 5.5 m respectively with the tray spacing of 0.35 m. The Aspen Plus® RADFRAC model has been used for the development of steady-state and dynamic simulation. Moreover, Universal Quasi-Chemical (UNIQUAC) model has been used as the thermodynamic package. The developed steady-state file has been exported to

Aspen Plus Dynamics® for the control study and data generation. Various controllers are installed in the dynamic simulation i.e. flow, top and bottom compositions, column pressure, and top and bottom level controllers. The detailed description of the development of steady-state and dynamic simulation can be obtained from our previous publications [4, 5, 7, 25, 38]. The Aspen Plus dynamic simulation is shown in Figure 1.
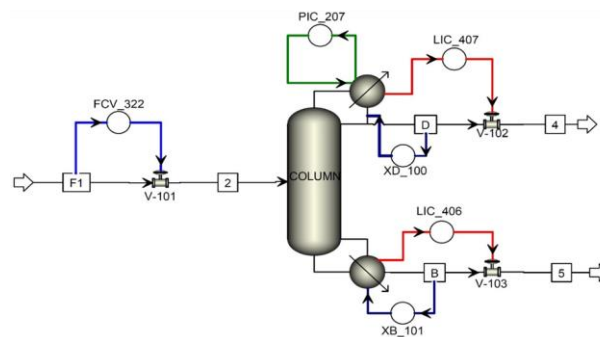
Figure 1 Aspen Plus® Dynamic Simulation of Distillation Column

2.2 NARX Network Based Fault Detection

Nonlinear Autoregressive with Exogenous Input (NARX) network has been used in this study for the detection of tray faults in distillation column. The NARX network is developed in MATLAB® 2018a. The step by step methodology has been presented in Table 1. The training data for the NARX network has been obtained from Aspen Plus® dynamic simulation for normal and abnormal conditions. In the next stage, the data has been normalized in the range of [0 1] to minimize the effect of larger values on the smaller ones. The training and testing dataset have been divided into 60% and 40% respectively. The data selected for testing has not been used for the training purpose. Once the network has been trained with the defined input/output datasets, the next step is to define the upper and lower threshold limits based on normal operating ranges. In this study, the control limit has been defined by using Walter theory, which is also known as Shewhart Control Chart [39].

The mean for x can be written as $\bar{x}$, while the standard deviation is σ^x. The upper control limit (x_{max}), Lower control limit (x_{min}) and the central line (x_0) can be presented as;

$$x_{max} = \bar{x} + \lambda\sigma^x \qquad (1)$$

$$x_{min} = \bar{x} - \lambda\sigma^x \qquad (2)$$

$$x_0 = \bar{x} \qquad (3)$$

Where λ is generally known as the distance from the center line which can be expressed in standard deviation units. It is assumed that 99.7% of the data

will fall inside the control limit if the observed variables can be approximated by the normal distribution. Hence, the data which crosses the defined control limit is identified as the fault flag/fault signature.

$$\Psi_{(t)} = \begin{cases} 1 \Leftrightarrow \left|\hat{y} - \bar{y}\right| > 3\sigma^y \\ 0 \Leftrightarrow \left|\hat{y} - \bar{y}\right| < 3\sigma^y \end{cases} \quad (4)$$

Where $\Psi_{(t)}$ is the fault flag. To identify the fault flag, the x_{max} and x_{min} must be set as defined in Equations (1-2). If the values of the predictive variables are within the defined thresholds, $\Psi_{(t)} = 0$ and the system is considered as normal. When the predictions exceed the control limits, a fault flag is generated. The final stage is to evaluate the performance of the proposed fault detection algorithm. NARX Network based fault detection scheme is mentioned in Figure 2 and the details of proposed Algorithm for using fault detection framework is presented in Table 2. The detailed methodology of NARX network can be found in our previous publication [4]. For the performance evaluation, Missed Detection Rate (MDR) and the Detection Delay (DD) has been used. They are defined as follow;

$$MDR = \frac{\text{No. of fault samples identified as normal}}{\text{Total no. of fault samples}} \times 100 \quad (5)$$

$$DD = \text{number of samples between } T_a \text{ and } T_f \quad (6)$$

Where,
T_a = is the time at which the alarm is raised
T_f = is the time at which the process variable moves from the fault-free region of operation into the faulty region of operation.

Table 1 Proposed Algorithm for Development of Fault Detection Framework

| |
|---|
| 1. Develop a representative dynamic simulation of the system. |
| 2. Select manipulated and observed variables. |
| 3. Generate timeseries input-response data for different normal scenarios. |
| 4. Divide data into training (60%) and testing (40%). |
| 5. Train NARX network detection model using the training data. |
| 6. Test the trained model using testing dataset. |
| 7. Find the standard deviation and mean. |
| 8. Define the central line, upper control limit and lower control limit for the observed variables using Equations (1) – (3). |
| 9. Define fault flag using equation (4). |
| 10. Evaluate the performance of the detection scheme using selected indices (MDR and DD) using Equations (5) and (6). |
| 11. If the performance is satisfactory, the model is ready for fault detection of the system, otherwise, repeat steps 3-10. |

Table 2 Proposed Algorithm for Using Fault Detection Framework

1. Generate timeseries input-response data of the system.
2. Train and test the NARX network using generated dataset.
3. Apply control limits on the system.
4. If the variable exceeds control limits, the fault flag is triggered.
5. Evaluate the performance of the proposed algorithm based on MDR, DD and FAR.

2.3 Normal and Fault Conditions

2.3.1 Normal Condition

In this case, the data has been generated when the column is running at normal condition i.e. no-fault state. The simulation has been done to collect 1500 samples for the training of NARX network. It has been assumed that all the parameters are in the normal range. However, by giving a new setpoint to the controllers, it is observed that all the variables are in the defined range after taking control action by the controllers into account.
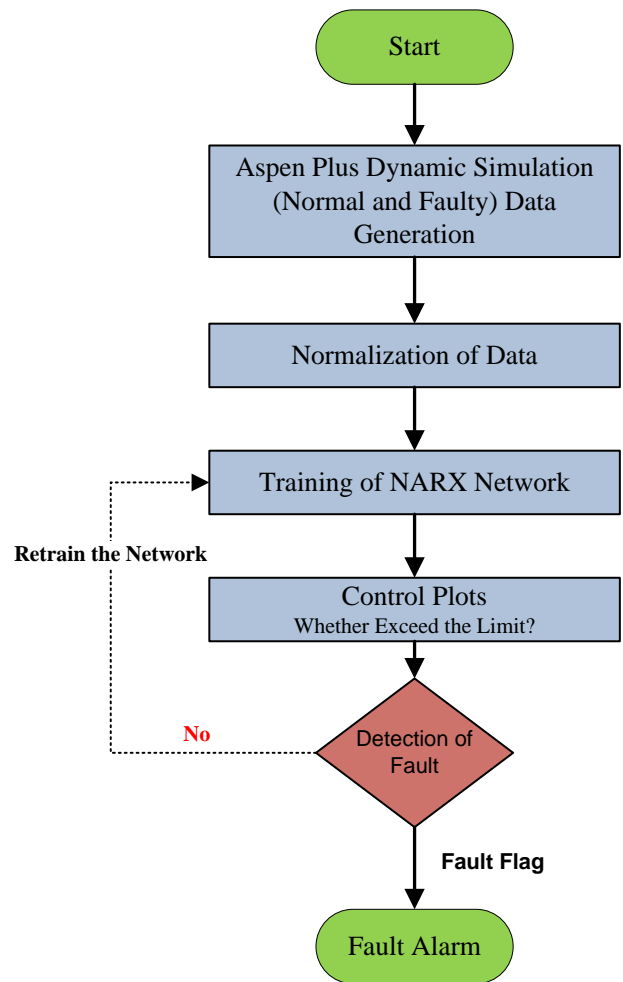
Figure 2 NARX Network based Fault Detection Scheme

The distillation column response at normal conditions is presented in Figure 3.

2.3.2 Feed Tray Upset (Efficiency Reduction) [F1]

Fault 1 is simulated by introducing a feed tray upset in the distillation column. The liquid level in the column, vapor velocity, and purity of the top and bottom products are significantly influenced by the low efficiency of the feed tray. The abrupt changes in differential pressure of the column and separation efficiency occur due to weeping in the column. This phenomenon considerably decreases the liquid-vapor separation at each stage, resulting in the reduction of tray efficiency. To simulate this upset, feed tray efficiency is reduced to 1%.

2.3.3 Low Efficiency in Refining Section [F2]

Fault 2 is simulated by reducing the efficiency in the refining section. The refining section comprises all trays above the feed tray. Therefore, a fault, i.e., low tray efficiency is introduced in all stages of the refining section (2nd– 6th) to observe the changed behaviour of the distillation column. In this case, the tray efficiencies are reduced to 1%.

3.0 RESULTS AND DISCUSSION

The normal and faulty data has been used for the timely detection of faults in distillation column. Figure 3 shows the response of input and output variables when there is no fault in the system. It can be seen that column pressure, top and bottom compositions are close to the steady-state values and showing very few fluctuations.
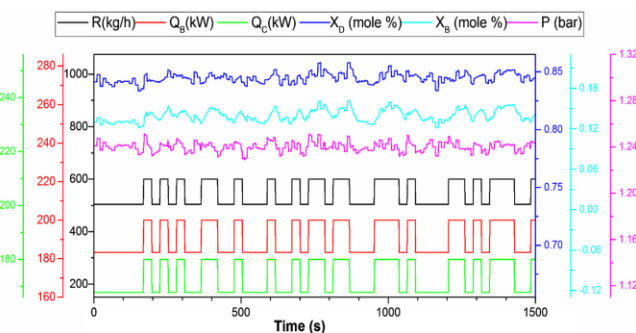

Figure 3 Data Obtained at Normal Condition of Distillation Column

Fault 1 (F_1) is associated with the low efficiency at the feed stage (6th stage). The feed stage efficiency has been reduced to 1% to observe the column behaviour. Fault 1 is introduced in the column at t = 5.0 hr. It can be observed from Figure 4 that once the fault occurs in the column the top composition has suddenly increased to 86 mole% and then has decreased to 82 mole%.
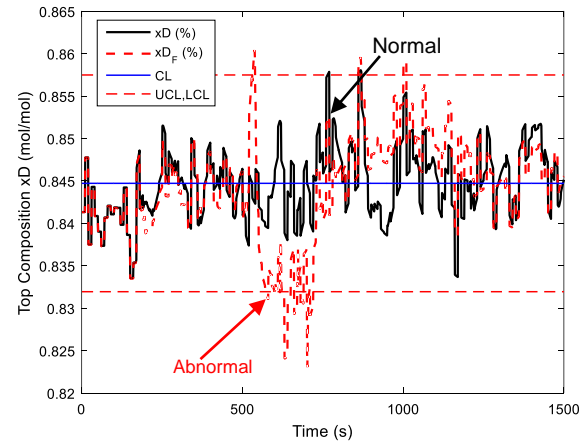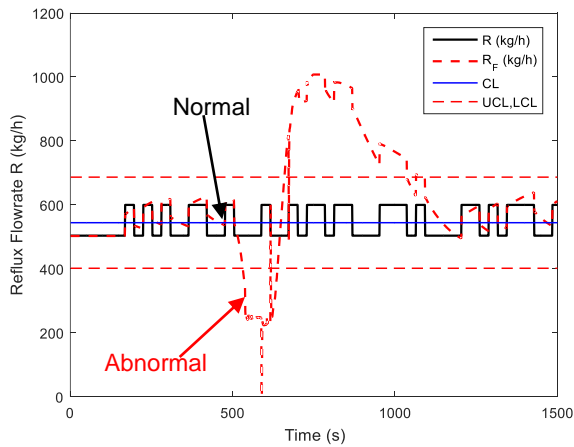

Figure 4 NARX network-based detection in top composition for F_1

It is difficult to observe the abnormal behaviour of the column while monitoring the bottom composition presented in Figure 5. It can be observed that it does not cross the threshold limit since the controller has taken appropriate action to keep the bottom composition in the defined limit.
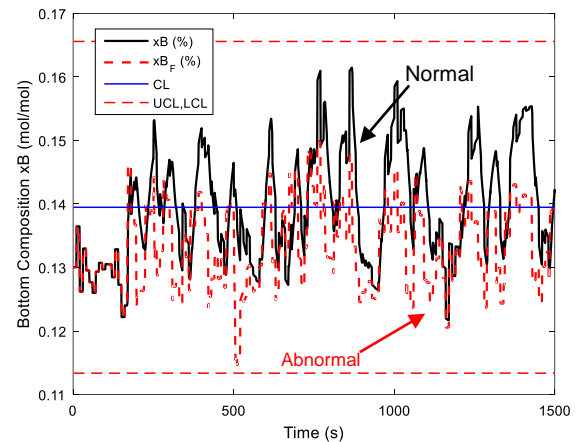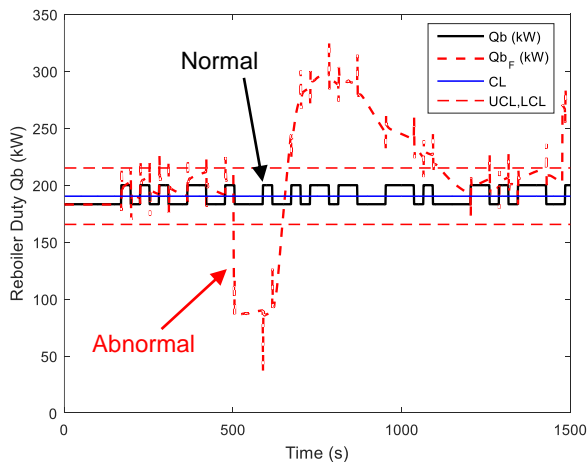

Figure 5 NARX network-based detection in bottom composition for F_1

The reflux flow shown in Figure 6 has also increased by twice the normal value to maintain the top composition in the column. A similar trend can be seen in the reboiler duty as shown in Figure 7.
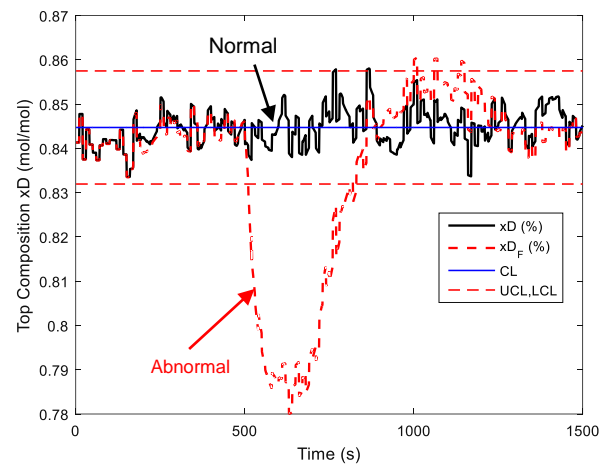
Figure 6 NARX network-based detection in reflux flow rate for F_1

Figure 8 NARX network-based detection in top composition for F_2

Fault 2 (F_2) shows the decrease of column efficiency in the refining section i.e. from (2nd – 6th stage). Theoretically, it is expected from the column operating at 100% efficiency that the vapors leaving the tray are in equilibrium with the liquid leaving the same tray. Hence it is assumed for this case that VLE across the tray is disturbed due to which the efficiency in the refining section is decreased from 100% to 1%. The fault occurs at t = 5.0 hr. It can be observed that once the fault occurs the top composition is increased first and then decreased to 78.0 mole% as shown in Figure 8. However, the bottom composition does not show any significant changes as presented in Figure 9.
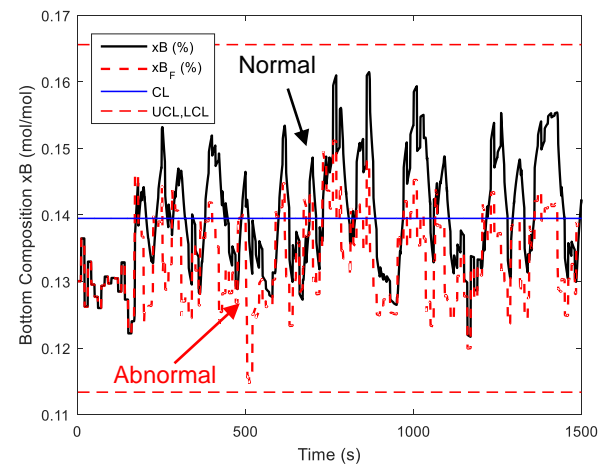

Figure 9 NARX network-based detection in bottom composition for F_2

Figure 7 NARX network-based detection in reboiler duty for F_1

It can be seen in Figure 10 that the normal range of the reflux is 500-600 kg/h. However, it has increased to a higher value once the fault occurs in the refining section at t = 5.0 hr. The reflux has been increased to a higher value of approximately 1050 kg/h which has significantly affected the top composition and other parameters. The reboiler duty has also increased from 150 kW to approximately 280 kW due to which the column performance has been disturbed as shown in Figure 11.

The fault is introduced in the top section of the column hence the adverse effects of this fault take enough time to reach the bottom of the column. Therefore, the controller is able to take remedial action and keep the bottom composition within its defined limits.
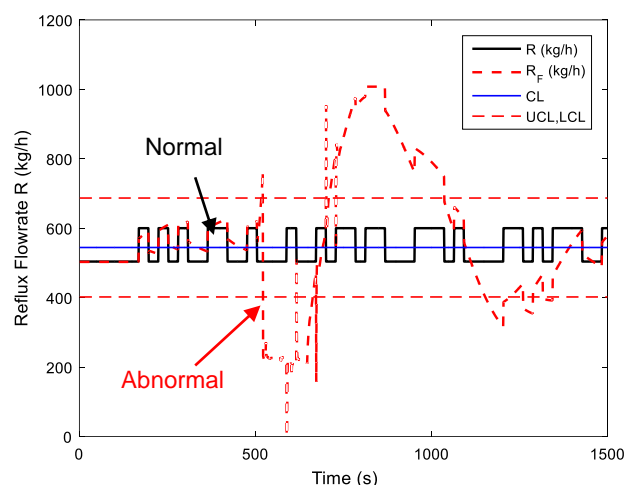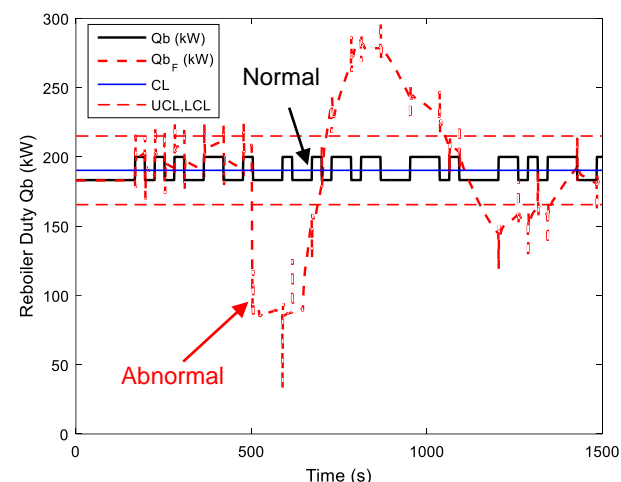
Figure 10 NARX network-based detection in reflux flow rate for F_2

Figure 11 NARX network-based detection in reboiler duty for F_2

The performance evaluation of the proposed NARX network has been done by Missed Detection Rate (MDR) and the Detection Delay (DD). Table 3 shows the MDR and DD for both types of tray faults in distillation column. The main objective of MDR is to define the percentage of samples identified as normal in the faulty dataset. However, the detection delay is the measure of the difference of samples between the actual instance of fault occurrence and the instance of alarm raised. It can be observed that both the faults have almost similar MDR and DD. The algorithm was able to detect the fault with 15-16 sec. Therefore, the detection algorithm is able to identify the abnormality in the column effectively.

Table 3 Missed Detection Rate & Detection Delay for Tray Faults

Fault ID	Missed Detection Rate MDR (%)	Detection Delay DD (sec)
F1	0.001	15
F2	0.003	16

4.0 CONCLUSION

The proposed NARX network-based data-driven algorithm for fault detection is found to be very effective for the detection of tray faults in the distillation column. Tray faults have been introduced in the distillation column to observe the abnormal behaviour of the column. APD-MATLAB co-simulation has been used for the generation of data. Results showed that the NARX network has the ability to capture the nonlinearity of the distillation column accurately. 70% of the data was used to train the neural network model, while 30% was used for testing and validation. The proposed model was found to be adequate for the representation of system behaviour, and thus suitable for fault detection efficiently. The performance indices and reliability of the proposed fault detection algorithm ware evaluated by MDR and DD.

Acknowledgement

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