

Fault isolation during transient conditions on a heated two-tank system: a multiway PCA approach

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Abstract

This study aimed to employ a Multiway Principal Component Analysis (MPCA) approach for fault detection and isolation during transient conditions on a benchmark heated two-tank system, which closely resembles a chemical process. The significance lies in the system’s similarity to chemical processes, characterised by controllable variables, noise, disturbances, and changes in operating modes. The data generated by the system can include both faulty system data and data under Normal Operating Conditions (NOC). Building on prior studies that focused on fault detection and isolation during steady state conditions, this research employed the MPCA approach to enhance the ability to detect and isolate faults during transient conditions. For the model’s training, essential to Fault Detection and Isolation (FDI), training data are generated from both a simulated model of the system and the practical system. The simulated model’s data are then validated against the practical system data. Following the model’s training, the MPCA approach, validated through relevant literature, is applied to detect and isolate faults using test data. This test data are generated from both the simulated model and the practical system. Performance metrics, including detection rate, false alarm rate, time until detection, and contribution plots, are employed to evaluate the effectiveness of the MPCA method. Results indicate that the MPCA method successfully detected and isolated faults using the SPE and T^2 control charts for most faults, provided the right minimum number of experimental and simulated training runs under NOC. Due to extended run times in practical experiments, a combination of practical and simulated data were utilized to achieve effective fault detection and isolation. In conclusion, the research affirms the feasibility of detecting and isolating faults in the benchmark heated two-tank system using the MPCA method during transient conditions.

Keywords: Fault detection and isolation; Benchmark heated two-tank system; Multiway Principal Component Analysis; Transient.

Contents

List of Figures	6
List of Tables	8
1 Introduction	1
1.1 Background	1
1.2 Research question	3
1.3 Research objectives and method	3
1.3.1 Experimental design	3
1.3.2 Simulated heated two-tank process model	3
1.3.3 Experimental data from the heated two-tank system	4
1.3.4 FDI using MPCA	4
1.3.5 Evaluating results obtained from MPCA	4
1.4 Dissertation overview	4
2 Literature survey	6
2.1 Introduction	6
2.2 Fault detection and isolation during transient conditions	6
2.3 Heated two-tank system	7
2.4 FDI using multiway principal component analysis	8
2.5 Critical review	10
3 MPCA and fault detection	12
3.1 Introduction	12
3.2 Unfolding	13
3.3 Data pre-processing	14
3.4 PCA	14
3.4.1 Number of principal components	16
3.5 Control limits	17
3.5.1 Hotelling's T square	17
3.5.2 Square prediction error	18
3.6 Contribution plot	18
3.7 Imputation	19
3.8 Conclusion	20

4	Benchmark heated two-tank system	21
4.1	Introduction	21
4.2	Benchmark heated two-tank system	21
4.2.1	Coupled liquid tanks illustration	24
4.2.2	Continuous stirred tank heater	24
4.2.3	Hardware	25
4.2.4	Instrumentation	27
4.3	Model of heated two-tank system	28
4.4	Simulated and practical data	31
4.5	Simulated data compared to practical	33
4.6	Faults emulated	34
4.6.1	Pipe leakage	34
4.6.2	Heating malfunction	34
4.6.3	Blockage	35
4.6.4	Stuck valve	35
4.7	Conclusion	35
5	Experimental design	36
5.1	Introduction	36
5.2	Practical experiments	37
5.2.1	Normal operation	37
5.2.2	Practical experiments descriptions	37
5.3	Simulated experiments	39
5.4	Combination of data	39
5.5	Conclusion	40
6	Results	41
6.1	Introduction	41
6.2	Training and test data	41
6.3	Fault detection for different scenarios	43
6.3.1	Fault detection using practical or simulated data	43
6.3.2	Fault detection using a combination of practical and simulated data	45
6.3.3	Comparison of different data variations	46
6.4	Transition monitoring	47
6.4.1	Transition monitoring using SPE	50
6.4.2	Transition monitoring using T^2	55
6.4.3	Fault isolation for the different faults	59
6.5	Conclusion	64
7	Conclusion	65
7.1	Introduction	65

7.2	Reflection on objectives	65
7.2.1	Experimental design	65
7.2.2	Simulated heated two-tank process model	65
7.2.3	Experimental data from the heated two-tank system	66
7.2.4	FDI using MPCA	66
7.2.5	Evaluating results obtained from MPCA	66
7.3	Future work	67
7.4	Closure	67
	Bibliography	68
	Appendices	71
	Appendix A Heated two-tank Simulink model	72
	Appendix B Heated two-tank system data	73
	Appendix C Heated two-tank system model data	74
	Appendix D MPCA source code	75

List of Figures

3.1	Illustration of matrix unfolding $\mathbf{X}$	13
3.2	Data matrix X with left-out samples	16
4.1	Full view illustration of the heated two-tank system	22
4.2	Two-tank thermofluid system	23
4.3	Coupled liquid tanks	24
4.4	Continuous stirred tank heater	25
4.5	A broad view of the heated two-tank system	25
4.6	Heat pump used in heated two-tank plant	26
4.7	Gas heater used for heating of water in the system	26
4.8	Agitator installed to ensure uniform heat distribution	27
4.9	Practical vs. simulated tank level data	31
4.10	Practical vs. simulated tank temperature data	32
4.11	Practical vs. simulated tank cold water flow	32
4.12	Practical vs. simulated data for the heat exchanger flow rate	33
6.1	Practical normal operation transition control charts	51
6.2	Simulated normal operation transition control charts with a control limit at 1	51
6.3	Practical fault stuck valve tank 1 with a control limit at 1	52
6.4	Practical fault stuck valve tank 2	52
6.5	Practical fault agitator fault tank 1	52
6.6	Practical agitator fault tank 2	53
6.7	Practical agitator fault tanks 1 and 2	53
6.8	Practical 30% leakage fault tank 1	54
6.9	Practical 30% leakage fault tank 2	54
6.10	Practical 30% blockage between tank 1 and 2	54
6.11	Simulated 30% blockage between tank 1 and tank 2	55
6.12	Practical normal operation transition control charts	55
6.13	Simulated normal operation transition control charts	56
6.14	Practical stuck valve fault tank 1	56
6.15	Practical stuck valve fault tank 2	57
6.16	Practical agitator fault tank 1	57

6.17	Practical agitator fault tank 2	57
6.18	Practical agitator fault on tank 1 and 2	58
6.19	Practical leakage 30% fault on tank 1	58
6.20	Practical leakage 30% fault on tank 2	58
6.21	Practical blockage 30% fault between tank 1 and tank 2	59
6.22	Simulated blockage 30% fault between tank 1 and tank 2	59
6.23	Contribution plots of the agitator fault in tank 1 using simulated and combined training data	60
6.24	Contribution plots of the agitator fault in tank 2 using simulated and combined training data	61
6.25	Contribution plots of the agitator fault in tank 1 using simulated and combined training data	61
6.26	Contribution plots of the agitator fault in tank 2 using simulated and combined training data	62
6.27	Contribution plots of the agitator fault in tanks 1 and 2 using simu- lated and combined training data	62
6.28	Contribution plots of leakage fault in tank 1 using simulated and combined training data	62
6.29	Contribution plots of leakage fault in tank 2 using simulated and combined training data	63
6.30	Contribution plots of practical blockage fault between tanks 1 and 2 using simulated and combined training data	63
6.31	Contribution plots of simulated blockage fault between tanks 1 and 2 using simulated and combined training data	64
A.1	Full view illustration of the heated two-tank system	72

List of Tables

4.1	Process variables - Tank 1	23
4.2	Process variables - Tank 2	23
4.3	NRMSE values of different variables	33
4.4	Faults emulated in the system	34
5.1	NOC and faulty experiments of the practical system	38
5.2	NOC and faulty transitions of the simulated model	39
6.1	Test data to be used to determine the fault detection performance .	42
6.2	SPE false alarm rate using practical or simulated training data . . .	43
6.3	SPE fault detection rate using practical or simulated training data .	44
6.4	T^2 false alarm rate using practical or simulated training data	44
6.5	T^2 fault detection rate using practical or simulated training data . .	44
6.6	SPE false alarm rate using practical and simulated training data . .	45
6.7	SPE fault detection rate using practical and simulated training data	45
6.8	T^2 false alarm rate using practical and simulated training data . . .	46
6.9	T^2 fault detection rate using practical and simulated training data .	46
6.10	Overall performance for practical and simulated data at different principal components and runs	47
6.11	Overall performance for combined practical and simulated data at different principal components and runs	47
6.12	Fault detection rate at 200 transition runs and 30 PCs	48
6.13	Fault detection rate at 200 transition runs and 30 PCs	49
6.14	Time in seconds until fault detection using 200 runs and 30 PCs . .	50
6.15	Variables used in contribution plot	60

Table of abbreviations

MPCA Multiway Principal Component Analysis	2
FDI Fault Detection and Isolation	2
NOC Normal Operating Conditions	2
PCA Principal Component Analysis	2
PCs Principal Components	4
SPE Squared Prediction Error	4
T-square Hotelling's t-squared statistic	4
DNN Deep Neural Network	7
FDD Fault Detection and Diagnosis	7
CLTS Coupled Liquid Tank System	7
TSR Trimmed Score Regression	19
KDR-PCR Known Data Regression using the Principal Component Regression approach	19
NRMSE Normalised Root Mean Squared Error	33

Chapter 1

Introduction

1.1 Background

In response to the escalating demand for reliability, safety, and efficiency in chemical processes and related industries [1], a substantial number of variables are systematically regulated within a closed-loop control system. This control mechanism involves a continuous feedback loop to ensure precise and optimised performance in the face of dynamic operational conditions. While process controllers are effective in managing most disturbances within a system, some anomalies, referred to as faults, remain beyond their control [2]. Faults in chemical processes may manifest as variations in disturbance parameters, alterations in process parameters, sensor malfunctions, and actuator faults [2]. To ensure safety and minimise the risk of producing subpar products, implementing fault detection and diagnosis in a system is crucial [3]. Early detection of faults, while the system is still within a manageable state, can prevent the escalation of abnormal events [4].

Fault detection methods can be broadly categorised into two approaches: model-based and data-driven [5], [6], [4]. Model-based fault detection relies on mathematical models derived from first principles. The accuracy of these models is crucial for effective fault detection [7]. Nevertheless, the limitations of model-based methods become evident in their inability to adequately address the complexity of modern intricate systems [8].

Data-driven approaches become particularly relevant when dealing with large volumes of accessible data. These methods transform historical data into a priori knowledge essential for diagnostic systems. The widespread adoption of data-driven methods in industrial applications can be attributed to their minimal reliance on prior knowledge about the system and their relatively simpler modelling process in comparison to model-based approaches. This approach is especially favored in steady-state scenarios, where the complexities of developing specialised dynamic models for a system pose significant challenges [4]. The development of sensor technology has led to the incorporation of new variables into systems, generating more extensive datasets for process analysis. While this increase in data are valuable, it also increases the system's complexity, which poses challenges for fault detection. The statistical approach, particularly within the history-based method, has been extensively researched for its robust detection performance. Although its diagnostic capabilities may not be as advanced as some other approaches, in industrial applications, the emphasis is often on detection rather than diagnosis.

Multivariate statistical techniques, such as Principal Component Analysis (PCA), are employed for the analysis of extensive datasets, as they reduce dimensionality while preserving essential information [4]. PCA is a linear dimension reduction technique for capturing dataset variance that allows for meaningful analysis of noise and correlation. Single plot charts (e.g., T^2 and Q) are used to condense large datasets to allow for easy interpretation and trend identification. The reduced dimensionality enhances a system's fault detection capabilities [2]. However, a limitation of PCA is that it is time invariant, whereas most processes are time varying, which necessitates recursive adjustment of the PCA model over time [4].

An adapted PCA approach called Multiway Principal Component Analysis (MPCA) is suggested to address these limitations. MPCA rearranges a three-dimensional array of variables, time, batches, or transitions into a two-dimensional data matrix, which is subsequently analysed using PCA [9]. The MPCA technique is capable of mitigating non-linear dynamics, enabling the detection of faults over time. However, it requires substantial amounts of data to perform effectively.

1.2 Research question

Can a fault occurring during the transition between operating modes in a two-tank heated system be successfully detected and isolated?

1.3 Research objectives and method

This section outlines the research objectives and explains the methodology employed to achieve them.

1.3.1 Experimental design

An experimental design was carried out to ensure that the simulated and practical datasets were suitable for the study. The requirements for the data are the following:

- There should be controlled variables
- The experimental system should allow the modes of operation to change
- Normal and faulty operations
- Noise or disturbances

The controlled variables, change of operating modes and noise or disturbances are requirements for the system in the study to mimic an industrial process. The normal operation data are needed to have training and control data. The faulty operations is the same operations just with a fault induced. This data are needed to see if the MPCA technique can detect and isolate a fault. Meeting these requirements is essential to establish the validity of MPCA as a technique for fault detection and isolation (FDI) during transitions.

1.3.2 Simulated heated two-tank process model

The heated two-tank process model was developed by Linder and Auret [10] in MATLAB Simulink and then modified to match the practical heated two-tank system. The simulated model was validated by using the practical experimental data of the heated two-tank system. Normal simulated data, which are data of the same operation with no fault induced were generated from the simulated model with the parameters used for this study.

1.3.3 Experimental data from the heated two-tank system

An operational heated two-tank system was utilised for practical testing. The experimental data, including flow, level, and temperature measurements, were recorded using a PLC.

1.3.4 FDI using MPCA

The MPCA technique was developed in MATLAB and applied to the heated two-tank data. The validation of the MPCA technique was conducted by referring to existing literature on MPCA. To see if the MPCA technique was correctly implemented, the MPCA technique was tested on other data from literature and validated by observing if the results are similar. The data underwent unfolding, and PCA was employed to extract the Principal Components (PCs). Subsequently, multivariate control charts Hotelling's t-squared statistic (T-square) and Squared Prediction Error (SPE) were constructed to detect faults. In case of fault detection through the control charts, contribution plots were utilised to isolate the specific fault.

1.3.5 Evaluating results obtained from MPCA

The evaluation of the technique's performance was based on several criteria:

- The time required to detect a fault was calculated from the onset of the induced fault until detection.
- False alarms or instances where a fault was detected in the absence of an actual fault were noted.
- Detection accuracy was measured by determining the time in seconds in which the technique successfully detected a fault relative to the time since the system induced the fault.

The MPCA technique was validated for its ability to detect and isolate faults using practical, simulated, and a combination of practical and simulated data.

1.4 Dissertation overview

Chapter 2 serves as a literature survey, emphasising the study's relevance, offering an overview of various MPCA variations, and justifying the heated two-tank system's

selection as a benchmark for testing FDI techniques.

In Chapter 3, the MPCA technique is comprehensively explained, including its modelling process. Each step's rationale is elucidated, and the method is verified through comparison with existing literature.

Chapter 4 delves into the heated two-tank system, exploring both its practical and simulated aspects. The faults to be emulated within the system are detailed.

In Chapter 5, the MPCA technique is implemented using practical and simulated data, independently and in tandem. The analysis involves scrutinising both normal and faulty transitions.

Chapter 6 focuses on evaluating the MPCA technique's detection accuracy, false alarms, and time required for detection. Results from applying the technique to experimental and simulated data are compared for validation.

Chapter 7, the concluding chapter, summarises the study's findings and proposes recommendations for future research endeavours.

Chapter 2

Literature survey

2.1 Introduction

The literature survey critically examines pertinent articles related to three key areas: FDI in processes undergoing transitions; the heated two-tank system as a benchmark for emulating faults during transitions in industrial systems; and various adaptations of MPCA for FDI. This comprehensive review aims to provide a thorough understanding of the current state of research in these domains.

2.2 Fault detection and isolation during transient conditions

Models designed for FDI under steady-state conditions may prove inadequate when a system undergoes a transition. Relying solely on steady-state analysis during transitions, especially if these transitions are prolonged, poses a challenge. Additionally, detecting faults becomes more challenging during transitions due to the difficulty in establishing nominal values and thresholds in such dynamic situations [11].

The Tennessee Eastman process serves as a benchmark for evaluating fault detection techniques in transient regions. This system encompasses 20 faults, categorised into four types: step, random variation, slow drift, and sticking faults. Notably, the original paper reports four faults as unknown [12].

Park and Ahn [13] introduced a Deep Neural Network (DNN) for Fault Detection and Diagnosis (FDD) in a liquid-propellant rocket engine, particularly during transient startup tests. The DNN used historical process data to identify input parameters and validate simulation results. Unlike the traditional red line cutoff method commonly employed in liquid-propellant rocket engines, which requires additional inspection for fault identification, the proposed DNN for FDD exhibited superior performance.

Bhagwat et al. [14] developed a model-based fault detection method scheme to address the challenge of decomposing nonlinear transitions into multiple linear modelling regimes. The study was motivated by the fact that, in nonlinear processes, transitions are typically executed manually, leading to unusual conditions and making them more susceptible to faults, especially due to inadvertent operator errors. The approach employed Kalman filters and open-loop observers for state estimation, generating residuals from the resulting linear models. These residuals were then analysed using thresholds, fault tags, and logic charts to enable online FDI. The multilinear model-based fault detection technique was successfully implemented in MATLAB to detect process faults and operator errors in the startup transition of a nonlinear pH neutralisation reactor.

In a paper by Calado and Costa [15], a fuzzy neural network was designed for detecting and diagnosing faults during transient conditions, encompassing both incipient and abrupt faults in a process. The fault detection mechanism relies on a knowledge base incorporating heuristic rules derived from a combination of deep and shallow knowledge about the system. The implementation of this fuzzy neural network for FDD proved successful in an industrial chemical process.

2.3 Heated two-tank system

Abid et al. [16] employed a Coupled Liquid Tank System (CLTS) to emulate faults and assess their detectability. The CLTS was chosen for its resemblance to the characteristics of chemical processes in which liquid tanks are used to store, pump, or transfer liquids between tanks. The tanks in this system are interconnected, with their flow and level being interdependent and requiring control. The inclusion of a horizontal tank introduces nonlinearities, a common feature in chemical processes.

The potential faults in the CLTS were classified into three groups.

1. Actuator fault:

- The pump is the sole actuator in this system, and a potential fault scenario involves the pump failing to deliver the desired flow rate.

2. Sensor faults:

- For the CLTS system used in this study, the sensors consist of a floating potentiometer and a rotary potentiometer to measure the water levels in the tanks. System failure may occur if the potentiometers are displaced from their normal positions or if the floats are broken.

3. Component faults:

- The potential component or process faults that may occur include leakages in the tanks, blockages, or leakages in the valves.

Tanjin et al. [17] used a continuous stirred tank heater model constructed from first principles, incorporating real disturbance data obtained from a pilot plant situated at the University of Alberta. The system had a heat exchanger that circulates steam and an agitator to stir the water. It features one outlet flow and two input flows, where one is hot and the other is cold. Two faults were induced in the system.

1. Gradual increase in cold water valve demand:

- The cold water level, valve, and output are affected by this fault. When the demand for cold water valves increases, the output flow rate also increases. Hence, the output flow rate and level of the system increase.

2. Steam valve stiction:

- The steam valve gets stuck in a specific position, which increases the temperature in the tank.

2.4 FDI using multiway principal component analysis

In a study by Nomikos and MacGregor [9], MPCA was employed in batch processes characterised by time-varying trajectories with a finite duration. The MPCA model condensed the data trajectories into a lower dimension that effectively encapsulated information from past batches.

This technique enables the analysis of the operation and quality of the process, and it facilitates online monitoring through the use of control charts for new batches. The control limits are set based on historical process data.

Nomikos and MacGregor [9] initiated their study by constructing an MPCA model using historical data obtained from a polymerisation reactor. The system's measured variables include temperature, pressure, and flow rate. Following the model's development, post-analysis is conducted on the batch data supplied by the polymerisation reactor. In situations where new batch data are available for a time interval during which the process is still ongoing, predictions can be made to facilitate online monitoring of the new batch. Control limits are established with control charts that monitor the T-scores and SPE of the new batch processes.

In a paper by Jeffy et al. [18], MPCA was employed to analyse batch data from a milk pasteurisation unit. Only four distinct batches were available, featuring measured variables temperature, pressure, and agitation speed. Given the limited number of batches, the MPCA model faced challenges in accurately describing the nominal conditions of the batch operation. To overcome this limitation, additional data were generated to simulate both normal variation and fault conditions within the process. Despite the scarcity of real data, a statistically robust model was developed by leveraging the generated data from the system model.

Garcia et al. [19] used MPCA to monitor start-ups and transitions between steady-states, particularly in situations where nonlinear behaviour is prevalent. The two systems were monitored: an evaporation sector of a sugar factory and a two-tank system. Classic PCA was found to be inadequate for distinguishing between normal operation and faulty operations during transitions in these systems.

Russel et al. [2] define a fault as an unpermitted deviation. Fault detection involves determining whether a fault has occurred. Control charts based on multivariate statistics are instrumental in detecting faults. Two different control charts for detecting faults, as mentioned by Russel et al. [2] are Hotelling's T^2 and the SPE.

The SPE control chart, as used by Garcia et al. [19] in their study monitoring the evaporation sector of a sugar factory and a two-tank system, demonstrated greater sensitivity and faster detection than Hotelling's statistic. The monitoring was also done at every particular time instant instead of over the whole time period.

In a study by Nomikos and MacGregor, time-varying data were used over a finite duration. The data were collected from a polymerisation reactor. The article emphasises the necessity of successful normal data to create control charts and compares them with future process data. Online monitoring is conducted when a fault is detected before the end of the transition duration, assessing if a process trajectory deviates from the normal average trajectory [9].

In a case study by Ferrer [20], a fault could be isolated using a contribution plot. This was done by considering the SPE control chart when an out-of-control observation was signalled. By comparing normal operation with the out-of-control k -th time variables, the variables responsible for the fault can be isolated.

2.5 Critical review

Various FDI methods can be integrated and adapted for improved performance. These techniques are categorised into two main groups with subcategories: model-based and history-based. Model-based techniques are developed using prior knowledge of the system, while history-based techniques are created by utilising the historical data of a process [4].

Three additional methods, distinct from MPCA, are included in the literature survey to demonstrate that various techniques have been considered for FDI in the transient region. The first method examined is a history-based DNN proposed by Park and Ahn [13] to detect faults in transient startup and replace the red cutoff line in a liquid-propellant rocket engine. The next technique considered was that by Bhagwat et al. [14]. This model-based technique used open-loop observers and Kalman filters for state estimation to generate residuals that could be used for fault detection later on. In the last technique, Calado and Costa [15] used a fuzzy neural network that was used to detect faults in the transient region of a chemical process.

A benchmark called the Tennessee Eastman system has been widely utilised in multiple studies for FDI. The four types of faults (step, random variation, slow drift, and sticking) present in the Tennessee Eastman [12] should also be applicable to the heated two-tank system used in this study. Adil et al. [21] conducted FDI on a system similar to the benchmark heated two-tank system, indicating its suitability for FDI testing purposes. The heated two-tank is a nonlinear system where the output is not directly proportional to the input, mirroring real-world systems. Additionally, it features a control system commonly used in the industry for enhanced performance, although such control systems may also mask faults.

MPCA was selected for its ability to effectively handle a substantial volume of data with relatively low computational requirements for FDI in the transient region of the system. MPCA stands out as a data-driven technique capable of detecting faults in transient conditions, making it well-suited for scenarios involving extensive data sets.

MPCA and fault detection

3.1 Introduction

PCA is widely used in chemical process monitoring [2]. PCA operates on the principle of linear dimensionality reduction, effectively reducing the dimensions of a multivariate dataset containing several interrelated variables. This technique involves the application of linear transformation to the data to generate new uncorrelated variables from the initially correlated variables within the dataset.

In the presence of a transient in a process, the covariance matrix, utilised in constructing the PCA model, may undergo changes. This can result in the PCA monitoring process erroneously identifying normal transient behaviour as a fault [19]. Employing MPCA proves to be a viable solution to this issue.

MPCA unfolds a three-way array into a two-dimensional data matrix that is subsequently mean-centred. This mean-centring process removes each mean trajectory in each column, effectively eliminating the main non-linear and dynamic components in the data, allowing the application of PCA to datasets with transitions. However, it's worth noting that MPCA demands a larger volume of data to achieve satisfactory performance.

The initial step in modelling the MPCA technique involves unfolding a three-way array of data under normal operation into a two-dimensional data matrix. In doing this, the process variable trajectories are contained in the two-dimensional data matrix. Following the creation of the two-dimensional data matrix, data conditioning is applied to enhance its compatibility with the technique. Subsequently, cross-validation is performed to determine the optimal number of PCs for deployment in the PCA.

After using the PCA to project the data into low-dimensional latent variable spaces, control limits can be calculated using normal data for different statistics. The control limits are then established for the data statistics to determine whether a new transition is normal or faulty.

3.2 Unfolding

In a transition, data are typically available for variables $j = 1, \dots, J$ and time $k = 1, \dots, K$. These data, originating from the same run of a process, can be categorised into intervals $i = 1, \dots, I$, if there are I transitions. This available data can further be organised into a three-way array $\mathbf{X}(I \times J \times K)$ as illustrated in Figure 3.1. The unfolding process is crucial in the MPCA technique and involves transforming the three-way array into a two-dimensional data matrix $\mathbf{X}(I \times JK)$. In this transformation, one direction is kept unaltered, while the other directions are combined, as demonstrated in [9] and depicted in Figure 3.1.

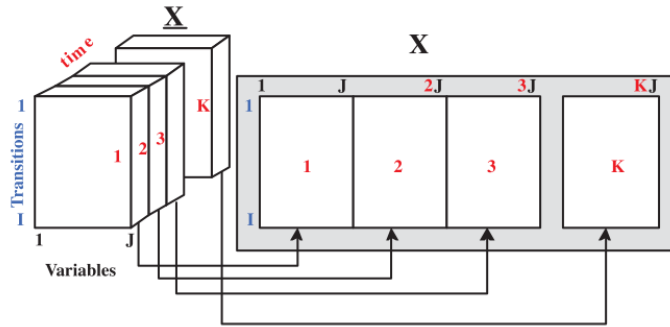


Figure 3.1: Illustration of matrix unfolding $\mathbf{X}$ [19]

3.3 Data pre-processing

Data preprocessing aims to enhance the performance of the MPCA technique and involves applying transformations and filters to the data. The following processes are included in the preprocessing stage: moving average, mean centring, and scaling to unit variance. Firstly, the moving average is applied to smooth out time fluctuations and prevent zeros after mean centring due to all the values being the same at a specific time and variable for all the transitions. The average moving or rolling is calculated over a moving window for different times. The moving average is applied before the unfolding to each of the transition runs $\mathbf{B}_i(K \times J)$ for all the variables.

$$\mathbf{B}_{MA_{i,j(k)}} = \frac{1}{N} \sum_{k=N}^k b_{i,j(k)} \quad (3.1)$$

In (3.1), N is the size of the window, i represents the transition, j represents the variables and k is the time instance. Following the application of the moving average to each column of the transition runs, $\mathbf{B}_{MA_i}$ is obtained and unfolded to $X(I \times JK)$. Subsequently, the means of the columns in the dataset are subtracted to perform mean centring. This step is crucial for removing the mean trajectory of each variable, effectively eliminating the primary non-linear dynamics for each variable.

Then, the dataset is mean-centred and each column is scaled to unit variance to address the variations in measurement. Scaling is accomplished by dividing each column by its standard deviation [9]. The reason for scaling each variable to a unit variance is to assign equal weight to each variable. Additionally, this allows for the flexibility of adjusting the weight of any variable if there is a preference for assigning more weight to a specific variable.

3.4 PCA

The first step in applying the PCA technique on the unfolded dataset $\mathbf{X} \in \mathbb{R}^{I \times JK}$ with I rows and JK columns is to create a covariance matrix $\mathbf{S}$. The covariance matrix shows the extent to which two random variables vary in tandem. The diagonal entries of the covariance matrix represent the variances, while the other entries denote the covariances [2].

$$\mathbf{X} = \begin{bmatrix} x_{111} & x_{121} & \cdots & x_{1J1} & x_{112} & x_{121} & \cdots & x_{1J2} & \cdots & x_{11K} & x_{12K} & \cdots & x_{1JK} \\ x_{211} & x_{221} & \cdots & x_{2J1} & x_{212} & x_{221} & \cdots & x_{2J2} & \cdots & x_{21K} & x_{22K} & \cdots & x_{2JK} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ x_{I11} & x_{I21} & \cdots & x_{IJ1} & x_{I12} & x_{I21} & \cdots & x_{IJ2} & \cdots & x_{I1K} & x_{I2K} & \cdots & x_{IJK} \end{bmatrix} \quad (3.2)$$

$$\mathbf{S} = \frac{1}{JK - 1} \mathbf{X}^T \mathbf{X} \quad (3.3)$$

After the covariance matrix $\mathbf{S} \in \mathbb{R}^{JK \times JK}$ is determined, singular value decomposition can be performed on the covariance matrix:

$$\mathbf{S} = \mathbf{V} \mathbf{\Lambda} \mathbf{V}^T. \quad (3.4)$$

Matrix $\mathbf{V} \in \mathbb{R}^{JK \times JK}$ contains the loading vectors, which are orthonormal column vectors providing the directions of maximum variability. The diagonal matrix $\mathbf{\Lambda} \in \mathbb{R}^{JK \times JK}$ contains the nonnegative real eigenvalues in decreasing magnitude ($\lambda_1 \geq \lambda_2 \geq \dots \lambda_m \geq 0$). The eigenvalues describes the magnitude of variance [2].

To capture the maximum variability of the data set, the loading vectors corresponding to the largest eigenvalues. The loading matrix $\mathbf{P}_{1:A} \in \mathbb{R}^{JK \times A}$ is obtained from the loading vectors corresponding to the first eigenvalues or PCs. Loading matrix $\mathbf{P}_{1:A}$ transforms data matrix $\mathbf{X}$ into a reduced dimension space, which is the score matrix:

$$\mathbf{T} = \mathbf{X} \mathbf{P}_{1:A}. \quad (3.5)$$

The projection of $\mathbf{T}$ into the score space:

$$\hat{\mathbf{X}} = \mathbf{T} \mathbf{P}_{1:A}^T. \quad (3.6)$$

The residual matrix can be obtained from the difference between $\mathbf{X}$ and $\hat{\mathbf{X}}$:

$$\mathbf{E} = \mathbf{X} - \hat{\mathbf{X}}. \quad (3.7)$$

Lastly, the original data space can be reconstructed:

$$\mathbf{X} = \mathbf{T} \mathbf{P}_{1:A}^T + \mathbf{E}. \quad (3.8)$$

PCA power arises as it can provide a more parsimonious depiction of the covariance structure data. PCA offers an approximation of $\mathbf{X}$ with just a few PCs.

3.4.1 Number of principal components

Cross-validation, a resampling technique, is employed to determine the optimal number of PCs [22]. This method predicts the left-out observations for different PCs, and the goodness-of-fit between the data and model is used to determine the most suitable number of PCs [23].

Cross-validation by eigenvector is utilised, a method that involves leaving out samples without the loss of generality and predicting the left-out samples with the model. The left-out samples are predicted by independently predicting each variable of the omitted samples. This is accomplished through the following procedure [22]:

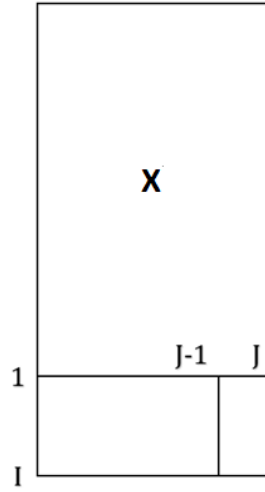


Figure 3.2: Data matrix $\mathbf{X}$ with left-out samples

$$\mathbf{t}^{(-j)T} = \mathbf{x}_i^{(-j)T} \mathbf{P}^{(-j)} (\mathbf{P}^{(-j)T} \mathbf{P}^{(-j)})^{-1}, \quad (3.9)$$

where $\mathbf{P}^{(-j)}$ is the loading matrix obtained from the PCA model of the remaining data with the j th row excluded, and $\mathbf{x}_i^{(-j)T}$ is the row vector of the left-out data with the j th element excluded from the row vector.

To estimate the element x_{ij} of the left-out data as:

$$\hat{x}_{ij}(f) = \mathbf{t}^{(-j)} \mathbf{p}_j^T, \quad (3.10)$$

where $\mathbf{p}_j$ is the j th row of $\mathbf{P}$. Lastly, calculate the prediction error (3.11) of the (ij) th element and use the prediction error to calculate the *PRESS* (predicted residual sum of squares) (3.12).

$$e_{ij}(f) = x_{ij} - \hat{x}_{ij}(f) \quad (3.11)$$

$$PRESS(f) = \sum_{i=1}^I \sum_{j=1}^J (e_{ij}(f))^2 \quad (3.12)$$

The criterion for selecting the number of PCs is based on the global minimum value obtained for the specific factor's *PRESS*.

3.5 Control limits

Two multivariate control charts can be employed to monitor the system. Detection of a system fault is triggered if the values of the squared prediction error (SPE) and Hotelling's statistic T^2 exceed the calculated fixed threshold [19]. To streamline both control charts, the upper control limit threshold can be set to a unitary value of 1, and then the statistics are normalised for the transitions.

3.5.1 Hotelling's T square

A fault is detected using the T^2 statistic when there is a variation in latent variables that is not accounted for by normal system variation. The T^2 statistic can be calculated as follows:

$$T^2 = \mathbf{x}^T \mathbf{P} (\mathbf{\Lambda}^{-1}) \mathbf{x}, \quad (3.13)$$

using the observation vector x . To detect outliers, the threshold for the T^2 statistic is calculated using the following equation:

$$T_\alpha^2 = \frac{(I-1)^2}{I(I-A)} F_\alpha(A, I-A). \quad (3.14)$$

Considering I transitions and A PCs, the critical value for significance level (expressed as $(100(1-\alpha)\%)$) is derived from the Fisher-Snedecor distribution with A

and $I - A$ degrees of freedom, as indicated by Russel et al. [2]. These authors note that Hotelling's statistic T^2 remains unaffected by smaller singular values and effectively characterises the normal behaviour of the process.

3.5.2 Square prediction error

The SPE statistic gauges the cumulative variation in the residual space rather than measure individual loading vectors, ensuring that it remains robust even in the presence of smaller singular values and avoiding inaccuracies. The T^2 statistic is highly sensitive to inaccuracies in the projected space, as it measures the variation along the loading vectors [2]. In contrast, the SPE statistic is calculated at each specific instant k , providing the instantaneous perpendicular distance to the reduced space:

$$Q = \sum_{c=1}^J \mathbf{e}(c)^2. \quad (3.15)$$

The value $\mathbf{e}$ is calculated in the current measured vector $\mathbf{z}^T \in \mathbb{R}^{J \times 1}$ at the time instant k

$$\mathbf{e} = \mathbf{z}^T - \hat{\mathbf{z}}^T, \quad (3.16)$$

with

$$\hat{\mathbf{z}} = \hat{\boldsymbol{\tau}}_{1:A} \mathbf{P}_{1:A}, \quad (3.17)$$

where v is the variance and m is the mean required to calculate the upper limit of the SPE statistic using the chi-square distribution in the following equation:

$$Q_{\alpha k} = g_k \chi_{h_k, \alpha}^2, \quad (3.18)$$

with

$$g_k = \frac{v_k}{2m_k} \quad (3.19)$$

$$h_k = \frac{2m_k^2}{v_k} \quad (3.20)$$

[19]. Using the SPE and T^2 statistics along with their respective upper limits, a fault can be detected when the calculated statistic exceeds the established upper limit. This implies that an unusual deviation from the normal process behaviour, beyond the acceptable threshold, has occurred.

3.6 Contribution plot

Contribution plots can be used to isolate the fault. Abnormal deviation points in the transition can be used to derive a contribution plot [20]. The highest statistical

point, whether T^2 or SPE, is selected to identify abnormal deviations over time, enabling the calculation of each variable's contribution. The following equation is used to calculate the contribution plot for the T^2 statistic:

$$Cont(\mathbf{t}_{new,A}; \mathbf{x}_{new,k}) = \mathbf{p}_A \mathbf{k} \mathbf{x}_{new,k}. \quad (3.21)$$

The following equation is used to calculate the contribution plot for the SPE statistic:

$$Cont(\mathbf{Q}; \mathbf{x}_{new,k}) = \mathbf{e}_{new,k}^2 = (\mathbf{x}_{new,k} - \mathbf{x}_{new,k}^*)^2. \quad (3.22)$$

3.7 Imputation

To enable online fault detection, where both past and current values are accessible but future transition values are not, two distinct methods can be considered. The first method involves the accurate approach of calculating and storing an MPCA model for each time step. However, this approach is encumbered by significant storage requirements, especially when dealing with large datasets.

The second method opts for PCA without relying on MPCA. In this alternative, it assumes that variables adhere to a multinormal distribution at each time interval. Nevertheless, this method comes with its challenges. It necessitates the storage of a covariance matrix at each time interval, and this matrix becomes ill-conditioned due to the presence of highly correlated variables.

Each approach presents trade-offs, and the choice between them depends on the specific considerations and constraints of the given scenario. [9].

In a study by Garcia et al., [19], Trimmed Score Regression (TSR) and Known Data Regression using the Principal Component Regression approach (KDR-PCR) yielded good results. Accordingly, the TSR method was used in this study to predict future values to be able to do online fault detection due to missing values. The KDR-PCR method can be used if the TSR method does not produce satisfactory results. The TSR approach, expressed by the following equation, enables the estimation of the score vector for computing missing values, facilitating the implementation of online monitoring:

$$\hat{\boldsymbol{\tau}} = \boldsymbol{\Lambda}_{1:A} \mathbf{P}_{1:A}^{*T} \mathbf{P}_{1:A}^* (\mathbf{P}_{1:A}^* \mathbf{P}^* \boldsymbol{\Lambda} \mathbf{P}^{*T} \mathbf{P}_{1:A}^{*T})^{-1} \mathbf{P}_{1:A}^{*T} \mathbf{z}^*, \quad (3.23)$$

$\mathbf{z}$ can be partitioned in

$$\mathbf{z} = \begin{bmatrix} \mathbf{z}^* \\ \mathbf{z}^\# \end{bmatrix}, \quad (3.24)$$

where the past and current values are $\mathbf{z}^*(KJ - M \times 1)$ and the unknown values are $\mathbf{z}^\#$. The loading matrix $\mathbf{P}$ can be partitioned into the following:

$$\mathbf{P} = \begin{bmatrix} \mathbf{P}^* \\ \mathbf{P}^\# \end{bmatrix} = \begin{bmatrix} \mathbf{P}_{1:A} & \mathbf{P}_{A+1:H} \end{bmatrix} = \begin{bmatrix} \mathbf{P}_{1:A}^* & \mathbf{P}_{A+1:H}^* \\ \mathbf{P}_{1:A}^\# & \mathbf{P}_{A+1:H}^\# \end{bmatrix}. \quad (3.25)$$

Refer to Appendix D for the source code where the MPCA technique is implemented.

3.8 Conclusion

This chapter discussed the application of the MPCA technique and the use of statistics to create control charts for the purposes of fault detection on the heated two-tank system. The steps that were followed in modelling the MPCA technique were verified from literature. The approach used in this study has produced good results in similar systems.

Chapter 4

Benchmark heated two-tank system

4.1 Introduction

The benchmark heated two-tank system is a laboratory setup used for FDI. It is inexpensive and quick to build compared to a full-scale or prototype industrial system. New methodologies for a controller design or FDI can be tested on this system at an earlier stage. The purpose of the system is not to replicate the precise physical properties of an industrial system but rather to simulate the same problems or faults that are typically encountered in a large-scale system [21]. The benchmark heated two-tank system is a multi-domain system with different measured values, such as temperature, flow rate, and liquid level.

This system resembles that of manufacturing industries like petrochemical, paper-making, and water treatment requiring temperature, liquid level, and flow control [16]. The non-linear behaviour of water flowing from one tank to another, the noise in the system, and the control give the fault detection technique validity because these are also encountered in industrial systems.

The heated two-tank system was simulated in Simulink, a MATLAB-based graphical programming environment. It was modelled using differential equations and adapted according to the parameters specified for the practical system used in this study.

4.2 Benchmark heated two-tank system

The heated two-tank system consists of three tanks. Tank 1 is situated at the highest elevation, with tank 2 positioned below it, and the reservoir tank is situated

on the ground (see Figure 4.1). Water is pumped from the reservoir into tanks 1 and 2 respectively. Water flows under gravity from tank 1 to tank 2 and from tank 2 into the reservoir. The levels in the tanks are controlled by adjusting the flow rate of the water from the reservoir into the tanks.

In the heating segment of the system, a gas heater is employed for heating, while a heat pump is utilised for cooling. Tanks 1 and 2 feature independent heat exchanger coils, receiving hot water from a buffer tank heated by the gas heater. The water, heated by the heat exchanger coils, undergoes cooling in the cold reservoir through the heat pump, maintaining a consistent temperature in the cold reservoir. Control of the temperature in tanks 1 and 2 is achieved by adjusting the flow rate through the heat exchanger coils.



Figure 4.1: Full view illustration of the heated two-tank system

The system used in the study is different from other coupled liquid tanks due to the addition of helical coils for heating the water. The water in the tanks is heated through the transfer of thermal energy from warm water circulating in the coils to the cold water present in the two tanks.

In the following section, a more detailed examination is undertaken of various components of the system. Tables 4.1 and 4.2 are used to describe the different sections.

Table 4.1: Process variables - Tank 1

Variable	Description	Units
L_1	Level of water in tank 1	[m]
F_1	Flow of water into tank 1	[m ³ /s]
$F_{1,out}$	Flow of water out tank 1	[m ³ /s]
F_3	Flow of water through heat exchanger in tank 1	[m ³ /s]
$T_{1,in}$	Temperature of cold water flow into tank 1	[C°]
T_1	Temperature in tank 1	[C°]
T_3	Temperature of hot water flow in tank 1 coil	[C°]

Table 4.2: Process variables - Tank 2

Variable	Description	Units
L_2	Level of water in tank 2	[m]
F_2	Flow of water into tank 2	[m ³ /s]
$F_{2,out}$	Flow of water out tank 2	[m ³ /s]
F_4	Flow of water through heat exchanger in tank 2	[m ³ /s]
$T_{2,in}$	Temperature of cold water flow into tank 2	[C°]
T_2	Temperature in tank 2	[C°]
T_4	Temperature of hot water flow in tank 2 coil	[C°]

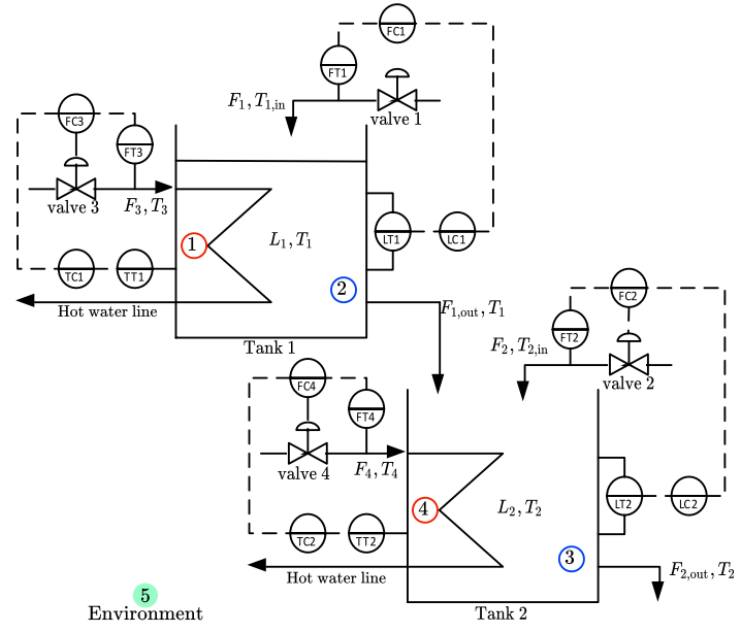


Figure 4.2: Two-tank thermofluid system [24]

Figure 4.2 shows the different flows and variables schematically for a better understanding of the system. Appendix B has the data generated from the benchmark heated two-tank system.

4.2.1 Coupled liquid tanks illustration

The coupled liquid tanks work as a closed-loop system where water flows from the cold reservoir tank into the tanks and then back into the cold reservoir tank from tank 2.

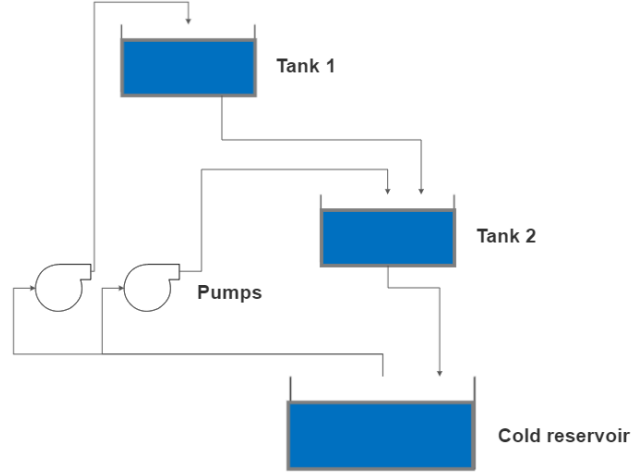


Figure 4.3: Coupled liquid tanks

To regulate the tank levels, the flow into the tanks (F_1 and F_2) is managed by adjusting the aperture of the valves. The flow is adjusted, increasing or decreasing, based on the predefined level and the measured difference in tank levels.

4.2.2 Continuous stirred tank heater

To facilitate heating in the system, each tank is equipped with an agitator to ensure thorough mixing of water, thereby maintaining uniform temperature across the tanks and outlet flows. The water in each tank is heated through the circulation of water that passes through coils, which are heated by the gas heater.

Figure 4.4 shows a continuous stirred tank heater which is similar to the one used in this study.

The temperature in tanks 1 and 2 is controlled by changing the flow rate F_3 and F_4 of heated water in the heat exchanger coils, which alters the heat transferred to cold water in tanks 1 and 2. The valves also control the flow rate. The heated water that passes through the coils is heated by a gas geyser.

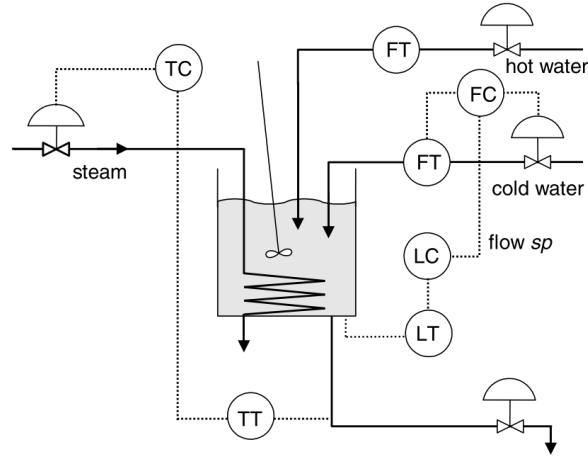


Figure 4.4: Continuous stirred tank heater [25]

4.2.3 Hardware

In this subsection, the different hardware that is used in the system is discussed. Figure 4.5 gives an overview of the system. Tank 1 can be seen at the top, tank 2 below it, and the cold water reservoir on the ground. The water flows from the reservoir into tanks 1 and 2 and then back into the cold reservoir from tank 2.



Figure 4.5: A broad view of the heated two-tank system

The heat pump shown in Figure 4.6 is an Enerflow EIP09 MT1 heat pump with a cooling capacity of 11.2 kW. The heat pump is used to cool the water in the reservoir and thereby maintain the cold water inlet temperature.



Figure 4.6: Heat pump used in heated two-tank plant

The gas heater shown on the left side of Figure 4.7 is a Bosch Optiflow 26 l gas heater with an output of 45 [kW], which heats the water sourced from the Kwikhot 400 Duel Superline 100 l buffer tank on the right side of Figure 4.7. The buffer tank is added to maintain a constant temperature as the water circulates through the heat-exchanger coils.



Figure 4.7: Gas heater used for heating of water in the system

Afromix direct-drive agitators are added (red motors above the tanks) to the system, which mixes the water to ensure the tank temperature and outlet temperature are the same. The red motor can be seen in Figure 4.8.



Figure 4.8: Agitator installed to ensure uniform heat distribution

The system employs five pumps, with two dedicated to circulating hot water. These pumps facilitate the circulation of hot water through the gas heater and back into the buffer tank. Another pump is responsible for circulating water through the heat exchanger coils, returning it to the buffer tank. Specifically, the Pedrollo CPM 130 pump employed for the hot water flow boasts an output of 0.37 kW, a maximum head of 23 m, and a flow rate of 80 l/min. Two cold water pumps are used to pump water into tanks 1 and 2. The third pump is used to circulate water from the heat pump back into the cold water reservoir. The pump used for the cold water flow has an output of 0.25 kW, a maximum head of 27 m, and flow rate of 80 l/min.

The control valves that are used to control the flow of hot water through the coils, the cold water into tanks 1 and 2, and the outlet flow of the tanks are the Burkert type 3285 electromotive control valve (brass). The valve has a diameter of 15 mm and a control signal of 4 - 20 mA , 0 - 10 V or PWM of 800 Hz

4.2.4 Instrumentation

The system incorporates various instrumentation to monitor different variables, with a focus on level, temperature, and water flow. All the instrumentation employed is sourced from IFM. For level measurement, a continuous level sensor (guided wave radar) is installed in tanks 1 and 2, featuring a probe length ranging from 100 mm to 1600 mm. Temperature measurements in the buffer tank and tanks 1 and 2 are

conducted using PT 1000 temperature transmitters with a range of 0 to 150°C. Flow meters, equipped with backflow prevention, are utilised for measuring the flow of hot and cold water; these IFM flow meters have a capacity to measure from 2 l/min to 100 l/min.

4.3 Model of heated two-tank system

The Matlab Simulink model for the heated two-tank system was created by Lindner and Auret [10]. Subsequently, the model was modified to incorporate process faults and align with the specifications of the laboratory setup. The simulated data utilised in this study was obtained from the adapted model. In the forthcoming subsection, the differential equations essential for the Simulink model is detailed, while the Simulink model itself can be found in Appendix A. Additionally, Appendix C contains the data generated from the simulated heated two-tank model.

Mass and energy balances

The mass balance and energy balance for the system was used in the Simulink model. They were also used for the system's model verification.

Mass balances

The variation in flow rates between the inlet and outlet of the tanks induces a positive or negative alteration in the tank volumes. It is noteworthy that the hot water flowing through the heat exchangers remains distinct from the cold water, and as such, is excluded from the mass balance equations. By applying the law of conservation of mass, the following equation for the mass flow in a tank can be derived:

$$\frac{dm_{CV}}{dt} = \dot{m}_i - \dot{m}_e, \quad (4.1)$$

,where m_{CV} is the mass of the control volume, $\dot{m}_i$ is the inlet mass flow, and $\dot{m}_e$ is the outlet mass flow. From equation 4.1, the flow rate is obtained, which is used later.

$$\frac{\rho(dV_{CV})}{dt} = \rho(\dot{V}_i - \dot{V}_e) \quad (4.2)$$

The equation for the flow rate follows:

$$\frac{dV_{CV}}{dt} = \dot{V}_i - \dot{V}_e. \quad (4.3)$$

The flow rate for tank 1 can be reformulated to obtain the following equation:

$$\frac{dV_1}{dt} = F_1 - F_{1,out}. \quad (4.4)$$

While the cross-sectional area of tank 1 remains constant, the level fluctuates, resulting in a derivative term for the volume. Consequently, the outlet flow rate of the tank is contingent upon the water level within the tank. This flow is intricately linked to the pressure exerted by the water[26]. This relationship has been approximated by Marlin [26]:

$$F_{1,out} = k_L \sqrt{L_1}. \quad (4.5)$$

Substituting equation 4.5 into equation 4.4 renders the following:

$$A_1 \frac{dL_1}{dt} = F_1 - k_L \sqrt{L_1}. \quad (4.6)$$

The flow rate of tank 2 is similar, but with the added outlet flow of tank 1:

$$A_2 \frac{dL_2}{dt} = F_2 + k_L \sqrt{L_1} - k_L \sqrt{L_2}. \quad (4.7)$$

Energy balances

The energy balances are done to determine the energy into and out of the system. This helps in determining the temperature of the water in the two tanks and heating coils. The energy balance for the system can be given as:

$$\frac{dU}{dt} = \dot{H}_{in} - \dot{H}_{out} + Q. \quad (4.8)$$

The following is the equation for the change in internal energy U:

$$\frac{dU}{dt} = \rho C_p \frac{dVT}{dt}. \quad (4.9)$$

The enthalpy of the inlet stream of water can be determined by:

$$H_i = \rho C_p F_i (T_i - T_{ref}). \quad (4.10)$$

Substituting equation 4.9 and 4.10 into equation 4.8, the following energy balance is obtained for tank 1 (assuming $T_{ref}=0$):

$$\rho C_p \frac{dV_1 T_1}{dt} = \rho C_p (F_1 T_{1,in} - F_{1,out} T_1) + Q. \quad (4.11)$$

The temperature of the stream exiting the tank is assumed to be equal to the tank temperature, given the presumption of perfect mixing within the tank. To achieve near-perfect mixing, both tanks are equipped with agitators.

The heat that is transferred from the water in the heating coils to the water in tank 1 is represented by Q , and the corresponding energy balance equation is as follows:

$$Q = \rho C_p F_3 (T_3 - T_{out}). \quad (4.12)$$

Rearranging equation 4.12 to isolate T_{out} as the subject of the equation yields:

$$T_{out} = T_3 - \frac{Q}{\rho C_p F_3}. \quad (4.13)$$

Utilising the overall heat transfer coefficient to compute the heat transfer, it is assumed that the wall and outer film resistance of the coils are negligible, with the inner film resistance predominantly influencing the heat transfer through the coils. The empirical equation for the coefficient of heat transfer related to the flow rate of the liquid described by Marlin [26] is as follows:

$$UA = a F_3^b. \quad (4.14)$$

Heat transfer can be calculated by multiplying the difference in temperature between the tank and the mean temperature of the coils.

$$Q = -a F_3^b \left(\frac{(T_1 - T_3) + (T_1 - T_{out})}{2} \right) \quad (4.15)$$

Substituting equation 4.13 into 4.15 to eliminate T_{out} gives:

$$Q = -\frac{aHeatF_3^{b+1}}{F_3 + \frac{aHeatF_3^b}{2\rho C_p}}(T_1 - T_3). \quad (4.16)$$

The heat transfer equation 4.16 is substituted in equation 4.8 to give the following energy balance for tank 1:

$$\rho C_p \frac{dV_1 T_1}{dt} = \rho C_p (F_1 T_{1,in} - F_{1,out} T_1) - \frac{aHeatF_3^{b+1}}{F_3 + \frac{aHeatF_3^b}{2\rho C_p}}(T_1 - T_3). \quad (4.17)$$

The energy balance for tank 2 is similar to tank 1's energy balance with the added outlet stream from tank 1 flowing into tank 2:

$$\rho C_p \frac{dV_2 T_2}{dt} = \rho C_p (F_{1,out} T_1 + F_2 T_{2,in} - F_{2,out} T_2) - \frac{aHeatF_4^{b+1}}{F_4 + \frac{aHeatF_4^b}{2\rho C_p}}(T_2 - T_4). \quad (4.18)$$

4.4 Simulated and practical data

To show how the simulated data compares to the practical data, each variable of the transition is compared in Figures 4.9-4.12, which represent graphs of the different variables. There is a change in the level and temperature for tank 1 and 2 for each transition run. In the figures, blue denotes the practical data and orange the simulated data.

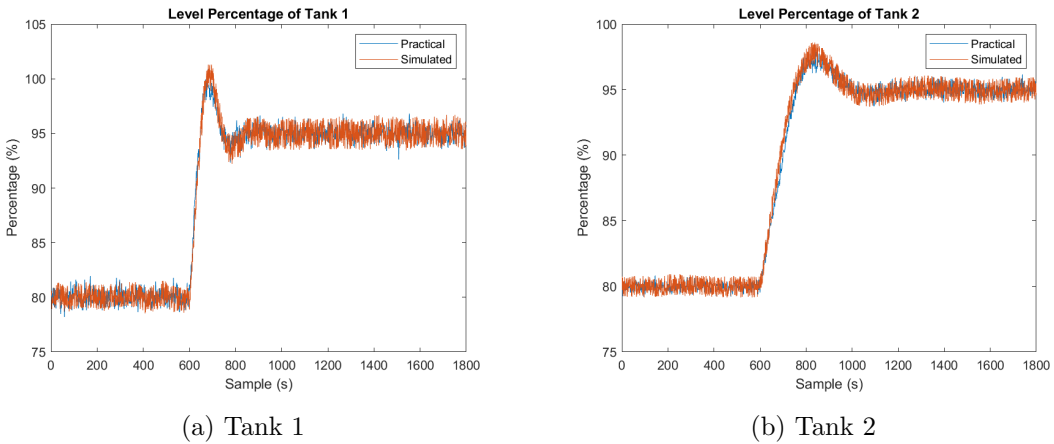


Figure 4.9: Practical vs. simulated tank level data

In figure 4.9 it can be seen that the level for tanks 1 and 2 increased from 600 s due to the change in level set point.

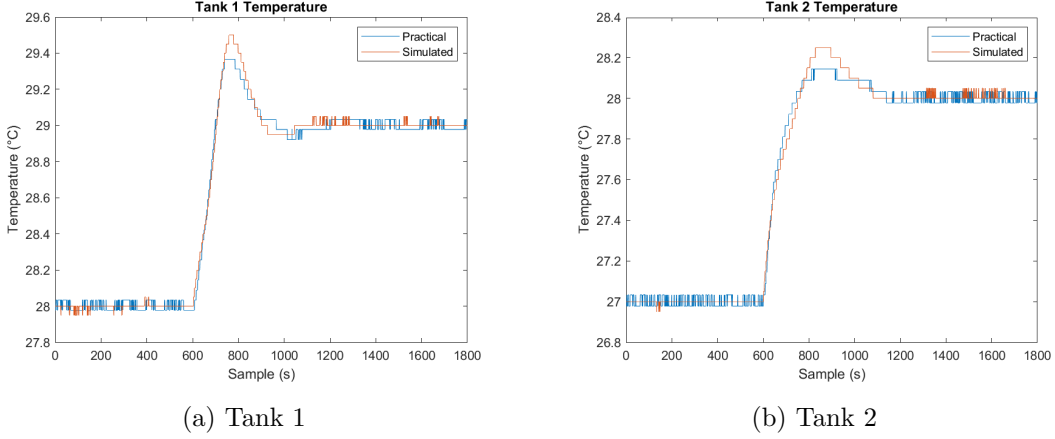


Figure 4.10: Practical vs. simulated tank temperature data

The set point for tank 1 is set at 28 C° and increased to 29 C° at 600 s. For tank 2 the set point is set at 27 C° and increased to 28° at 600 s.

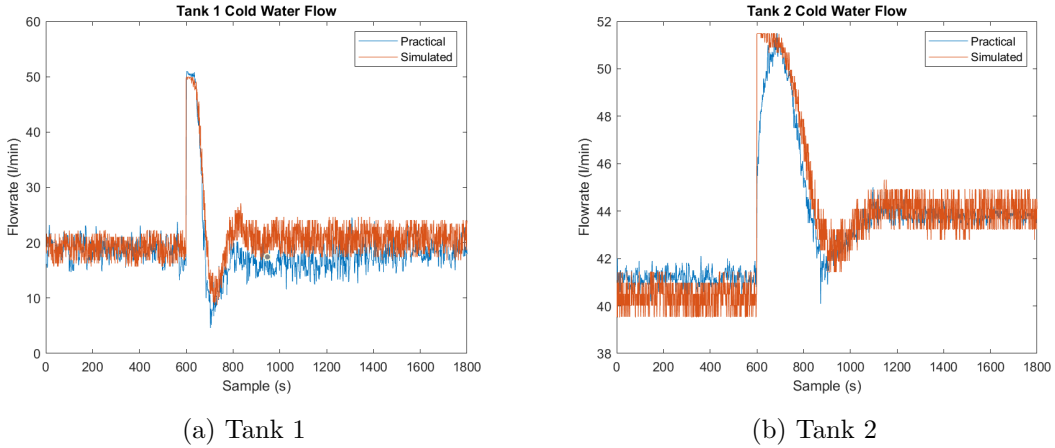


Figure 4.11: Practical vs. simulated tank cold water flow

A rise in flow rates can be seen in Figures 4.11 and 4.12. In Figure 4.11 the increase in cold water flow rate is attributed to a set point adjustment aiming to elevate the tank levels. Meanwhile, the augmented hot water flow rate in 4.12 is intended to boost the heat transferred to the tanks by amplifying the flow rate. This increase in heat is necessitated by the elevated temperature set point and the need to compensate for additional cold water introduced into the tanks.

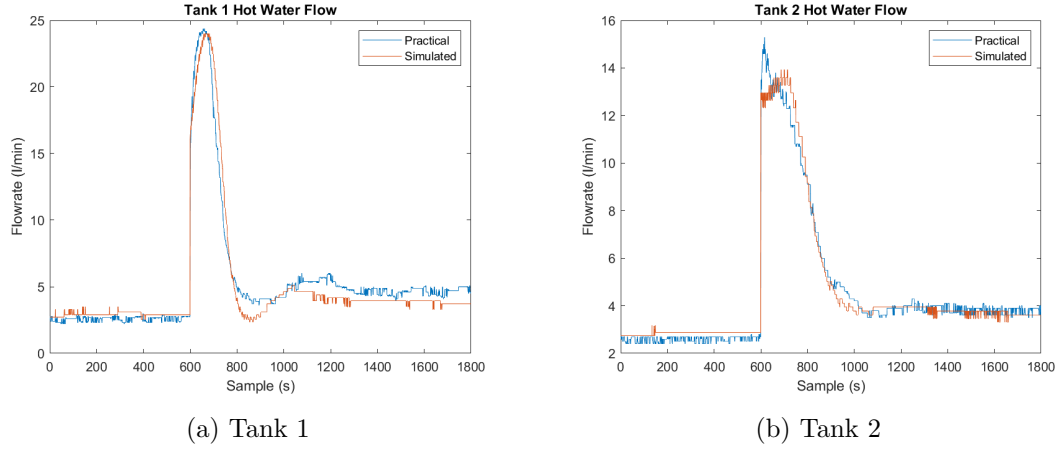


Figure 4.12: Practical vs. simulated data for the heat exchanger flow rate

4.5 Simulated data compared to practical

To assess the agreement between the simulated data and the practical data, the Normalised Root Mean Squared Error (NRMSE) was employed. A low NRMSE indicates accurate simulated data [27], with a value of zero signifying a perfect fit, a value of 1 indicating no improvement over a straight-line match, and values above 1 suggesting a poor fit.

The equation used to calculate the NRMSE is the following:

$$fit(j) = \frac{||x_{ref(:,j)} - x(:,j)||}{||x_{ref(:,j)} - mean(x_{ref(:,j)})||} \quad (4.19)$$

where J is the number of variables $j=1, \dots, J$.

Table 4.3: NRMSE values of different variables

Number	Description	NSRME values
1	Tank 1 level percentage	0.137
2	Tank 2 level percentage	0.096
3	Tank 1 temperature	0.085
4	Tank 2 temperature	0.089
5	Tank 1 cold water flow	0.765
6	Tank 2 cold water flow	0.432
7	Tank 1 hot water flow	0.224
8	Tank 2 hot water flow	0.153

All the values are predominantly below 0.25 for most variables, signifying a strong fit. The NSRME values for the cold water flow rates in tanks 1 and 2 are relatively higher compared to other variables but still remain below 1, indicating a reasonable

level of accuracy.

4.6 Faults emulated

The emulation of faults in this system during transient conditions, as opposed to steady-state, is strategic. Detecting faults in the transient region allows for time savings, and the escalation of a fault can be arrested by implementing an FDI technique adept at identifying faults during transience. Steady-state fault detection techniques often fall short in the transient region, typically detecting the fault only after the system has reverted to a steady state.

This section elaborate on the faults implemented in the transient region of the system, categorised into two types: actuator and component faults. The emulation of these faults is intended to demonstrate their impact on the measured variables within the system.

Table 4.4: Faults emulated in the system

Number	Description
1	Pipe leakage
2	Heating malfunction
3	Blockage between tank 1 and 2
4	Stuck valve

4.6.1 Pipe leakage

Pipe leakages, often occurring in aging systems, is emulated by opening a valve in the inlet flow of cold water to tanks 1 and 2. This diversion will redirect a small amount of water back to the cold reservoir tank. The controller will detect the diminished water inflow into the tanks and respond by increasing the inlet flow to compensate for the reduction. This fault type will transiently impact the system's set point values (level and temperature) before returning to normal. Pipe leakages are crucial to detect as they can escalate operational costs and, if unaddressed, potentially lead to a more severe pipe burst.

4.6.2 Heating malfunction

A malfunction in the heating system can arise from various issues. To simulate this, the heated two-tank system is altered by deactivating the agitators, thereby elevating the thermal resistance. In response, the flow rate of the heat exchanger

coils will increase in an attempt to counterbalance the heat loss in the tanks. A heating failure can lead to the production of inferior products or potential damage to turbines, especially if steam condenses back into water due to the loss of heat.

4.6.3 Blockage

Blockages can occur due to the accumulation of materials in the piping. To simulate blockages in the two-tank heated system, valves between tank 1 and tank 2 are partially closed, emulating the restriction of water flow. The size of the blockage will influence the controllers' ability to compensate for the fault and restore the system to standard output by adjusting the flow rate. A pipe blockage has the potential to lead to system failure, either through overflow or water shortage.

4.6.4 Stuck valve

Malfunctions in actuators or the accumulation of dirt can result in valves becoming stuck in a specific position. Once the valves are immobilised, the controller loses its ability to regulate the system variables at the set point, leading to a loss of control over the system.

4.7 Conclusion

In this chapter, an overview of the system was presented, accompanied by the rationale behind employing the heated two-tank system. This system stands out as a multi-domain configuration, incorporating the traditional coupled liquid tank system with an additional domain related to heat. It serves as a valuable platform for the early testing of FDI techniques, with potential applications in industrial or chemical processes.

The control of tank levels in the system is achieved through a flow meter and a control valve, governing the inflow of water. Simultaneously, temperature regulation in both tanks is accomplished by adjusting the flow rate of heated water circulating through helical coils. The energy transferred to the tanks is contingent on the flow rate, and thus, altering the flow rate induces changes in the temperature within the tanks. A comprehensive understanding of the system's specifications and functioning is essential for conducting efficient experiments, thereby addressing the problem statement posed in this study.

Experimental design

5.1 Introduction

The experimental design in this study is a systematic method that was used to organise the study efficiently, ensuring the acquisition of valid and reliable data to address the research question. The experimental design involved determining the sample size, specifying experimental manipulations, identifying the variables to be studied, and controlling independent variables that could influence the outcomes.

This study involved both practical and simulated experiments. The experiments conducted on the practical system include normal and faulty transitions. A transition in this paper refers to the change of operating modes by changing the set points for levels and temperatures in the system. Even though a fault can cause a transition, the fault detection and isolation are done in the transient region caused by the change of operating conditions. Normal transitions in the practical system were induced under the same operating conditions, and the transitions initiated at the same time, ensuring uniformity except for external factors such as noise and environmental differences. For faulty transitions, the same normal operation was conducted, with the exception of a fault induced by changing positions or switching off the agitators. MATLAB® was used as a simulation environment for data generation. The model was validated using the practical data of the system. The simulated model is the one discussed in Chapter 4.

Simulated experiments are relatively quick to conduct compared to practical experiments, but are not as reliable and accurate. The simulated model was validated with practical experiments. To simulate multiple experiments of the same process, adjustments were made to the noise, and an offset was included to replicate environ-

mental differences with each experiment. Practical experiments were carried out on the heated two-tank system, collecting real-world data. Transitions were induced under NOC and normal fault conditions for the same process.

Both simulated and practical experiments have advantages and drawbacks. To mitigate the drawbacks and obtain the best available data for the study, a combination of practical and simulated data were used.

5.2 Practical experiments

5.2.1 Normal operation

In practical experiments, the system is first brought to a steady state under NOC. Data collection occurs during the steady state for a duration of 600 seconds. Following this, a transition is induced, and data are collected for 1200 seconds after the transition initiates in the system. Various variables are recorded during a phase. The temperature of the cold reservoir is maintained at 24°C using heat pump for cooling, while the buffer tank for heating is kept at 47°C with the assistance of a gas geyser.

Each transition involves identical changes in set values for the temperature and tank level in both tanks 1 and 2. For the initial operating conditions, the temperature of tank 1 is set at 27°C and tank 2 is set at 28°C. These temperatures, close to the ambient temperature, ensure minimal heat exchange with the environment. Both tanks start with a level of 80% to prevent water spillage, particularly given that at levels below 80%, the water approaches the height of the agitator blades. The temperature setpoint for tank 1 is adjusted from 27°C to 28°C and from 28°C to 29°C for tank 2, maintaining a 1°C difference due to the system's dynamic temperature range. Larger temperature transitions would result in impractically long settling times. The level setpoints are altered to 95% full, prompting the control system to adjust the flow of cold and hot water to attain the required temperature and tank level set values. The change in temperature and water level represents the transitions.

5.2.2 Practical experiments descriptions

In total, 22 practical experiments were conducted, following the operational setup outlined in the above-mentioned section, with some of the runs incorporating induced faults. The induced faults exhibited distinct effects on various variables, and

the magnitude of these faults also varied. The number of each transition that was run for the same operation is given in Table 5.1. The description column delineates the specific differences in each run, while the fault implementation column elucidates how any faults were introduced, if applicable.

Table 5.1: NOC and faulty experiments of the practical system

Experiment	Unique ID	Description	Fault implementation
1 – 2	PNO1 - PNO2	Normal operating conditions training data	-
3 – 5	PNT1 - PNT3	Normal operating conditions test data	-
6	PFS1	Stuck valve tank 1	Cold inlet valve for tank 1 stuck at 20% open
7	PFS2	Stuck valve tank 2	Cold inlet valve for tank 2 stuck at 20% open
8	PFA1	Agitator fault tank 1	Agitator for tank 1 switched off
9	PFA2	Agitator fault tank 2	Agitator for tank 2 switched off
10	PFA12	Agitator fault tanks 1 and 2	Agitator for tanks 1 and 2 switched off
11	PFL11	Tank 1 leakage	Valve open at 10%
12	PFL12	Tank 1 leakage	Valve open at 20%
13	PFL13	Tank 1 leakage	Valve open at 30%
14	PFL21	Tank 2 leakage	Valve open at 10%
15	PFL22	Tank 2 leakage	Valve open at 20%
16	PFL23	Tank 2 leakage	Valve open at 30%
17	PFB11	Blockage between tank 1 and 2	Valve closed 10%
18	PFB21	Blockage between tank 1 and 2	Valve closed 20%
19 – 22	PFB31 - PFB34	Blockage between tank 1 and 2	Valve closed 30%

The blockage between tanks 1 and 2 at 30% valve closure was conducted four times to evaluate the repeatability of the performance.

5.3 Simulated experiments

To generate NOC simulations of the system, it is crucial to measure and apply the normal variance observed in experiments without faults. Two key differences between runs were identified for this purpose. The first difference is an offset, possibly arising from diverse environmental effects such as ambient temperature and latent heat. The second difference is attributed to noise or disturbances in the system, which can fluctuate depending on the operating mode.

The agitators in the system induce fluctuations in water levels, resulting in disturbances. Additionally, noise generated by motors and measuring sensors contributes to the overall system noise. The noise from practical signals is characterised and emulated in the simulated results.

Each simulation run was identical except for normal disturbances introduced into the system. These disturbances, mimicking practical data variations, are generated using white Gaussian noise with the same standard deviation. To ensure diversity in normal disturbances for each transition, a distinct seed for the white Gaussian noise was employed. Additionally, a random offset was incorporated to account for environmental effects.

A total of 405 simulated runs were generated and divided into training data for model training and test data to evaluate the technique's performance. SN training data range from SNO1 to SNO400 comprised 400 runs under NOC. Additionally, a faulty transition involving a blockage between two tanks in the 30% closed valve were simulated, denoted by unique IDs from SFB31 to SFB34, accounting for four simulated blockages. Five verification simulated transitions were reserved for testing the fault detection method, with unique IDs from SHO1 to SHO5.

Table 5.2: NOC and faulty transitions of the simulated model

Transition	Unique ID	Description	Fault implementation
1 – 400	SNO1 - SNO400	Normal operating conditions	-
401 – 405	SHO1 - SHO5	Normal operating conditions (testing runs)	-
406 – 409	SFB31 - SFB34	Blockage between tank 1 and 2	Valve closed 30%

5.4 Combination of data

The primary purpose of generating simulated data are to complement practical data with additional datasets. The 400 NOC simulations were combined with the five NOC practical experiments, forming various combinations and ranges to create diverse training sets. After training the model, its performance was assessed using

five normal simulated test data, five practical runs, 17 practical faulty runs, and four simulated faults. The limited number of simulated runs is a result of time constraints associated with running experiments.

5.5 Conclusion

The experimental design was set up to ensure the collection or generation of data from both the practical system and the simulated model, serving the overarching goal of addressing the research question. With the acquisition of comprehensive datasets, various combinations based on the quantity and type of runs can be effectively leveraged in tandem with the MPCA technique for fault detection using control charts. This strategic approach, incorporating both practical and simulated data, enhances the robustness and applicability of the analysis, facilitating a more nuanced understanding of fault detection dynamics within the studied system.

Chapter 6

Results

6.1 Introduction

The fault detection process involved the use of diverse combinations of practical and simulated data for training and testing, with subsequent measurement of performance using various metrics. The evaluation metrics encompassed the detection accuracy, false alarm rate of the test data, time to detect a fault, monitoring of a transition, and contribution plots. The detection accuracy was computed as the percentage of correctly identified experimental or simulated runs as faults. The false alarm rate represents the percentage of NOC test data incorrectly identified as faults. The time until fault detection is measured from the induction of the fault to the instant the fault is detected. Transition monitoring was used to assess each individual simulation or experiment (test data) to determine the number of time steps until the fault identification since the fault was induced. Contribution plots were generated to discern the variables with the most significant contribution to the detection of the fault.

6.2 Training and test data

The data used to train the model are split into three parts, the simulated runs, the practical experiments and a combination of the simulated runs and practical experiments. Table 6.1 details the test data that was used for the testing. The test data and training data are of the same operation with difference being it can be normal, faulty, simulated or practical data.

NOC experiments were used to calculate the false alarm rate by identifying how many experiments had been considered faults. Data containing the induced faults were utilised to calculate the detection rate by assessing the proportion of faults that were successfully identified.

Table 6.1: Test data to be used to determine the fault detection performance

Test data	Unique ID	Description
NOC data	PNO1	Practical NOC
	PNO2	Practical NOC
	SNO1	Simulated NOC
	SNO2	Simulated NOC
	SNO3	Simulated NOC
	SNO4	Simulated NOC
	SNO5	Simulated NOC
Faulty system data	PFS1	Stuck Valve Tank 1
	PFS2	Stuck Valve Tank 2
	PFA1	Agitator fault Tank 1
	PFA2	Agitator fault Tank 2
	PFA12	Agitator fault Tank 1 and 2
	PFL11	Tank 1 leakage 10%
	PFL12	Tank 1 leakage 20%
	PFL13	Tank 1 leakage 30%
	PFL21	Tank 2 leakage 10%
	PFL22	Tank 2 leakage 20%
	PFL23	Tank 2 leakage 30%
	PFB11	Blockage 10%
	PFB12	Blockage 20%
	PFB31	Blockage 30%
	PFB32	Blockage 30%
	PFB33	Blockage 30%
	PFB34	Blockage 30%
	SFB31	Simulated Blockage 30%
	SFB32	Simulated Blockage 30%
	SFB33	Simulated Blockage 30%
	SFB34	Simulated Blockage 30%

6.3 Fault detection for different scenarios

The results were derived from three distinct data configurations employed as training data for the model: practical data, simulated data, and a combination of both. These diverse datasets were utilised in training the MPCA model, introducing variability in the range of runs incorporated for model training. In the generation of control charts, different numbers of PCs were considered as influencing the outcomes of the results. Additionally, the variation in PCs was systematically explored to understand its effect on the performance of the fault detection method.

The false alarm percentages were obtained by calculating the percentage of NOC test data that were detected as faults. The NOC are PNO1 to PNO2 and SNO1 to SNO5. The detection rate was determined by calculating the percentage of faulty system data correctly identified as a fault, relative to the total faulty system data. A comprehensive performance table was compiled by combining various performance measures, providing a holistic overview to identify the scenarios where the best performance is achieved.

6.3.1 Fault detection using practical or simulated data

The results in Table 6.2, 6.3, 6.4 and 6.5 were derived by using PNO and SNO respectively to train the MPCA model.

Table 6.2 indicates that as the number of simulation runs for training increases and the PCs used for the control chart decrease, the false alarm rate decreases until 50 simulation runs. Beyond 50 simulation runs, no further false alarms are observed. The elevated false alarm rate with a low number of runs for training data are attributed to the control limit, as mentioned in the paper of Y. Kim [28]. With an increased number of runs, a control limit with lower false alarms can be established as the control limit relies on the variance and mean of the transitions. The variance and mean of the transitions are thus better characterised when a larger number of runs are available.

Table 6.2: SPE false alarm rate using practical or simulated training data

Principal components	PNO 3	Training data					
		SNO					
		5	25	50	100	200	400
5	100%	100%	0%	0%	0%	0%	0%
10	100%	100%	14%	0%	0%	0%	0%
20	100%	100%	100%	14%	0%	0%	0%
30	100%	100%	100%	29%	0%	0%	0%

When the robustness against false alarms increases, the fault detection sensitivity decreases. In table 6.3 it is evident that at a low number of PCs and a high number of training data (e.g., at 5 PCs and 400 runs), the detection rate is notably low.

Table 6.3: SPE fault detection rate using practical or simulated training data

Principal components	Training data						
	PNO 3	SNO					
		5	25	50	100	200	400
5	100%	100%	81%	76%	71%	38%	38%
10	100%	100%	90%	81%	76%	48%	38%
20	100%	100%	100%	86%	81%	71%	57%
30	100%	100%	100%	100%	81%	81%	71%

Table 6.4 is generated using the T^2 control chart. The T^2 control chart has fewer false alarms than the SPE, as seen in Table 6.5. Almost no false alarms are evident in Table 6.4. The T^2 control chart displays high robustness at a low number of transitions and high number of PCs.

Table 6.4: T^2 false alarm rate using practical or simulated training data

Principal components	Training data						
	PNO 3	SNO					
		5	25	50	100	200	400
5	0%	0%	0%	0%	0%	14%	14%
10	0%	0%	0%	0%	0%	0%	14%
20	0%	0%	0%	0%	0%	0%	0%
30	0%	0%	0%	0%	0%	0%	0%

The highest detection rate in Table 6.5 is 71% for any combination of data or PCs. At a high number of transitions and low number of PCs, the best performance is achieved as reported in table 6.5.

Table 6.5: T^2 fault detection rate using practical or simulated training data

Principal components	Training data						
	PNO 3	SNO					
		5	25	50	100	200	400
5	0%	0%	19%	43%	71%	71%	71%
10	0%	0%	24%	62%	71%	71%	71%
20	0%	0%	5%	29%	71%	71%	71%
30	0%	0%	0%	24%	57%	71%	71%

6.3.2 Fault detection using a combination of practical and simulated data

Tables 6.6, 6.7, 6.8 and 6.9 integrate the practical normal operation (PNO) and simulated normal operation (SNO) training data. 3 PNO runs were supplemented with varying sizes of SNO runs with the aim of assessing potential differences between the use of practical and simulated training data. The total of the combined practical and simulated training data equals the same number as the simulated run intervals in the previous section. Table 6.6 clarifies the amalgamation of practical and simulated data for training purposes and presents the corresponding false alarm rates utilising an SPE control chart.

Table 6.6: SPE false alarm rate using practical and simulated training data

Principal components	Training data PNO + SNO					
	3 + 2	3 + 22	3 + 47	3 + 97	3 + 197	3 + 397
5	100%	0%	0%	0%	0%	0%
10	100%	0%	0%	0%	0%	0%
20	100%	100%	0%	0%	0%	0%
30	100%	100%	14%	0%	0%	0%

Combining simulated and practical training data necessitates less training data to achieve comparable performance when compared to the exclusive use of simulated data. In the case of the SPE control chart, typically exhibiting a 14% false alarm rate with only 25 simulated runs at 10 PCs, Table 6.6 illustrates a 0% false alarm rate when combined training data are used.

The combined data performs equally well compared to utilising only simulated data. While both scenarios achieved a maximum detection rate of 81% at 0% false alarms, the amount of training data required for each to achieve these comparable results differed.

Table 6.7: SPE fault detection rate using practical and simulated training data

Principal components	Training data PNO + SNO					
	3 + 2	3 + 22	3 + 47	3 + 97	3 + 197	3 + 397
5	100%	76%	76%	67%	38%	38%
10	100%	81%	81%	76%	38%	38%
20	100%	100%	81%	81%	67%	57%
30	100%	100%	95%	81%	81%	71%

Table 6.8: T^2 false alarm rate using practical and simulated training data

Principal components	Training data PNO + SNO					
	3 + 2	3 + 22	3 + 47	3 + 97	3 + 197	3 + 397
5	0%	0%	0%	0%	14%	14%
10	0%	0%	0%	0%	14%	14%
20	0%	0%	0%	0%	0%	0%
30	0%	0%	0%	0%	0%	0%

Table 6.9 shows that, when combined, fewer simulated and experimental training runs are required to achieve the same detection rate when compared to the use of simulated data only. Interestingly, there is no notable difference in performance when using combined data for the T^2 control chart. In both cases, the maximum detection rate remains at 71% with a 0% false alarm rate.

Table 6.9: T^2 fault detection rate using practical and simulated training data

Principal components	Training data PNO + SNO					
	3 + 2	3 + 22	3 + 47	3 + 97	3 + 197	3 + 397
5	0%	10%	33%	71%	71%	71%
10	0%	19%	67%	71%	71%	71%
20	0%	5%	29%	71%	71%	71%
30	0%	0%	24%	67%	71%	71%

The average SPE detection rate for all the different variations was 79% and for T^2 it was 40%. The SPE had a higher false alarm rate than the T^2 with 32% false alarms compared to the 2% false alarms of the T^2 .

6.3.3 Comparison of different data variations

The overall performance was calculated first for the practical or simulated data and then for the combination of the data. The calculation of the overall performance is demonstrated by the following equation:

$$OVP = \frac{(200\% - FRS - FRT) + DRS + DRT}{4} \quad (6.1)$$

The false alarm rate of the SPE (FRS) and the T^2 (FRT) are subtracted from 200%. The detection rate of SPE (DRS) and the T^2 (DRT) are added and then the sum is divided by 4 to get a value up to 100%.

Tables 6.10 and 6.11 indicate that the best performance is observed at 20 PCs and

100 runs, as well as at 30 PCs and 200 runs, across different configurations of PCs and training data runs.

Table 6.10: Overall performance for practical and simulated data at different principal components and runs

Principal components	PNO 5	Training data SNO					
		5	25	50	100	200	400
5	50%	50%	75%	80%	86%	74%	74%
10	50%	50%	75%	86%	87%	80%	74%
20	50%	50%	51%	75%	88%	86%	82%
30	50%	50%	50%	74%	85%	88%	86%

Table 6.11: Overall performance for combined practical and simulated data at different principal components and runs

Principal components	Training data PNO + SNO					
	3 + 2	3 + 22	3 + 47	3 + 97	3 + 197	3 + 397
5	50%	71%	77%	85%	74%	74%
10	50%	75%	87%	87%	74%	74%
20	50%	51%	77%	88%	85%	82%
30	50%	50%	76%	87%	88%	86%

For transition monitoring, the model was established using 30 PCs and 200 runs to set up the control charts.

6.4 Transition monitoring

The preceding section aimed to assess whether the test experiments or simulated runs were successfully detected as faults. This section discussed the results from employing 200 runs of simulated or practical and simulated training data, along with 30 PCs, to establish the control chart. The objective was to calculate the time taken to detect a fault, the percentage of fault detections since the fault was induced, and the percentage of false alarms for each transition in various experiments or simulated runs.

The two experimental and five simulated NOC test runs were used to obtain the initial metric, the false alarm percentage (%). Calculating this percentage for each run involves dividing the number of time steps flagged as faulty from the start to the end of the run by the total duration of the run.

In Table 6.12 the false alarm percentages are generally low and appear normal, except for the experiment PNO1 when using the T^2 control chart. The combined data show a 14% and 33% false alarm rate using the T^2 control chart. This discrepancy might be attributed to environmental effects during the experiment as it is repeated multiple times, creating an impression of a fault.

Table 6.12: Fault detection rate at 200 transition runs and 30 PCs

Unique ID	Description	Simulated data		Simulated and practical data	
		SPE	T^2	SPE	T^2
PNO1	Practical NOC	3%	14%	3%	33%
PNO2	Practical NOC	2%	0%	2%	0%
SNO1	Simulated NOC	0%	0%	0%	0%
SNO2	Simulated NOC	0%	0%	0%	0%
SNO3	Simulated NOC	0%	0%	0%	0%
SNO4	Simulated NOC	0%	0%	0%	0%
SNO5	Simulated NOC	0%	0%	0%	0%

The detection rate in Table 6.13 was calculated by taking the number of faulty signals since the fault was induced in the system and divided by the total time as total number of time steps. This calculation was performed for each transition in various practical and simulated faulty system data, utilising either the SPE or T^2 control chart to classify time steps as faulty or normal.

Table 6.13 presents the detection rate for each transition, comparing simulated-only data with a combination of simulated and practical data to create both the SPE and T^2 control charts. The differences between the various data sets used are minimal, regardless of the control chart employed.

Detection rates approaching or reaching 100% were observed for faults involving stuck valves and agitator issues. However, faults PFL11, PFL12, PFL21, PFB11, and PFB12 exhibited detection rates lower than 50% across all metrics. Notably, fault PFL13 demonstrated a high detection rate using the SPE control chart but a low detection rate with the T^2 control chart.

Table 6.13: Fault detection rate at 200 transition runs and 30 PCs

Unique ID	Description	Simulated data		Simulated and practical data	
		SPE	T^2	SPE	T^2
PFS1	Stuck valve Tank 1	100%	100%	100%	100%
PFS2	Stuck valve Tank 2	100%	100%	100%	100%
PFA1	Agitator fault Tank 1	94%	98%	94%	99%
PFA2	Agitator fault Tank 2	56%	100%	55%	99%
PFA12	Agitator fault Tank 1 and 2	93%	100%	93%	99%
PFL11	Tank 1 leakage 10%	3%	0%	0%	0%
PFL12	Tank 1 leakage 20%	34%	0%	30%	6%
PFL13	Tank 1 leakage 30%	97%	9%	94%	30%
PFL21	Tank 2 leakage 10%	10%	0%	8%	0%
PFL22	Tank 2 leakage 20%	81%	95%	83%	96%
PFL23	Tank 2 leakage 30%	100%	96%	100%	97%
PFB11	Blockage 10%	9%	0%	6%	0%
PFB12	Blockage 20%	13%	0%	11%	5%
PFB31	Blockage 30%	29%	94%	29%	95%
PFB32	Blockage 30%	28%	93%	29%	94%
PFB33	Blockage 30%	28%	93%	28%	94%
PFB34	Blockage 30%	27%	93%	28%	94%
SFB31	Simulated blockage 30%	44%	77%	42%	76%
SFB32	Simulated blockage 30%	43%	79%	41%	78%
SFB33	Simulated blockage 30%	44%	69%	45%	64%
SFB34	Simulated blockage 30%	44%	74%	42%	74%

Table 6.14 shows the time it took to detect a fault since its was induced into the system. The SPE control chart detected the fault sooner than the T^2 control chart. The stuck valve and agitator faults were detected sooner than the leakage and blockage faults.

Comparing the simulated and practical blockages with 30% valve closure reveals that the practical blockage was detected earlier than the simulated one. When examining both simulated and practical training data, some leakage faults are apparent, where no time is detected until the fault occurs because the control chart never signalled the fault.

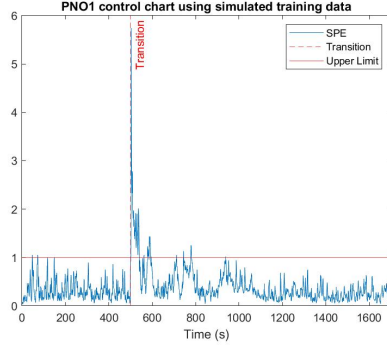
Table 6.14: Time in seconds until fault detection using 200 runs and 30 PCs

Unique ID	Description	Simulated Data (s)		Simulated and practical data (s)	
		SPE	T^2	SPE	T^2
PFS1	Stuck valve Tank 1	1	1	1	1
PFS2	Stuck valve Tank 2	2	2	1	2
PFA1	Agitator fault Tank 1	4	4	1	4
PFA2	Agitator fault Tank 2	3	3	7	3
PFA12	Agitator fault Tank 1 and 2	3	3	8	4
PFL11	Tank 1 leakage 10%	3	3	∞	∞
PFL12	Tank 1 leakage 20%	4	4	∞	32
PFL13	Tank 1 leakage 30%	10	10	73	19
PFL21	Tank 2 leakage 10%	14	14	∞	32
PFL22	Tank 2 leakage 20%	2	2	62	9
PFL23	Tank 2 leakage 30%	4	4	48	6
PFB11	Blockage 10%	2	2	∞	2
PFB12	Blockage 20%	2	2	∞	2
PFB31	Blockage 30%	2	2	74	2
PFB32	Blockage 30%	2	2	90	3
PFB33	Blockage 30%	12	12	81	14
PFB34	Blockage 30%	2	2	92	2
SFB31	Simulated blockage 30%	57	57	277	57
SFB32	Simulated blockage 30%	59	59	252	60
SFB33	Simulated blockage 30%	44	44	379	44
SFB34	Simulated blockage 30%	48	304	48	304

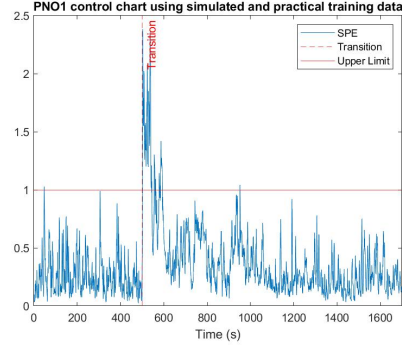
6.4.1 Transition monitoring using SPE

The figures below depict the statistical values represented in blue at each time step. The horizontal red line indicates the normalised control limit at the value 1, and the vertical dashed red line denotes when the transition occurred at 500 s.

In Figure 6.1a, a small spike above the control limit can be observed, which is the 3% false signals detected from PNO1 using simulated training data. As seen in Figure 6.1b, there is no point above the control limit that produces a false alarm rate of 3%.



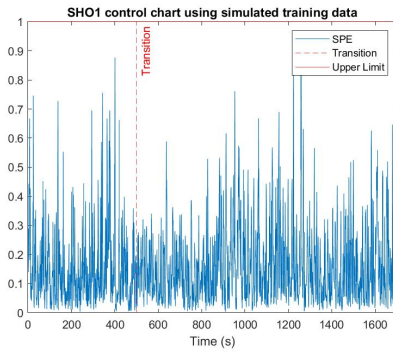
(a) Simulated data



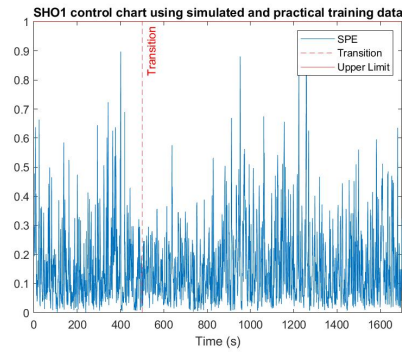
(b) Simulated and practical data

Figure 6.1: Practical normal operation transition control charts

Figure 6.2 reveals that, when employing simulated data as test data, none of the data points exceed the established control limit set at 1.



(a) Simulated data

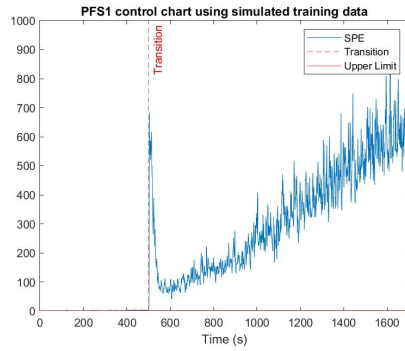


(b) Simulated and practical data

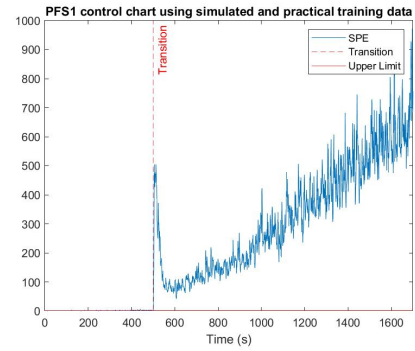
Figure 6.2: Simulated normal operation transition control charts with a control limit at 1

Among all the faults, the stuck valve exhibits the most significant fault magnitude, causing the control limit, set at 1, to be overshadowed by the extensive fault. The SPE statistic markedly surpasses one, reaching a maximum value above 900 in Figure 6.3 and exceeding 3000 in Figure 6.4. The elevated fault magnitude is attributed to the control system's inability to compensate for the stuck valve fault, as seen in Figure 6.3 where a spike is observed followed by a gradual increase in the value.

In Figure 6.5 a peak is observed at 800 s, indicating a significant delay in encountering the fault. In Figure 6.6, two peaks are observed in the data, at the beginning of the transition and at 700 s, respectively.

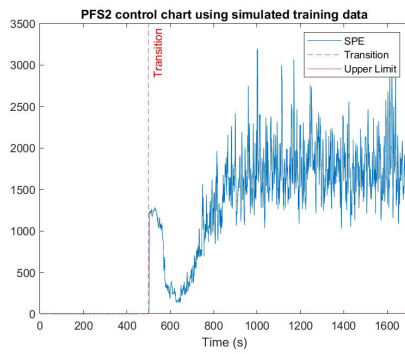


(a) Simulated data

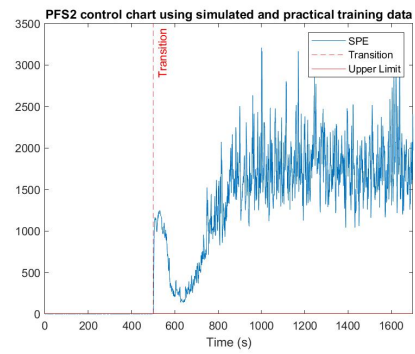


(b) Simulated and practical data

Figure 6.3: Practical fault stuck valve tank 1 with a control limit at 1

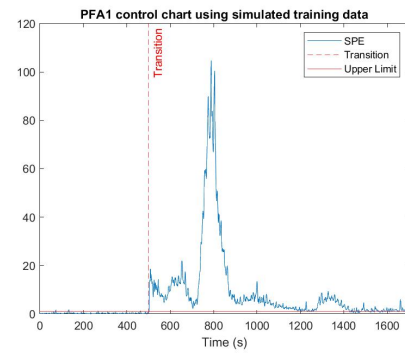


(a) Simulated data

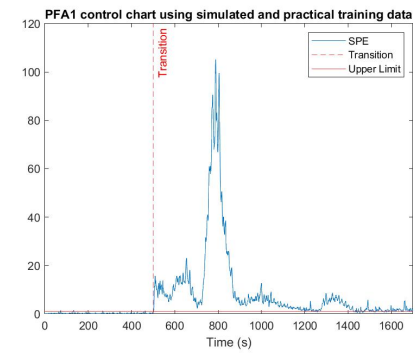


(b) Simulated and practical data

Figure 6.4: Practical fault stuck valve tank 2

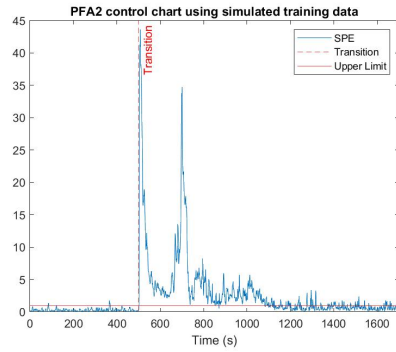


(a) Simulated data

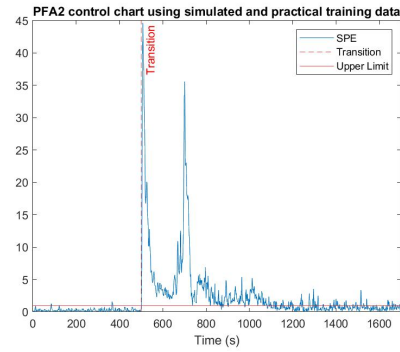


(b) Simulated and practical data

Figure 6.5: Practical fault agitator fault tank 1



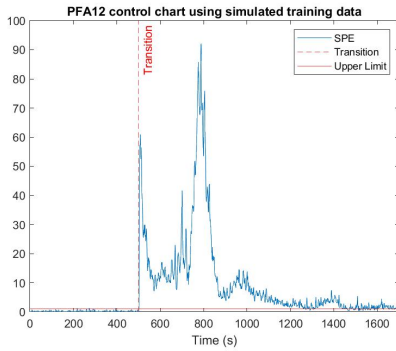
(a) Simulated data



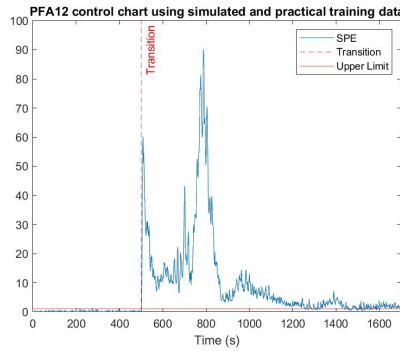
(b) Simulated and practical data

Figure 6.6: Practical agitator fault tank 2

Figure 6.8 reveals that the control system nearly conceals the fault. Initially, there is an uptick in the SPE statistic, followed by a subsequent decrease, nearly dropping below the control limit.



(a) Simulated data



(b) Simulated and practical data

Figure 6.7: Practical agitator fault tanks 1 and 2

The fault magnitude in Figure 6.9 also decreases after the initial increase.

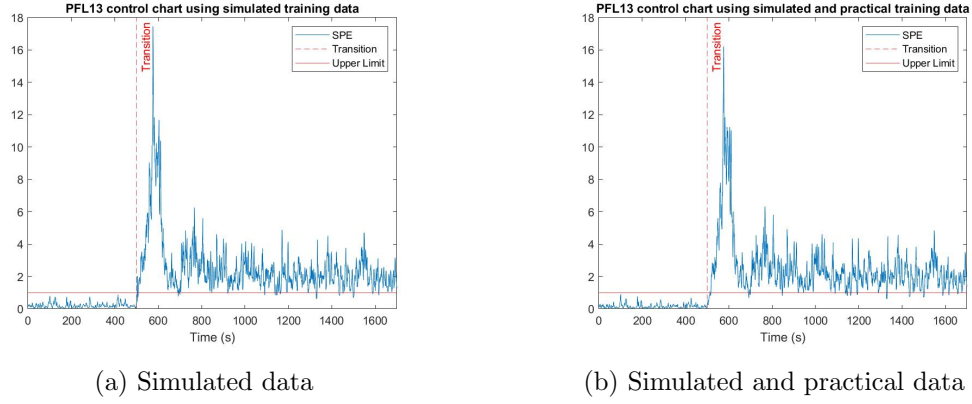


Figure 6.8: Practical 30% leakage fault tank 1

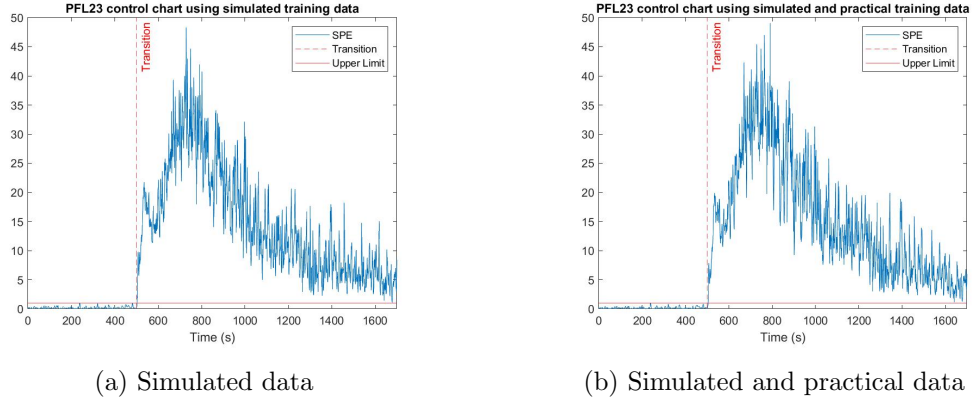


Figure 6.9: Practical 30% leakage fault tank 2

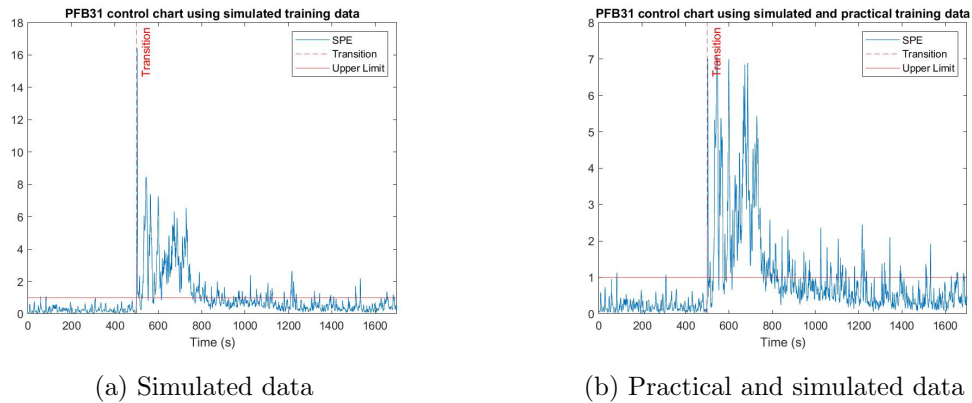
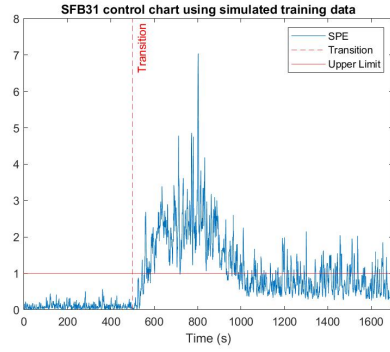
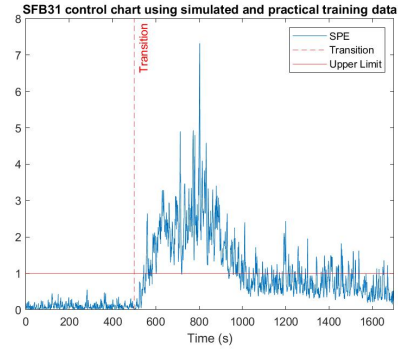


Figure 6.10: Practical 30% blockage between tank 1 and 2

The blockage fault proved particularly challenging to detect, as evident in Figures 6.10 and 6.11. A spike is noticeable at the onset of the transitions, but detection diminishes thereafter.



(a) Simulated data

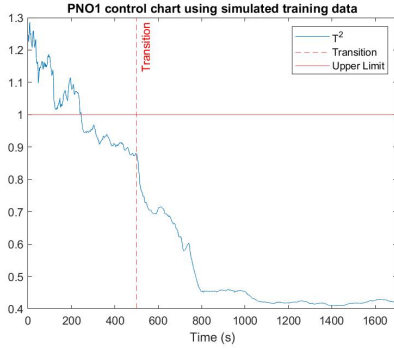


(b) Practical and simulated data

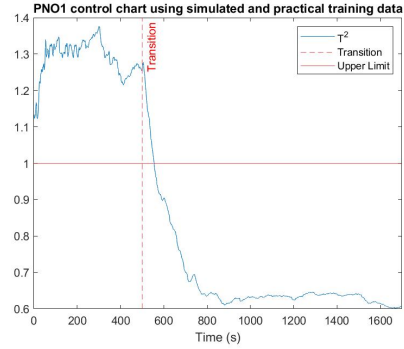
Figure 6.11: Simulated 30% blockage between tank 1 and tank 2

6.4.2 Transition monitoring using T^2

The T^2 control chart of PNO1 can be seen in Figures 6.12a and 6.12b. As mentioned in the previous section and seen Table 6.12, the control chart utilising simulated data exhibited a 14% false alarm rate, while the control chart with both simulated and practical data registered a 33% false alarm rate. The instances exceeding the control limit are minimal and could be attributed to environmental changes. Another plausible explanation is that the system may not have fully reached steady state at the commencement of the experiment.



(a) Simulated data



(b) Simulated and practical data

Figure 6.12: Practical normal operation transition control charts

The simulated normal operation has 0% false alarm rate, as seen in Figure 6.13

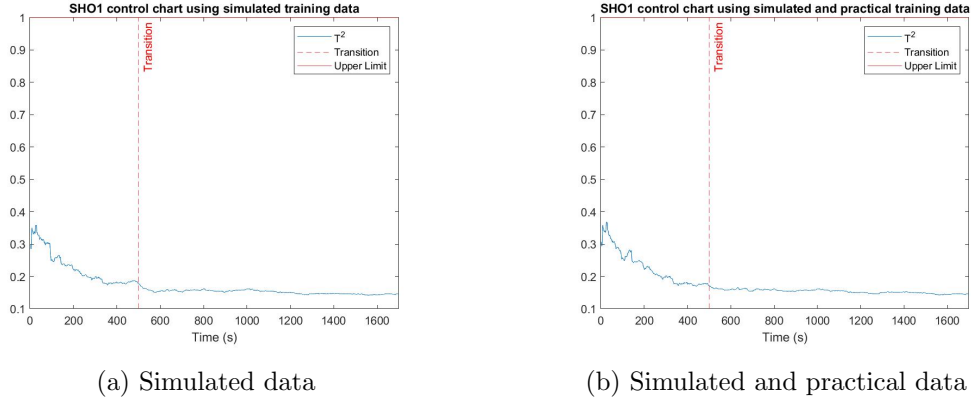


Figure 6.13: Simulated normal operation transition control charts

Similar to the case of PNO1 discussed above, normal operation is identified as a fault in Figure 6.14 during the stuck valve fault transition. In a faulty transition, normal operation corresponds to the period before the fault is induced. This issue can be addressed by adjusting the number of transitions used for training and modifying the PCs used for the control chart. This is observed at three points, namely, PN01, PFS1, and PFA1.

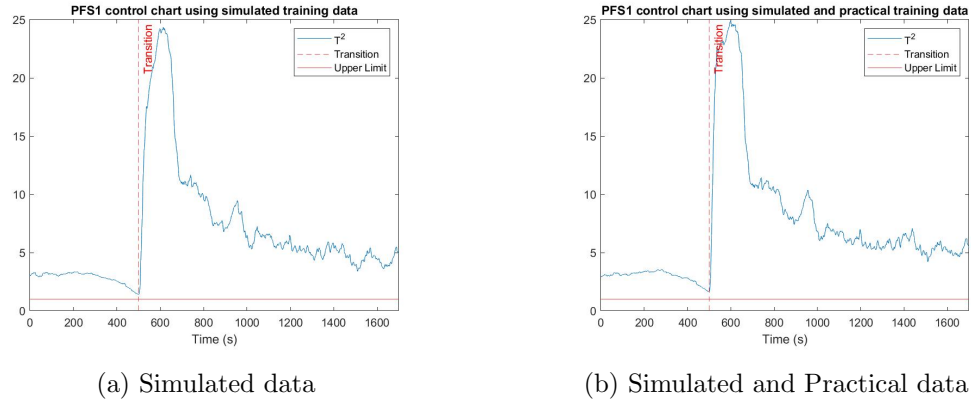
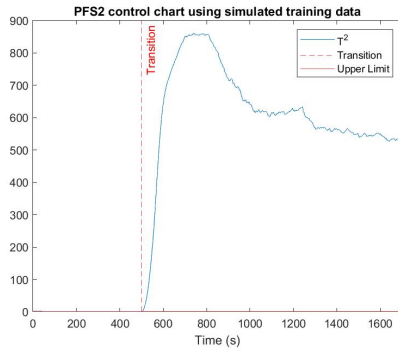
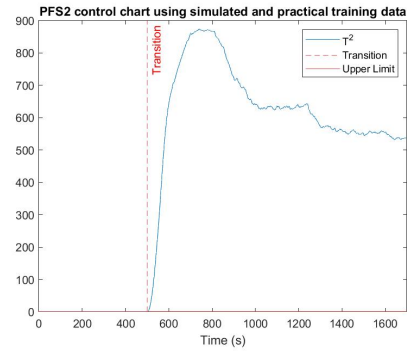


Figure 6.14: Practical stuck valve fault tank 1



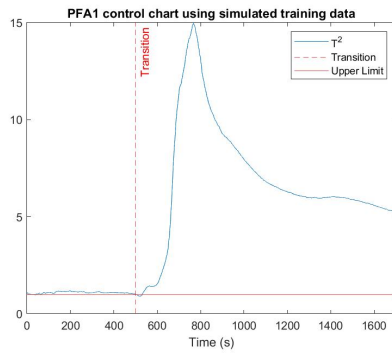
(a) Simulated data



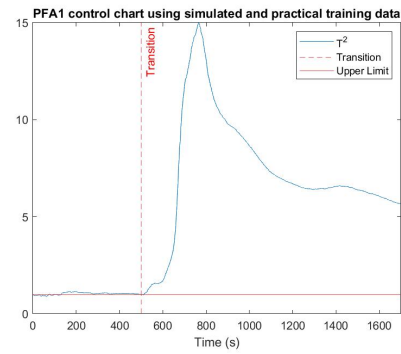
(b) Simulated and Practical data

Figure 6.15: Practical stuck valve fault tank 2

The figures illustrating various agitator faults exhibit similar patterns, with differences in fault magnitudes. Notably, Figure 6.18 displays that the highest fault magnitude is achieved when both agitators are switched off.

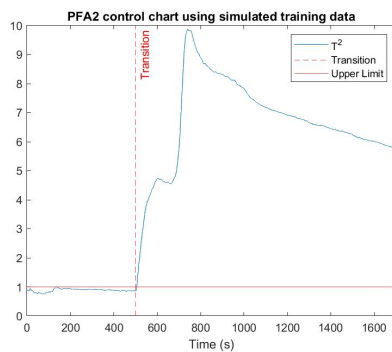


(a) Simulated data

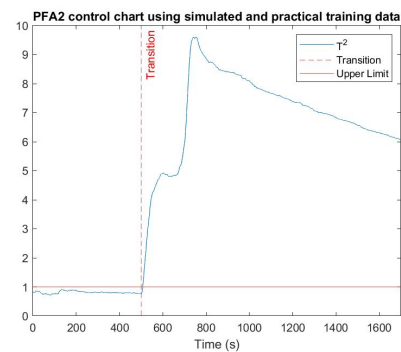


(b) Simulated and Practical data

Figure 6.16: Practical agitator fault tank 1

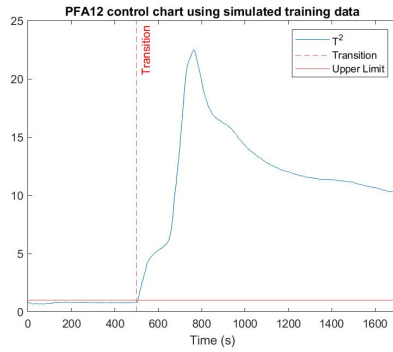


(a) Simulated data

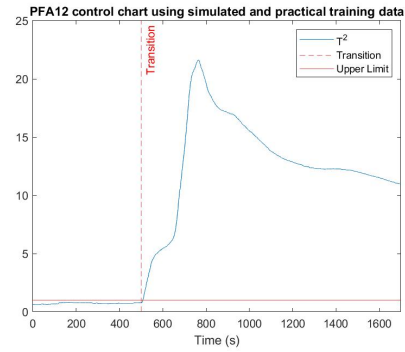


(b) Simulated and Practical data

Figure 6.17: Practical agitator fault tank 2



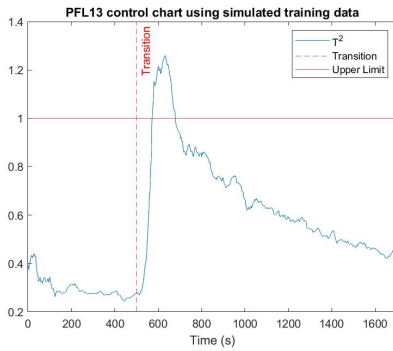
(a) Simulated data



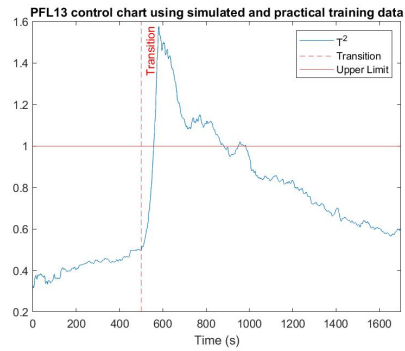
(b) Simulated and Practical data

Figure 6.18: Practical agitator fault on tank 1 and 2

In Figure 6.19, the control chart barely detected the leakage in tank 1. However, in Figure 6.20, representing the leakage in tank 2, the fault is more apparent as the statistic continues to increase, indicating a clear detection compared to the leakage in tank 1.

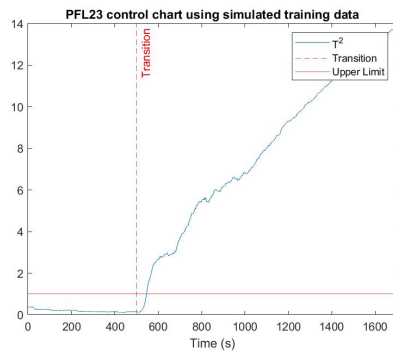


(a) Simulated data

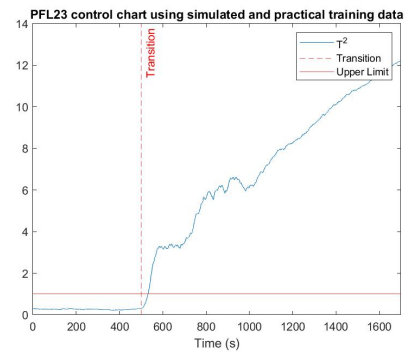


(b) Simulated and Practical data

Figure 6.19: Practical leakage 30% fault on tank 1



(a) Simulated data



(b) Simulated and Practical data

Figure 6.20: Practical leakage 30% fault on tank 2

The practical Figure 6.21 and the simulated Figure 6.22 appear similar, with the main distinction being the steeper slope in the practical transition. This steeper slope denotes a the faster time until detection in the practical experiment. The steeper slope in the practical data can be due to the slower response or the magnitude of the fault which can be different.

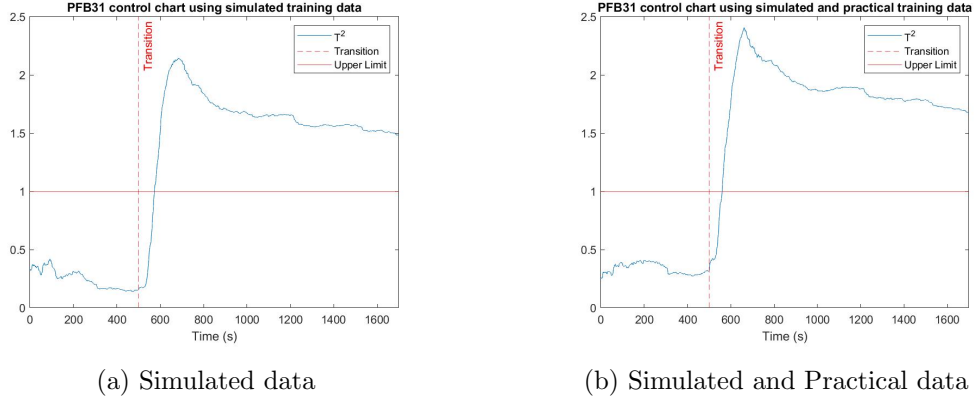


Figure 6.21: Practical blockage 30% fault between tank 1 and tank 2

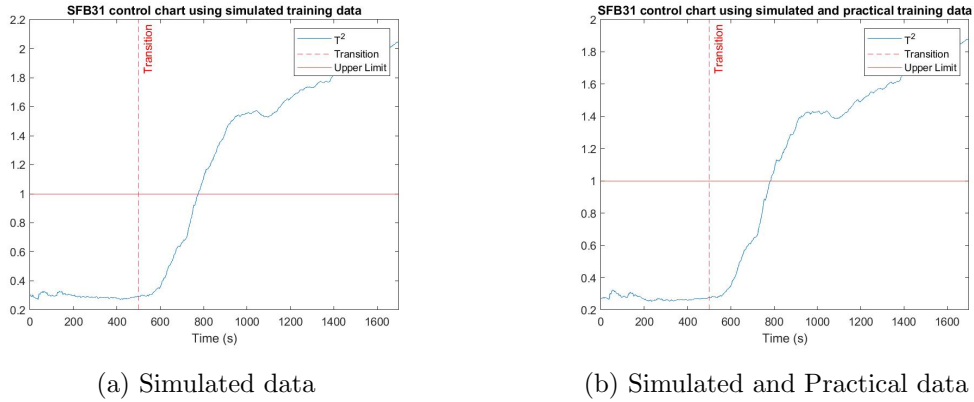


Figure 6.22: Simulated blockage 30% fault between tank 1 and tank 2

6.4.3 Fault isolation for the different faults

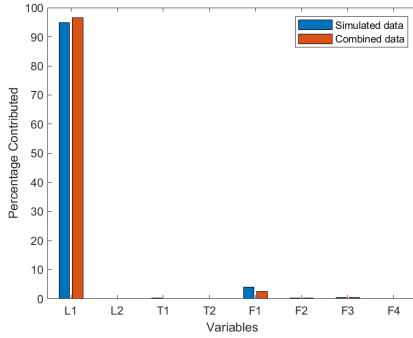
The last part of the results addresses the isolation of faults by determining the variables with the greatest contribution to the detection of a fault. In this system, eight variables are used, as shown in Table 6.15.

The contribution of each variable is represented as a percentage of the total contribution by all variables. Figure 6.23 shows the variable contributions for both SPE and T^2 . A comparison is drawn between the simulated data (depicted by blue bars) and the combined data (depicted by orange bars).

Table 6.15: Variables used in contribution plot

Variable	Description
L1	Level of water in tank 1
L2	Level of water in tank 2
T1	Temperature in tank 1
T2	Temperature in tank 2
F1	Flow of water into tank 1
F2	Flow of water into tank 2
F3	Flow of water through heat exchanger in tank 1
F4	Flow of water through heat exchanger in tank 2

Upon closer inspection of Figure 6.23 it is evident that the variable L1 (level of tank 1) contributes the most to the stuck valve fault. This high contribution is attributed to the fact that when the stuck valve occurs, the control for the level of tank 1 is disabled, emphasising the significance of L1 in detecting the fault.



(a) SPE contribution plot

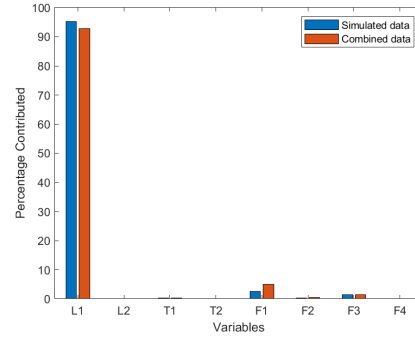
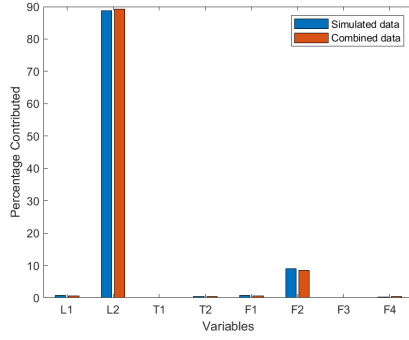
(b) T^2 contribution plot

Figure 6.23: Contribution plots of the agitator fault in tank 1 using simulated and combined training data

The stuck valve fault for tank 2 in Figure 6.24 is similar to the stuck valve fault of tank 1. The variable that contributed the most to the fault is also the level of the tank in which the fault was induced.

The variables with the greatest contribution to the agitator fault are T1 (temperature in tank 1) and F3 (flow rate through heat exchanger in tank 1). This fault in tank 1 results in decreased heat transfer to the water in tank 1, elucidating why the variables contributing most to fault detection are closely associated with temperature.



(a) SPE contribution plot

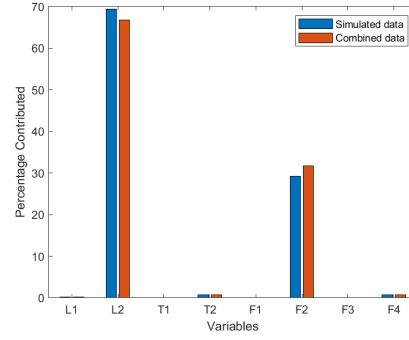
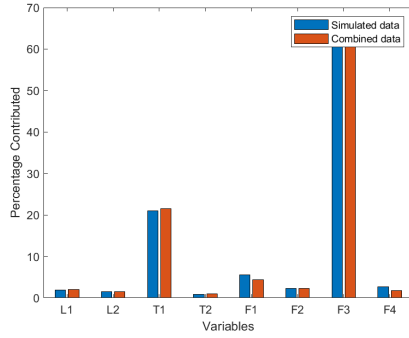
(b) T^2 contribution plot

Figure 6.24: Contribution plots of the agitator fault in tank 2 using simulated and combined training data



(a) SPE contribution plot

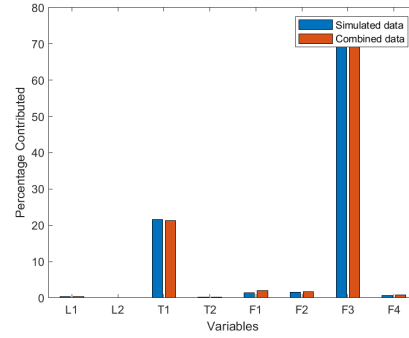
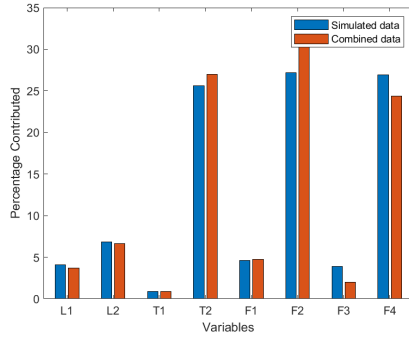
(b) T^2 contribution plot

Figure 6.25: Contribution plots of the agitator fault in tank 1 using simulated and combined training data

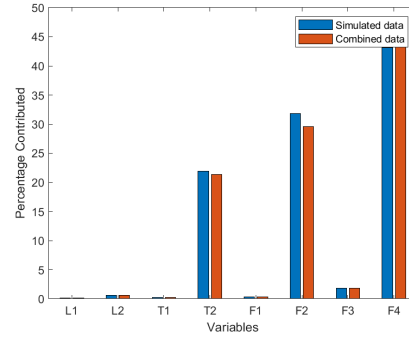
Upon examining Figure 6.26, it is evident that the variables exerting the most significant influence on the fault are T2 (temperature in tank 2), F4 (flow rate through the heat exchanger in tank 2), and F2 (cold water flow into tank 2). While it was anticipated that T2 and F4 would have the highest contributions, the increased contribution of F2 to the fault may be ascribed to alterations in the outflow from the tank resulting from the cessation of water mixing.

The variables contributing to the fault in Figure 6.27 are a combination of the variables delineated in Figures 6.25 and 6.26, as both faults are induced together.

The variable with the most significant contribution in the case of leakage in tank 1 with the 30% open valve is F1 (inlet flow into tank 1). The substantial contribution of F1 attributed to the direct impact of the leakage on the inlet flow.

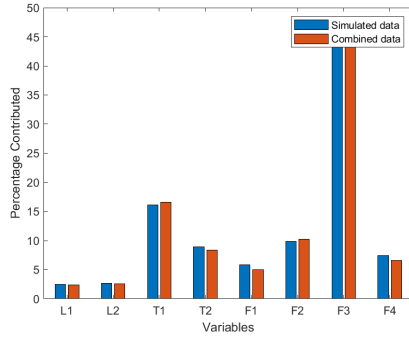


(a) SPE contribution plot

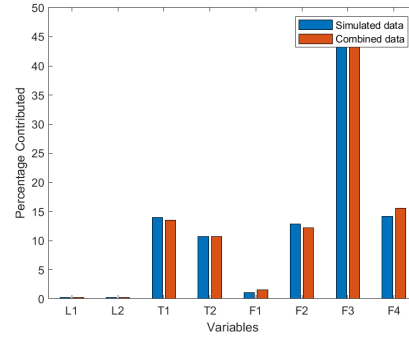


(b) T^2 contribution plot

Figure 6.26: Contribution plots of the agitator fault in tank 2 using simulated and combined training data

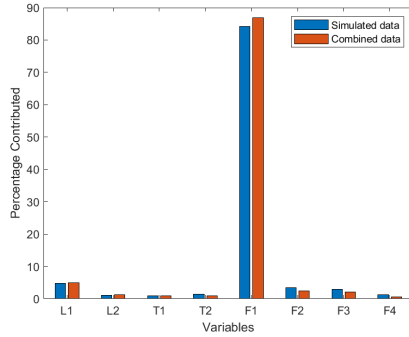


(a) SPE contribution plot

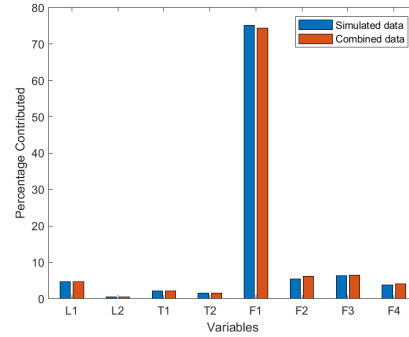


(b) T^2 contribution plot

Figure 6.27: Contribution plots of the agitator fault in tanks 1 and 2 using simulated and combined training data



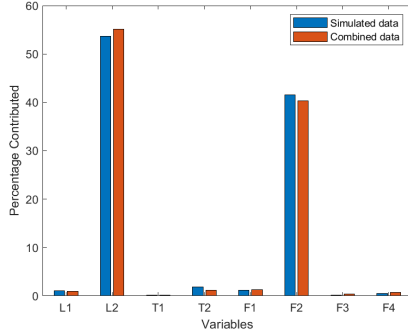
(a) SPE contribution plot



(b) T^2 contribution plot

Figure 6.28: Contribution plots of leakage fault in tank 1 using simulated and combined training data

Two variables stand out as having made the most significant contributions in detecting the leakage fault of tank 2: L2 (level in tank 2) and F2 (inlet flow of tank 2). In contrast to the leakage fault in tank 1, the detection of the fault in tank 2 involves both the level and the inlet flow variables.



(a) SPE contribution plot

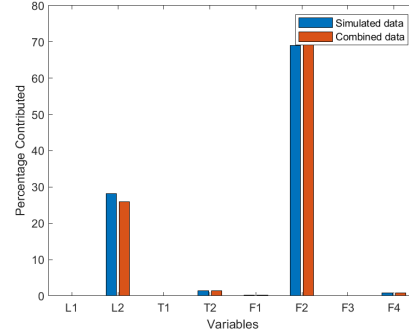
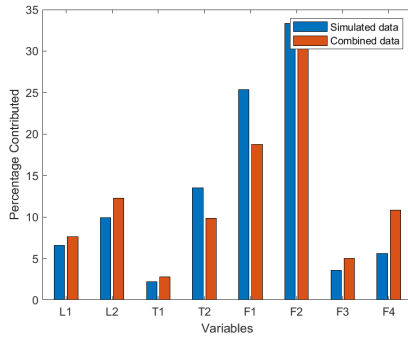
(b) T^2 contribution plot

Figure 6.29: Contribution plots of leakage fault in tank 2 using simulated and combined training data

The blockage fault between tanks 1 and 2 in practical experiments cannot be isolated conclusively. Figures 6.30a and 6.30b reveal that variable F2 consistently contributed the most to the fault. However, the contribution of other variables varies between the figures, making it challenging to pinpoint a single common denominator.



(a) SPE contribution plot

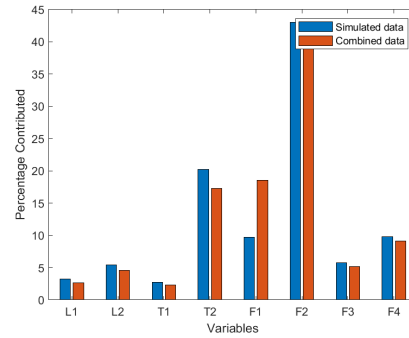
(b) T^2 contribution plot

Figure 6.30: Contribution plots of practical blockage fault between tanks 1 and 2 using simulated and combined training data

For the simulated blockage fault between tanks 1 and 2 the fault can also not be isolated, and the only variable whose contribution does not vary is F2.

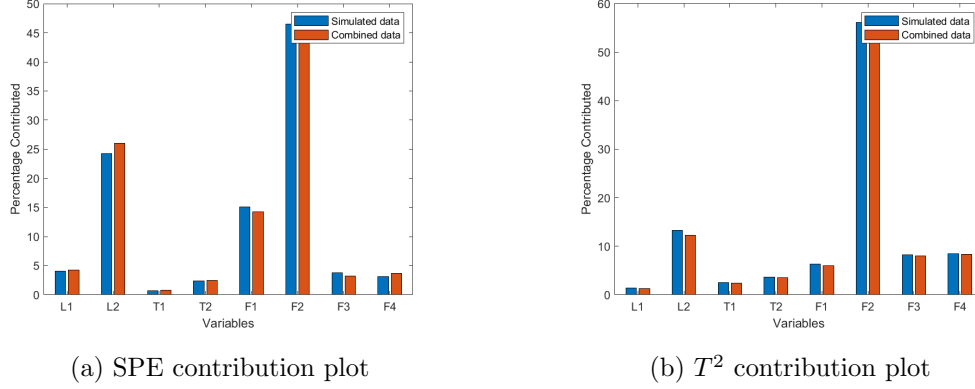


Figure 6.31: Contribution plots of simulated blockage fault between tanks 1 and 2 using simulated and combined training data

6.5 Conclusion

The successful detection of faulty system data were achieved by appropriately configuring the SPE and T^2 control charts with an optimal number of training data and PCs. Both experimental and simulated test data were effectively identified as faults, with the exception of instances where the fault magnitude was small, as observed in the case of tank leakage with a 10% valve opening. The fastest fault detection was achieved using SPE for the agitator and stuck valve faults. For the stuck valve and agitator faults, almost 100% of the time intervals since the fault was induced were correctly identified as faulty. Most faults could be isolated successfully, except for the blockage fault, where F2 was the only variable that could be reliably isolated among all variables.

Conclusion

7.1 Introduction

The research aimed to address the question of whether a fault in a transition of the benchmark heated two-tank system could be effectively detected using an MPCA approach. To answer this question, a comprehensive methodology was employed. An experimental design was meticulously structured to acquire both simulated and practical data, serving as training data for the model and as test data. Simulated data were generated through a Simulink model of the benchmark heated two-tank system, while practical data were collected from the physical system.

7.2 Reflection on objectives

7.2.1 Experimental design

The experimental design was done to determine a number of runs for various transitions within the same operation. It also ensured that the operation had noise, disturbances, change of operating modes, controllable variables and for the different runs faulty and normal operations.

7.2.2 Simulated heated two-tank process model

The study underscored that applying MPCA to the data and subsequently utilising control charts for fault detection is challenging when a limited number of practical experiments are available for training data. The integration of the benchmark heated

two-tank system model proved invaluable in supplementing practical experiments with simulated data, particularly in scenarios where conducting a sufficient number of practical experiments within a feasible timeframe is impractical. The heated two-tank process model was validated with practical data of the practical system and then used to generate simulated data that could be used for training of the MPCA model.

7.2.3 Experimental data from the heated two-tank system

Experimental data of 8 variables were collected from the physical heated two-tank system and multiple runs were done of the same operation where some operations were normal and others had a faults induced at different magnitudes.

7.2.4 FDI using MPCA

Following the application of MPCA to the data, control charts were generated to detect and isolate faults. The outcomes revealed that specific faults were identifiable and isolatable under certain optimal conditions. The effectiveness depended on a sufficient number of experimental and simulated runs utilized for training data and the appropriate selection of PCs for constructing the control charts.

FDI were conducted on the test data using the SPE and T^2 control charts. However, these control charts exhibited limitations, failing to detect some faults and even misidentifying a practical normal operation run as faulty. Contribution plots were then constructed to pinpoint the variables that contributed the most to each fault. Notably, the blockage fault at 30% valve closure proved challenging to isolate.

7.2.5 Evaluating results obtained from MPCA

The performance of the MPCA approach was quantified through key metrics, including the fault detection rate, false alarm rate, and time until fault detection. This thorough methodology provided insights into the efficacy of MPCA in fault detection within the benchmark heated two-tank system.

However, some faults remained undetected under these conditions. Notably, the leakage fault at the 10% valve open of tanks 1 or 2, and the blockage fault at 10% valve closure could not be identified using either control chart. In contrast, all detected faults, except for the blockage at 30% valve closure, could be successfully isolated. In the case of the blockage at 30%, no common variable could be

pinpointed, except for the flow rate of cold water into tank 2.

7.3 Future work

The study can also be extended to include fault diagnosis. Other work that can be done is testing whether the technique also works on other systems with transient conditions. Improving the detection rate and achieving complete fault isolation warrants future research.

7.4 Closure

This study demonstrated the feasibility of detecting and isolating faults during change of operating conditions using MPCA in a benchmark heated two-tank system, provided the appropriate datasets were utilised. The undetected faults were those that did not significantly impact the heating or the level of the system. The study added value to similar studies like [19], [9] and [18] that also did fault detection and isolation during transient conditions.

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Appendices

Appendix A

Heated two-tank Simulink model

The Simulink model and the matlab scripts used to generate the data is in the link below:

[Heated two-tank Simulink model](#) The MultipleRuns matlab script can be used to generate data.

- SimulationInputs script is called with the MultipleRuns script and that script is responsible for all the input variables.
- MultipleRunVariables script is also called to generate different noise and normal disturbances for each run.
- The parsim function in Matlab is used to create the different simulated runs



Figure A.1: Full view illustration of the heated two-tank system

Appendix B

Heated two-tank system data

In appendix B is the training and test data generated from the practical system. The link below can be used to retrieve the data:

[Heated two-tank practical data](#)

The Matlab file contains 22 cells, which are all the runs of the practical data. The 8 columns in cells are the 8 variables, and the rows are the time in seconds.

Appendix C

Heated two-tank system model data

The simulated data of generated from the Simulink model of the heated two-tank system is stored in the links below:

- [Simulated normal test data](#) used to test fault detection and isolation.
- [Simulated normal training data](#) used to train fault detection and isolation model.
- [Simulated faulty test data](#) use to test fault detection and isolation.

Appendix D

MPCA source code

The code used to apply the MPCA technique to the data is in the link below:

[MPCA source code](#)

MainScript is the main script that calls all the scripts and functions.

- Training data and test data are loaded to Matlab.
- The input script is then called to get all the inputs for the MPCA model.
- The loaded data are then unfolded and standardised.
- PCA is then applied to the unfolded data.
- Lastly control limits and fault detections and isolation are done.