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Model predictive control monitoring using multivariate statistics

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ABSTRACT

Control loop monitoring has become an important research field over the past decade. Research has primarily targeted single-input single-output (SISO) feedback control systems with limited progress being made on the monitoring of multi-input multi-output (MIMO) control systems and large scale model predictive control (MPC) systems in particular. The size and complexity of MPC systems means that identifying and diagnosing problems with their operation can be challenging. This paper presents an MPC condition monitoring tool based on multivariate statistical process control (MSPC) techniques. The proposed tool uses intuitive charts to enable casual users of MPC technology to detect abnormal controller operation and to identify possible causes for this behaviour. Through its application to data collected from a large scale MPC system, the proposed technique is shown to be able to identify and diagnose poor control performance resulting from various issues including inappropriate interaction by process operators.

1. Introduction

Over the past decade the oil, gas, and chemical manufacturing industries have invested heavily in the implementation of advanced process control (APC) applications, of which the most popular form is model predictive control (MPC). MPC bridges process modelling, control and optimisation to enhance the profitability and stability of process operations. Sustaining the performance of the installed MPC system is usually dependent on various factors that affect their performance. As highlighted in AlGhazzawi et al. [3], the factors found to be most contributing to the poor performance of MPC applications from a practical point of view are:

- Lack of properly trained operators and support personnel.
- Lack of MPC condition monitoring applications.
- Significant process modifications and enhancements.
- Poor controller tuning and inaccurate models.
- Unresolved basic (regulatory and PID) control problems.

To address the above issues, academic researchers, practitioners, and control technology providers have developed a keen interest in monitoring the performance of control applications in general, and the condition monitoring of MPC applications in particular. This effort has resulted in a plethora of publications as well as several commercial tools aimed at monitoring the condition of control system applications.

Interest in control loop monitoring can be traced back to the work of Harris [10] who explained how the performance of a single-loop control system could be compared with what would be achieved if a minimum variance (minvar) controller were applied. It is rarely sensible to implement a minvar controller on an industrial system, however, their anticipated performance does provide a lower bound for the variance of the controlled variable. Harris [10] proposed a statistic, now referred to as the Harris index, which is defined as the ratio of the variance achievable using minvar control to the variance measured under the current control law. As the value of this statistic reduces then so too does the measured performance of the control system. The key advantage of the Harris approach to control loop monitoring is that only routine operating data is required to determine the performance of the control system. This fact has made the approach very attractive to industry and it is now applied as a matter of routine by many companies.

The Harris technique has been investigated and expanded in many studies over the last few years. Desborough and Harris [6], for example, extended the technique to make it suitable for MISO systems. Harris et al. [11] later adapted this work and developed an approach for MIMO systems. Further modifications to the approach have been proposed by Tyler and Morari [33], who accommodated the presence of non-minimum phase zeros and unstable poles in the performance criteria, and Kozub and Garcia [20], who suggested that the controller performance should be compared with the desired first order response of the closed loop system. Arguing that minvar performance is not a realistic goal for an industrial control system, many researchers have proposed alternative performance indices. Ko and Edgar [16], for example,

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adopted a strategy that used a PID controller as the benchmark control performance, whilst Horch and Isaksson [12] proposed a performance index that recognised that it may be desirable for at least one closed loop pole to be located away from the origin.

An overview of recent developments in control performance monitoring for MIMO applications was covered in Qin and Yu [30], where a number of control performance benchmarks other than the popular minimum variance were presented. Due to the nature of some MIMO systems with respect to strong interactions between variables, this work recommended diagnosing control performance relative to a benchmark, and suggested using multivariate statistics to help yield meaningful diagnosis. A case study on an industrial boiler was presented in this paper.

A comprehensive review of the current status of control performance monitoring is presented in Jelali [15]. This paper provides a thorough review of control performance monitoring literature over the past decade as well as a review of the commercially available tools and technologies for control performance monitoring. A set of comprehensive recommendations were also made, based on the current tools and an outline of the future needs in control loop monitoring was presented. In addition, a proposed methodology that combines several assessment benchmarks and methods was proposed. A further review of control monitoring techniques can be found in Huang and Shah [13].

More pertinent to MPC applications, Ko and Edgar [17,18] developed a monitoring scheme that compared the performance of an MPC system to that achievable using constrained minimum variance control. Patwardhan et al. [28] proposed a performance index which compared the cost function of the controller at any given time with the cost function from a period of time when the controller was assumed to be operating well. The fundamental problem with the vast majority of techniques applied to monitor the performance of control loops is that they rely on a measure of the errors between the controlled variables and set-points. However, the majority of industrial MPC systems tend to operate to soft constraint limits for controlled variables rather than set-points and hence there will not be an explicit error measurement for each controlled variable. This means that the techniques that have been proposed for MPC systems are unlikely to be suitable for industrial application.

Moreover, practical aspects of performance assessment of MPC was presented in the work of Agarwal et al. [1] where the relationship among process variability, constraints, and probabilistic economic performance of MPC was investigated. This proposed approach considered the uncertainties induced by the process variability and evaluated the economic performance through probabilistic calculations. Further development of this approach was presented in Agarwal et al. [2], where Bayesian inference was used for decision making in order to tune the constraints to achieve optimal economic MPC performance.

In the work of Xu et al. [36], it was shown that variance based performance assessment could be transferred to assessment of MPC performance. The MPC economic performance is evaluated by solving benefit potentials through either variability reduction of output variables or tuning constraints. Algorithms for MPC performance assessment and tuning guidelines for constraints and variance were developed in this paper using linear matrix inequalities and process data and steady-state gains.

An innovative technique for monitoring MPC performance has been proposed in the work of Loquasto III and Seborg [23]. Principal component analysis (PCA) and distance similarity factors were used to monitor MPC performance, where several PCA pattern classifiers were developed to monitor the control system, and to identify abnormal behaviour. This technique was used to monitor the performance of an MPC controlled Wood–Berry distillation column model. Another approach to monitor MPC performance was presented in Loquasto III and Seborg [24]; as in Loquasto III and Seborg [23], current MPC operation is compared to a simulated database of closed-loop MPC operation. However, in this work, neural network classifiers were used to determine whether or not the controller was exhibiting abnormal performance. The performance of the neural-network based classifiers in monitoring an MPC-controlled Wood–Berry distillation column model were examined for various scenarios including the detection of abnormal operation, model-plant mismatch, and abnormal disturbances.

As a result of the industry requirements for MPC monitoring tools, several leading process automation technology providers have developed tools to help monitor the condition of MPC applications. These systems address the needs of users to ensure that these controllers are functioning properly to ensure tangible benefits are realized from their operation. Examples of commercially available MPC monitoring tools are presented in Table 1.

The above mentioned tools provide MPC support staff with comprehensive information on controllers' performance, effectiveness, model accuracy, as well as a range of performance benchmarks for both the MPC controller and the regulatory or PID control layer. Such tools have contributed greatly over the past few years in ensuring that installed controllers are functioning properly for prolonged periods.

Although these tools provide great insight into the condition of control systems they are primarily aimed at expert users of MPC technology. Such users are typically senior process or control engineers with considerable experience in MPC applications. The information generated from the available monitoring tools focuses on control benchmarks, MPC specific parameters or even frequency domain analysis. Thus despite the benefits obtained from recent monitoring tools, there remains a need for a monitoring tool that would help the front-line users such as control room operators and junior engineers in understanding the MPC application condition without being required to have a thorough understanding of the theory, benchmarks or parameters of MPC technology. Consequently, the specific focus of the work described in this paper was to develop an MPC condition monitoring tool that serves the need for control room operators and casual users of MPC applications. The desired tool should provide users with information beyond the basic service factor, also referred to as up-time, or the primitive on/off indicator. Furthermore, it should draw the user's attention to abnormal behaviour in the controller performance, or possibly any process abnormality. It is worth noting that this tool does not replace the MPC monitoring tools mentioned earlier but rather complements such tools, since MPC technical support staff need the information provided by such tools for in-depth analysis and troubleshooting of controller performance.

In this paper, the ability of multivariate statistical process control (MSPC) techniques to monitor industrial MPC systems is investigated. Intuitive MSPC charts are used to assist plant operators and process engineers in monitoring the controller performance and help detect abnormal behaviour. The proposed technique compares current controller performance with that obtained from an

Table 1
Commercial MPC monitoring tools

Company	Tool	Supported MPC technology	Website
Honeywell	APC Scout®	RMPCT®	www.hps.honeywell.com
Aspen Tech	Aspen Watch®	DMCplus®	www.aspentech.com
Matrikon	Process Doctor®	RMPCT® DMCplus®	www.matrikon.com
Shell – Yokogawa	MDpro®	SMOC®	www.yokogawa.com

MSPC model derived from a data set representing optimum controller performance. This work compares the performance of the two most frequently used MSPC techniques, Principal Component Analysis (PCA) and Partial Least Squares (PLS) in monitoring MPC performance. Recursive techniques are also applied in designing the proposed monitoring tools so that it is able to track the time-varying nature of the process. The results presented in this paper provide an indication of the benefits provided by the proposed tool and the types of control system abnormality that the system is able to detect. Furthermore, many of the practical considerations involved when developing a multivariate statistical monitoring solution for application to an industrial MPC system are addressed. For example, which variables should be included in the analysis and how can time-varying and non-stationary dynamics be catered for in the model?

Although MSPC techniques have been used routinely for the detection of faults and abnormal conditions in industrial studies [25,19], the use of PCA/PLS methods to monitor the condition of an industrial MPC system based on data collected from an industrial process is considered novel.

2. Multivariate statistical process control (MSPC)

MSPC refers to a collection of algorithms that can be used to extract information from large multivariable data sets. Although the algorithms differ considerably, they share the similarity that they typically identify several artificial variables, as linear or nonlinear combinations of the original variables. The benefit that MSPC techniques offer is that in situations where there is a large amount of correlation between the original variables, such as with industrial process data, they can describe most of the information in the data set using a reduced number of artificial variables, which can make analysis of the data set, and process, simpler.

There have been many studies completed over the last few years which have highlighted how MSPC techniques can successfully be used to detect process faults and abnormalities (Kourti, 2005) [19], classify materials and products [26] and more recently be used to regulate complex processes [5]. These studies have tended to focus on two specific MSPC techniques, principal component analysis (PCA) and partial least squares (PLS). These two algorithms are described briefly in the following Sections 2.1 and 2.2. For further details regarding these algorithms, the reader is referred to Jackson [14] for PCA and Geladi and Kowalski [7] for PLS.

2.1. Principal component analysis

PCA is an unsupervised data analysis technique. The approach transforms a matrix containing m observations of n process variables, $\mathbf{Z}$, into a matrix of independent artificial variables, or scores, $\mathbf{t}_k$ (where $k = 1$ to n) of length m. The relationship between the scores and the original matrix, $\mathbf{Z}$ is defined as follows:

$$\mathbf{Z} = \sum_{k=1}^{np<n} \mathbf{t}_k \mathbf{p}_k^{\mathrm{T}} + \mathbf{E} \tag{1}$$

where the $\mathbf{p}_k$vectors, of length n, are known as the loadings. The loadings are equal to the eigenvectors of the data covariance matrix, $\mathbf{Z}^{\mathrm{T}}\mathbf{Z}$. The $\mathbf{t}_k$ and $\mathbf{p}_k$ pairs are ordered so that the first pair captures the largest amount of variation in the data and the last pair captures the least. In situations where there exists significant co-linearity it is generally found that a small number of principal components (np) can account for much of the power, and hence information, in the covariance matrix. The remaining power constitutes the error term $\mathbf{E}$. When Eq. (1) is applied to a single vector of new observations, $\mathbf{z}^{\mathrm{T}}$, the resulting term $\mathbf{e}$ is called the prediction error. There are several methods for determining a suitable value for np. In this work, the approach suggested by Wise and Gallagher [34] was adopted. This approach applies cross validation, with due consideration of the variance explained by the scores, to select an appropriate value for np.

Having identified the PCA model, two monitoring statistics are used to identify abnormal conditions. These abnormal conditions may be identified in the data that is used to develop the model or new data that may be subsequently collected and analysed in real-time. These two statistics, T^2 and SPE, are defined as follows:

$$T^2 = \sum_{k=1}^{np} \mathbf{t}_k \sigma_k^{-2} \mathbf{t}_k^{\mathrm{T}}$$

where σ_k^2 is the variance of the kth t score.

$$\mathrm{SPE} = \|\mathbf{E}\|_2^2$$

Provided any data presented to the PCA model is consistent with the data used to identify the model, then the values of the T^2 and SPE statistics should remain low, and below a statistical threshold limit. Elevated values of these statistics provide an indication of abnormal conditions. Goulding et al. [8] provide further information regarding the use of these statistics to detect and isolate abnormal conditions.

2.2. Partial least squares

PLS is a regression tool that can be applied whenever process variables can be partitioned into cause ($\mathbf{X}$) and effect ($\mathbf{Y}$) values. The method is commonly used in preference to alternative identification algorithms, such as multiple linear regression (MLR) when developing data driven models. Its advantage over these alternative identification algorithms is that it is able to produce accurate and robust models in situations where high levels of correlations exist between the cause variables [7].

The PLS algorithm is similar to PCA and selects factors of cause variables in a sequence which successively maximises the explained covariance between the cause and effect variables. Given a matrix of cause data, $\mathbf{X}$, and effect data, $\mathbf{Y}$, a factor of the cause data, $\mathbf{t}_1$, and effect data, $\mathbf{u}_1$, is evaluated, such that

$$\mathbf{X} = \sum_{k=1}^{np<nx} \mathbf{t}_k \mathbf{p}_k^{\mathrm{T}} + \mathbf{E} \quad \text{and} \quad \mathbf{Y} = \sum_{k=1}^{np<nx} \mathbf{u}_k \mathbf{q}_k^{\mathrm{T}} + \mathbf{F} \tag{2}$$

These equations are referred to as the outer relationships. The score vectors $\mathbf{t}_k$, which are different to those obtained using PCA are mutually orthogonal. These vectors and the $\mathbf{u}_k$ vectors are selected so as to maximise the covariance between each pair, ($\mathbf{t}_k$,$\mathbf{u}_k$). nx is the number of cause variables that are contained within matrix $\mathbf{X}$ and $\mathbf{E}$ and $\mathbf{F}$ are error matrices.

Linear regression is performed between the $\mathbf{t}_k$ and the $\mathbf{u}_k$, to produce the inner relationship, such that

$$\mathbf{u}_k = b_k \mathbf{t}_k + \varepsilon_k \tag{3}$$

where b_k is a regression coefficient, and ε_k refers to the prediction error. The PLS method provides the potential for a regularised model through selecting an appropriate number of scores, or latent variables, $\mathbf{u}_k$ in the model (np). Furthermore, it is often found that a relatively small number of the low-index latent variables can explain the greater part of the variation in both the cause and effect variables. Cross validation can be used to select the necessary number of latent variables.

As with PCA, several univariate statistics can be used to identify when new data is inconsistent with the data that was used to identify the PLS model. In this paper three statistics associated with the PLS algorithm have been used: T^2,SPE$_x$ and SPE$_y$ which are defined as follows:

$$T^2 = \sum_{k=1}^{np} \mathbf{t}_k \sigma_k^{-2} \mathbf{t}_k^T$$

where σ_k^2 is the variance of the kth t-score.

$$\mathrm{SPE}_x = \|\mathbf{E}\|_2^2$$
$$\mathrm{SPE}_y = \|\mathbf{F}\|_2^2$$

The key differences between PLS and PCA are that PLS considers the explicit relationship between cause and effect variables, which is particularly important when considering a multivariable control system. The statistics identified for PLS relate specifically to either the cause or effect variables, which can aid in the isolation of the cause of any abnormality.

3. Methodology

The general approach proposed in this paper for monitoring an industrial MPC system is based on designing a PCA or PLS model that will be used in real-time to identify abnormalities with the controller. The models are based on operating data from periods where the controller was operating in what is believed to be an optimal fashion. The methodology followed in developing the MPC condition monitor in this study involved the following steps:

1. Application design.
2. Data collection and analysis.
3. MPC monitor prototyping and testing.

Although this approach appears relatively straight forward, several issues need to be considered when developing MSPC models for practical industrial applications. These include the following:

- The design objectives and criteria for the monitoring system.
- Type of data used to develop the MSPC model.
- Process and control variables used in the model.
- MSPC technique best suited for the application.
- How can the information provided by the MSPC model be interpreted and what type of information does the model provide?

The following sections describe in detail how the above steps were followed in this study. The approach taken is believed to be relatively generic for developing industrial MPC monitoring systems, and recommendations are presented to deal with the issues associated with designing such an application for a specific industrial process example, which is a condensate fractionation process.

4. The condensate fractionation process description

The process investigated in this study was a condensate fractionation process. Fig. 1 shows a simplified process flow diagram of the process. This process separates a hydrocarbon feed into a mix of products for further processing or product blending. The plant feedstock is a condensate mixture from non-associated gas production that contains various mixtures of petroleum fractions that are separated into various products using the difference in volatility between the feed components by distillation. Process cold feed is pumped through the preheating train to heat the feed up to the required desalting temperature. The plant feed then enters a desalter (not shown in Fig. 1) where salt is removed and the first separation of light fractions occurs. The desalted feed is then fed to a preflash drum where light products and any remaining free water are removed. The preflash drum product is then heated by a set of heat exchangers before entering a preflash distillation column. In this column, feed is distilled into light, medium and heavy products, which are removed from the top, middle, and bottom sections of the column, respectively. Heavy product from the bottom of the preflash distillation column is further heated by two furnaces before entering the main fractionating distillation column. In the main column, feed is distilled into multiple products based on the difference in their boiling temperatures. The distilled products are collected at the column's top, middle, and lower sections and are further processed to produce motor gasoline, kerosene, jet fuel and diesel oils. A key objective of the process is tight control of the main fractionator column product specifications (properties) such as boiling points and flash points while maintaining maximum production rates subject to equipment safety and physical constraints.

This refining process is characterised by its relatively slow dynamics (settling time is around 2 h), large number of process

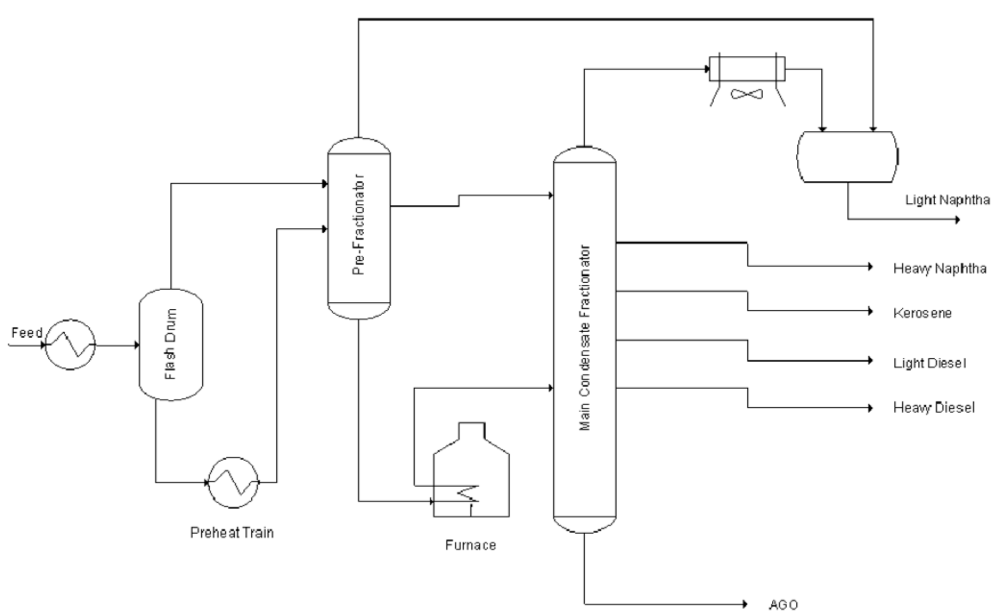

Fig. 1. Simplified flow diagram of the process.

variables, and process interactions. Process interaction not only exists between composition (property) control loops but also between process variables as well. For example, manipulating the process feed, furnace output temperature, or the main fractionator column overhead temperature affects all products composition as well as the production rate of several finished products. The complexity of operating heat integrated distillation processes was investigated in [21] and in [9] where modelling, simulation, and controllability analysis of such processes were investigated.

An important control objective in this process is controlling the composition (specification) of the six products of the process. A key challenge in controlling this process is to ensure all key product specifications are met in the presence of changing process conditions, interaction between various sections of the plant due to heat integration and disturbances, while monitoring a large number of process variables to ensure that the plant is well within its safety limits; in addition, operators have to also operate and monitor the condition of the installed MPC. An installed model predictive controller (MPC) system provides accurate control of critical product specifications, minimises the impact of process disturbances, and drives the process to operate closer to its economic optimum point. Six inferential models (soft-sensors) are implemented in the process to provide timely prediction of critical product specifications (composition) and to enable real-time control of these product specifications. The controller has 30 controlled variables (CV), 17 manipulated variables (MV) and 6 measured disturbance variables (DV), and is considered reasonably large with respect to industrial standards. The key MPC CV are the process feed flow, furnace outlet temperature, and the specifications (composition) of the main fractionator products: medium naphtha 90% boiling point, heavy naphtha 90% boiling point, kerosene flash point, kerosene 90% boiling point, light diesel 90% boiling point, and heavy diesel 90% boiling point. Since on-line analysers are not available to measure these specifications, soft-sensors are used to predict these product specifications at the top of the pre-fractionator distillation column, as well as top and side draw of the main condensate fractionator, these soft-sensors are among the controller CV. Other key CV are product flow rates and valve position of key control valves. Controller MV include feed flow setpoint, furnace outlet temperatures, main fractionator overhead temperature, reflux flows in both distillation columns, recycle flows of side products. Key MV that influence critical CV are mainly the reflux flows and furnace outlet temperatures. An embedded optimiser in the MPC is set to maximise valuable products flows while maintaining the product specifications. As described in Section 4 the measured DV in the process include changes in feed quality, blending flows in between the main fractionator column products, and ambient temperature. A summary of key MPC variables is presented in Table 2.

Table 2
Model predictive controller key variables

Controlled variables (CV)	Manipulated variables (MV)	Disturbance variables (DV)
Process feed flow	Feed flow setpoint,	Feed quality
Furnace outlet temperature	Furnace outlet temperatures,	Blending flow between products
Medium naphtha 90% boiling point	Main fractionator overhead temperature	Ambient temperature
Heavy naphtha 90% boiling point	Reflux flows in both distillation columns	
Kerosene flash point	Recycle flows of side products	
Kerosene 90% boiling point		
Light diesel 90% boiling point		
Product flow rates		
Valve position of key control valves		

5. MPC monitoring tool

This section presents in detail the steps followed during the design of the MPC monitoring tool. The design methodology was based on that presented by AlGhazzawi and Lennox [4] and Miletic et al. [27], however specific guidelines pertinent to the development of MPC monitors are given to assist in the development of industrial MSPC-based MPC monitoring applications.

5.1. Application design

The main objective for this work was to develop a practical condition monitoring tool able to provide timely information on the performance and condition of an industrial MPC system. The developed tool was designed to be used by process operators and engineers to detect and isolate any abnormality in the condition of an installed MPC system so that appropriate action could then be taken. Users of this tool need not be expert users of MPC technology since condition information and possible causes of abnormal operation is shown by intuitive charts.

The proposed MSPC monitor aims to address the following contributing factors to abnormal MPC behaviour; firstly the lack of properly trained operators and support personnel and secondly the lack of MPC condition monitoring applications. Users of the proposed tool should be able to easily detect and isolate abnormal controller condition through basic MSPC charts, namely the Hotelling (T^2), square prediction error (SPE), and contribution charts. The contribution charts will enable the user to identify the root cause of the abnormal MPC behaviour so that appropriate action can be taken. Operators and support personnel would only need to be trained on using the proposed tool and to have a basic understanding of MPC operation. With respect to the second factor, this serves as a high level monitor of the MPC condition, and together with any of the tools shown in Table 1 would form a hierarchical approach for the condition monitoring of MPC systems, where operators can rely on the proposed MSPC tool to detect abnormal behaviour in controller performance, and attempt to resolve the abnormality. However if the problem persists due to a major problem with the controller, then MPC support engineers can rely on the tools in Table 1 to identify the root cause of the abnormal behaviour.

Finally, and most importantly, the tool must be robust to cope with changing process behaviour and routine involvement and intervention of MPC users in the form of temporarily turning off certain CVs or changing setpoints or control limits of MV and CVs.

In summary, the aim of the proposed condition monitoring tool was to

- Identify abnormal MPC conditions and inadequate controller performance.
- Detect any violation of key MPC variables' limits and identify possible cause.
- Assist casual users and plant operators in monitoring the MPC performance.
- Withstand routine changes in controller variables and limits.
- Detect occurrences of loss of controller degrees of freedom or inappropriate CV/MV limits setting.

5.2. Data collection and analysis

Process data is of crucial importance when developing empirical models, and hence data collection and analysis is a major contributor to the success of practical MSPC applications. During this step, process data that represents optimal MPC operation must be collected. The issues that are addressed during this stage are as follows:

1. What is considered optimum controller behaviour?
2. How much data is available?
3. What is the condition of the collected data, and is it suitable for modelling purposes?

In this work, optimum controller performance was defined as periods where:

a. The MPC controller is "ON".
b. Critical CV and MV are active and within their specified targets (ranges or set points). By definition, critical CV/MVs are required to be active at all times as per MPC design.
c. All key control valves are within the controllable range. In this work this means valve opening more than 20% and less than 90%.
d. General process condition is normal, and process operating point is not different from that which the MPC models were developed for

The data set chosen to represent optimum MPC performance will provide the benchmark which controller condition at any given point in time is compared with. This data set will be used to develop the MSPC models to be used for the MPC condition monitor.

Since control valves constitute the final control element in the majority of process control loops, it is important to maintain them within their controllable rage. When a controller is unable to meet a required CV target due to a control valve being fully closed or fully open, the control valves is said to be saturated. Valve saturation affects that available degrees of freedom within an MPC system and it is often recommended that operators relax some of the control targets on certain less critical CVs to provide the controller with more degrees of freedom. Valve saturation periods are often overlooked when collecting process data for modelling

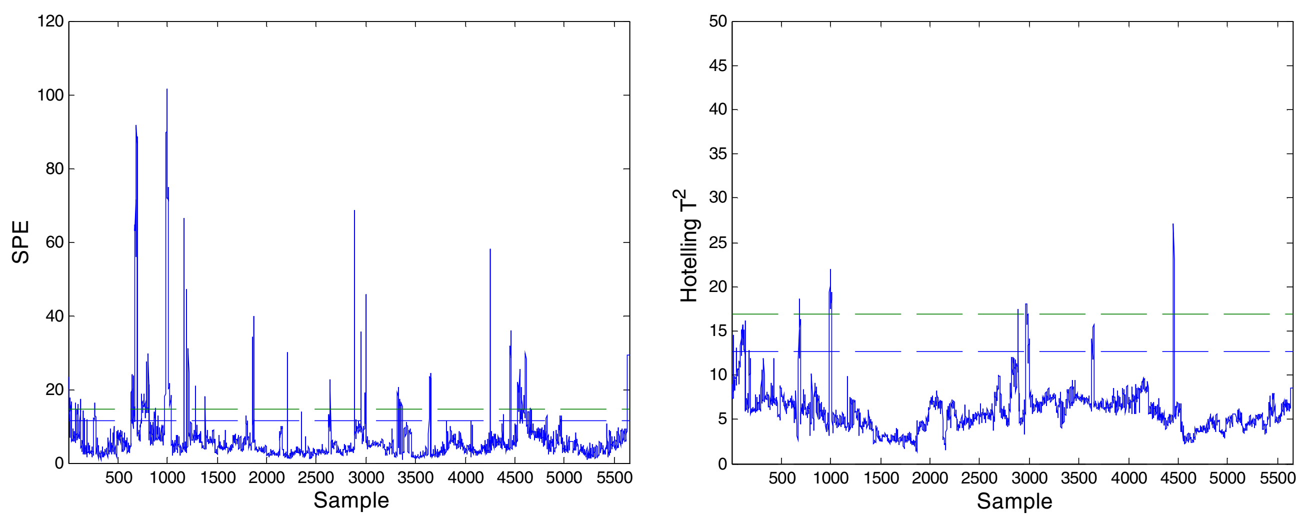

Fig. 2. Static PCA monitoring charts.

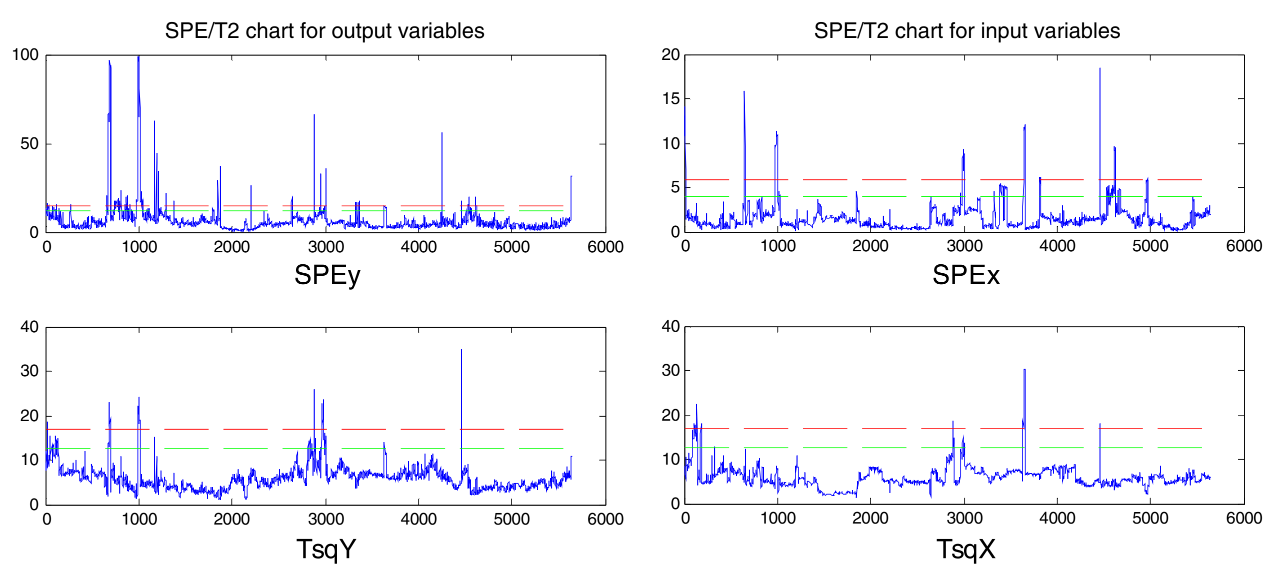

Fig. 3. Static PLS monitoring charts.

or analysis purposes. In this work, periods where control valves were saturated was not included in the modelling data set. Eliminating this data will help the condition monitoring tool to identify periods of valve saturation or loss of degrees of freedom. Another consideration made when identifying optimum MPC performance was to remove sections of collected data when one or more of the controller CVs and MVs were inactive or outside of their upper and lower targets.

MPC is a model-based control algorithm, where models of the process are derived from process testing where key MVs are perturbed to generate step response trends for the CVs. For an MPC system to function properly, it is imperative that controller models are representative of the process, and plant-model mismatch is minimal. To develop an effective MPC condition monitor, the process operating point should not be significantly different from that at the time when the MPC models were developed.

The process data used to develop the MSPC models in this study were collected from an installed data historian. MSPC models were developed from data collected from one year of operation, of which approximately eight months of data represented optimum operation. An issue that often affects data analysis and data-driven modelling techniques is the compression of data in plant historians. Although it is advisable to use uncompressed data when developing empirical models, it is not always possible to collect uncompressed data for extended periods of time. For more details on the effect of data compression and its effect on data driven methods, the reader is referred to Thornhill et al. [32]. The data used in this work was found to be acceptable for modelling purposes as per the guidelines set by Thornhill et al. [32]. As for data cleaning and filtering, the Hampel filter proposed by Pearson [29] was used for outlier detection and data cleaning. AlGhazzawi and Lennox [4] and Miletic et al. [27] provide further information on data processing for MSPC applications and the general approaches suggested in these papers were followed in this study.

5.3. MPC monitor prototype and testing

Once the design objectives were set, and modelling data had been collected and analysed, a prototype for the proposed MPC monitor was developed using static PCA and PLS models to evaluate their ability in tracking process conditions and identifying significant abnormalities and excursions. Control limits for both the SPE and T^2 charts are typically examined in this step so that appropriate levels can be specified to ensure that only significant abnormalities exceed these limits. To gain a better understanding of the data, static PCA and PLS models were initially developed using the

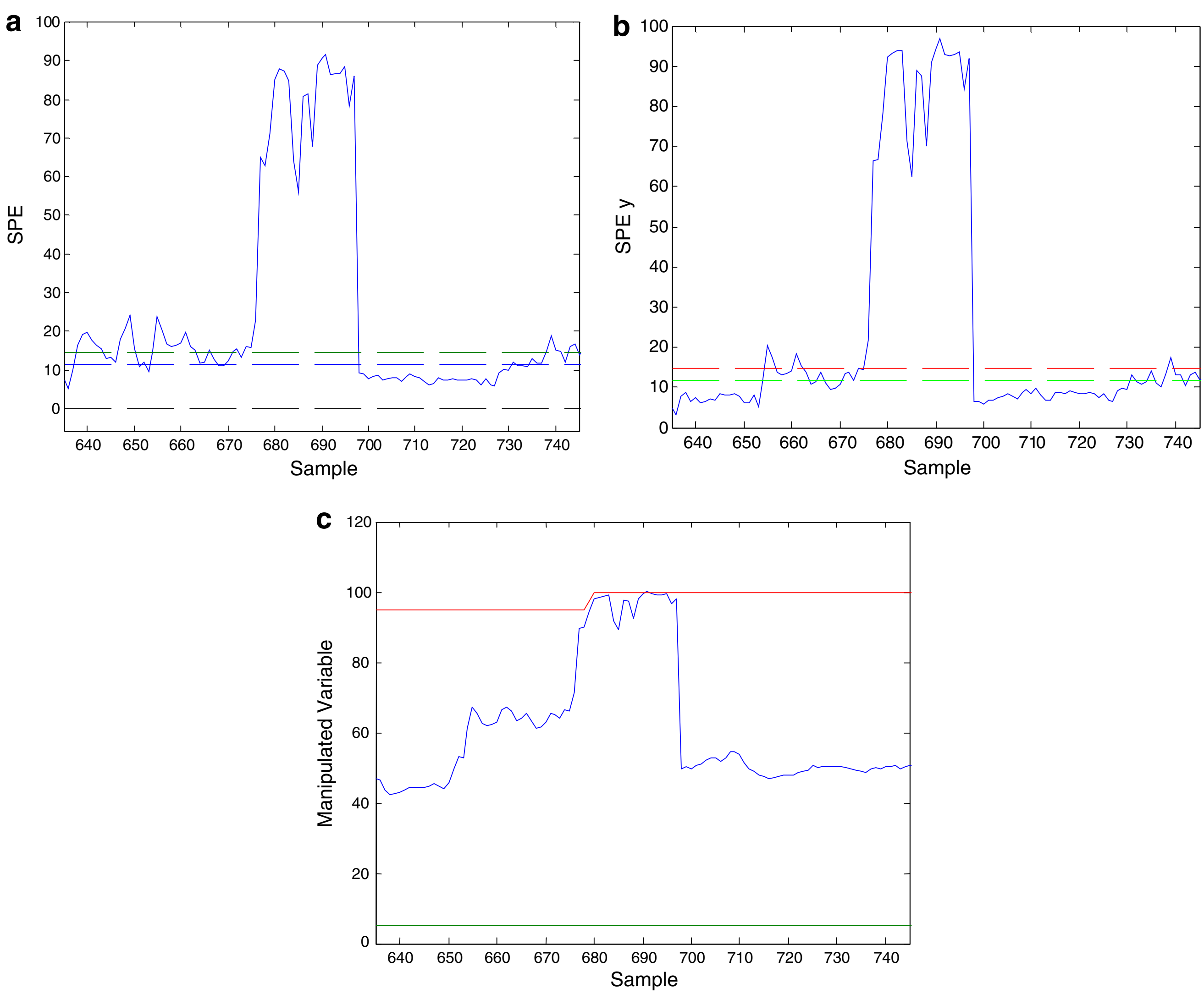

Fig. 4. Abnormal condition from valve saturation (a) PCA SPE chart, (b) PLS Output variables SPE chart, (c) valve output raw data.

full processed dataset. Figs. 2 and 3 show the T^2 and SPE of the PCA and PLS models, respectively. Both PCA and PLS models were developed with six principal components (latent variables) that helped explain 85% of the variability for PCA models, and for PLS models explained 90% and 78% of the variability of the input and output variables, respectively. The models used all MPC variables including the inferential estimates (soft-sensors) that were included in the controller. Tests were conducted to analyse the effects of removing any of these variables. By removing the measured disturbances, the developed monitor was found to be slightly more sensitive to issues relating to the control system itself, however, overall using all the variables was found to produce the most robust and useful monitoring system. The sample time was taken to be 60 min.

6. Results

This Section presents the results of the MPC condition monitor using both PCA and PLS models. In this study, eight months of operating data were used to develop the MSPC models and analyse the controller performance. During this period, the MPC controller was modified. In this modification several soft-sensors were updated and a number of the controller models were improved. Data was collected after its revamp and these data were used to test the ability of the condition monitoring tool to cope with such changes.

6.1. Static PCA/PLS models

The optimal operating data was used to develop static PCA and PLS models using the algorithms and equations presented in Section 2. Figs. 2 and 3 show the T^2 and SPE charts produced when this data were passed through the identified PCA and PLS models, respectively. Both models were tested for their ability to effectively monitor the condition of the MPC system. Key areas of interest were the ability of the developed MSPC models to detect abnormalities such as poor control performance and unmeasured disturbances.

The charts shown in Figs. 2 and 3 display a number of violations of the T^2 and SPE control limits, which were set at 90% and 95% confidence levels. For example, the violation around sample point 690 is shown in detail in Fig. 4. This upset was clearly reflected in both the PCA and PLS SPE charts. The contribution charts for this time instant highlighted that a saturated control valve was responsible for this abnormality. The raw measurement for the control valve is shown in Fig. 4c which clearly shows that the valve was saturated at the sample point analysed. The MSPC monitor was

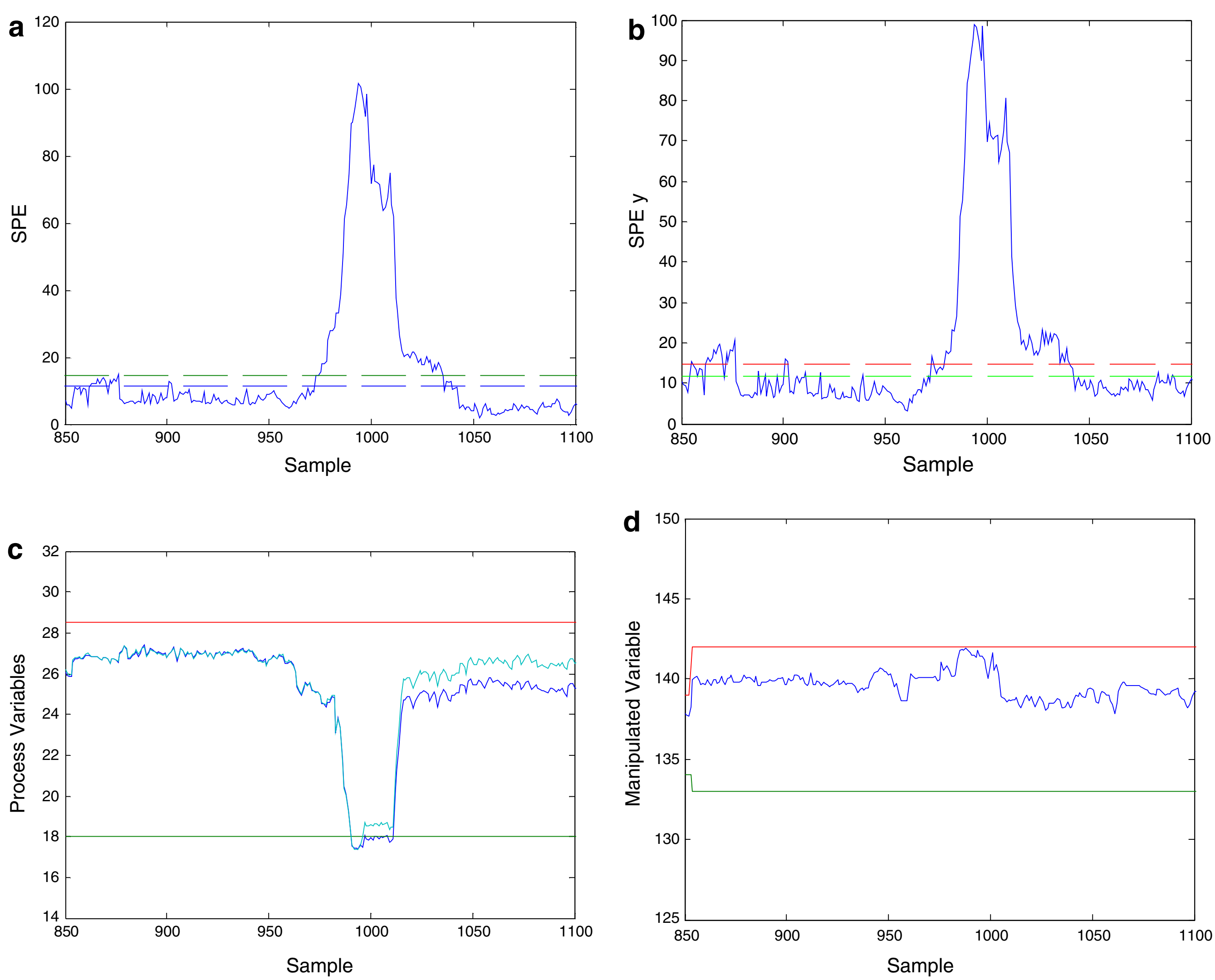

Fig. 5. Abnormal condition from process disturbance (a) PCA SPE chart, (b) PLS Output variables SPE chart, (c) raw data for variables causing abnormality, (d) raw data for MV controlling the variables in (c).

able to successfully identify the abnormality as well as isolate the cause, and thus could have helped operators address the problem upon its occurrence.

Another abnormality highlighted by the condition monitoring application was at sample number 1000. As shown in Fig. 5, a clear excursion of both the PCA and PLS output (effect) variable SPE

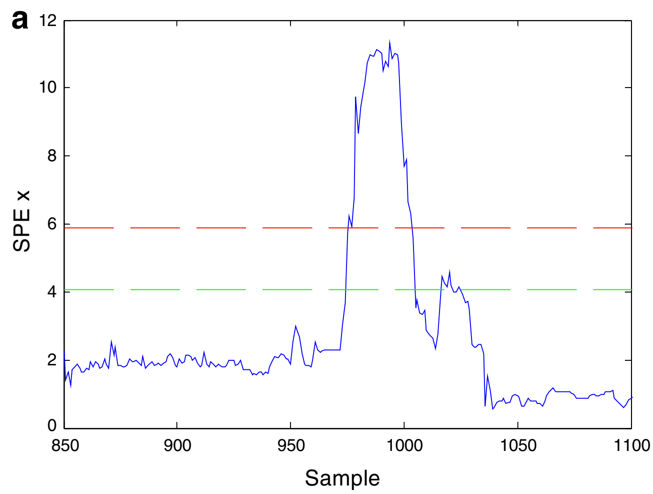

Fig. 6. Abnormal condition from controller MV (a) PLS input variables SPE chart, (b) raw data of MV with upper and lower limits.

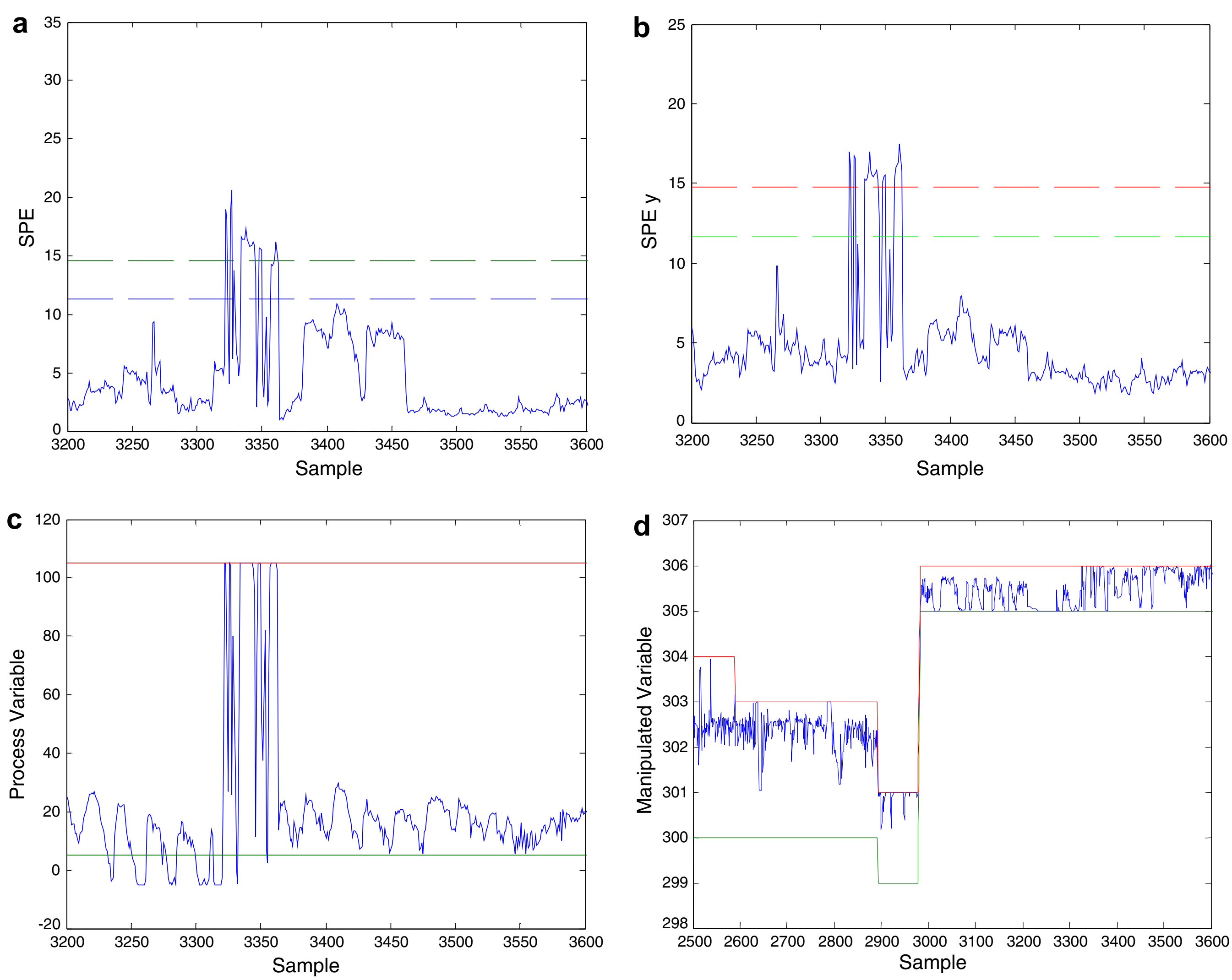

Fig. 7. Abnormal condition from poor control performance (a) PCA SPE chart, (b) PLS output variables SPE chart, (c) raw data for variable causing abnormality, (d) raw data for MV controlling the variables in (c).

occurs at this sample point. Contribution charts highlighted two CVs responsible for this abnormal condition. Fig. 5c shows the raw measurement of both these variables along with their lower and upper targets. The MV that was used to control the flow of both CVs, displayed in Fig. 5d, shows no abnormal movement at sample number 1000, and hence this upset was likely the result of an external disturbance upstream of the fractionation process that affected the flow of both variables. A likely cause of this was a drop in the supply line of these two flows. Early detection of this abnormality can help operators to provide appropriate measures through manual control or appropriate adjustments to MPC targets to compensate for this disturbance. Another non-related abnormality at approximately sample number 1000 was shown in the input (cause) variables SPE chart, Fig. 6. Analysis of the raw data of the contributing variable, which is shown in Fig. 6b, identifies an unusual behaviour with this MV, where it abruptly changes between its higher and lower limits. Although this is not an abnormal condition per say, it is not typical in this particular process to have an MV switch suddenly from one production target to another.

Fig. 7 shows an interesting observation recorded by both PCA and PLS charts between sample numbers 3300 and 3400. Examining the raw data for the CV contributing to this anomaly showed poor control behaviour for this valve output as shown in Fig. 7c. When the raw data and limits of the MV controlling this valve were analysed, it was evident that the reason for this poor control behaviour could be attributed to the pinched limits that the operators have set for the MV. Fig. 7d shows that the MV limits during the upset period were reduced to ±1 °C as opposed to the required ±3–4 °C range that is recommended and typically applied for this variable.

The results above have shown that PCA and PLS offer great potential for developing tools to monitor the behaviour of industrial MPC controllers. The developed prototype using static MSPC models was able to identify MPC abnormalities caused by disturbances, valve saturation and poor control performance due to the operators specifying inappropriate limits. In the following section the benefits offered in using a recursive condition monitor are detailed.

6.2. Recursive PCA/PLS modelling

This section describes the development and testing of recursive PCA/PLS models to the control monitoring system. It was anticipated that the recursive models would enable the monitoring tool to track processes that are time-varying and non-stationary, such

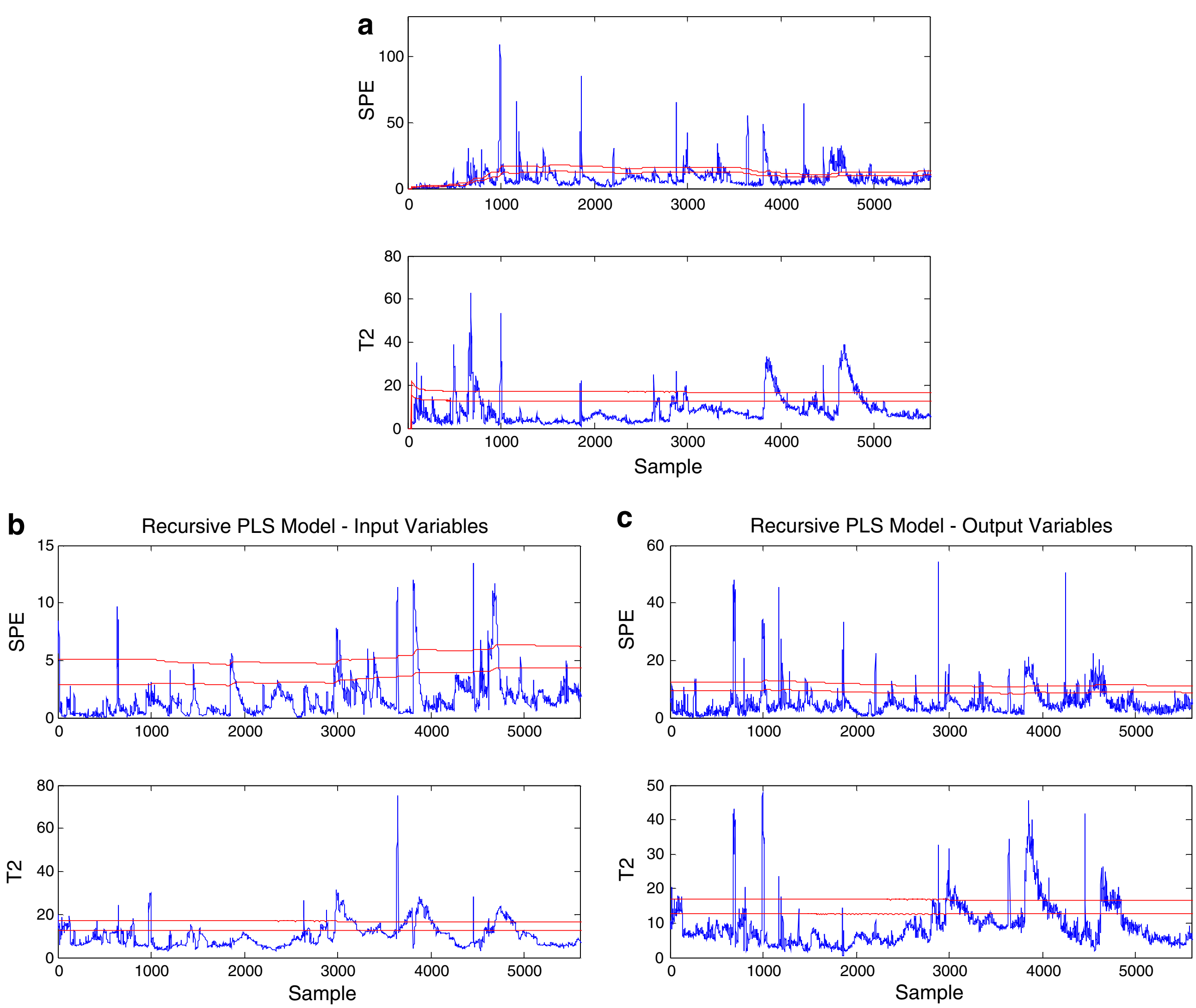

Fig. 8. Recursive models monitoring charts (a) recursive PCA T^2 and SPE charts, (b) recursive PLS input variables T^2 and SPE charts, (c) recursive PLS output variables T^2 and SPE charts.

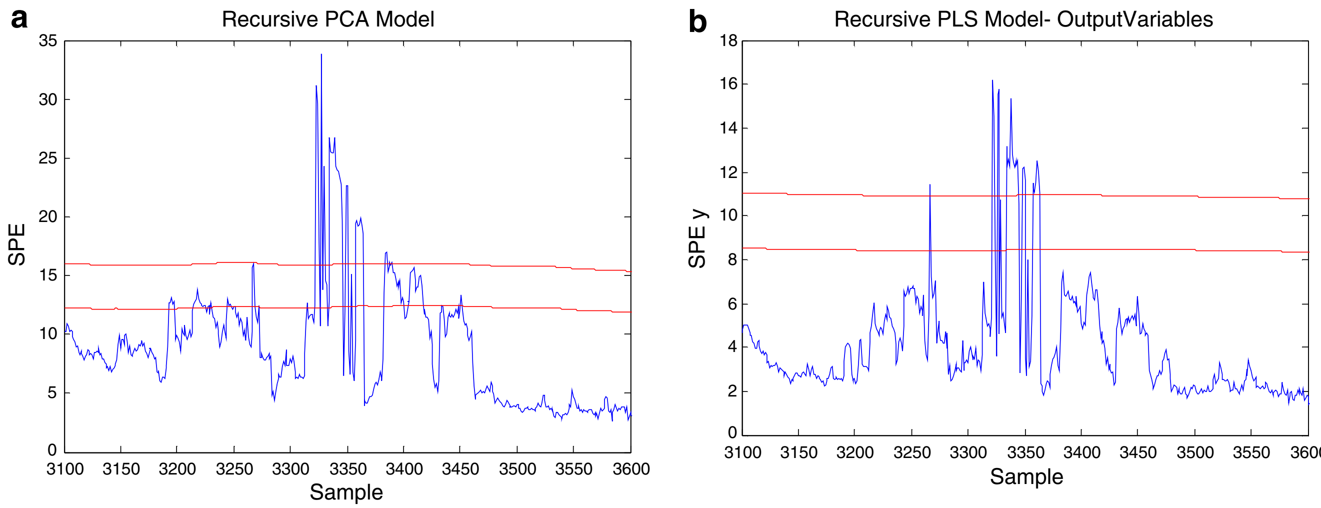

Fig. 9. Recursive models monitoring charts for poor control performance (a) recursive PCA SPE chart, (b) recursive PLS Output variables SPE charts.

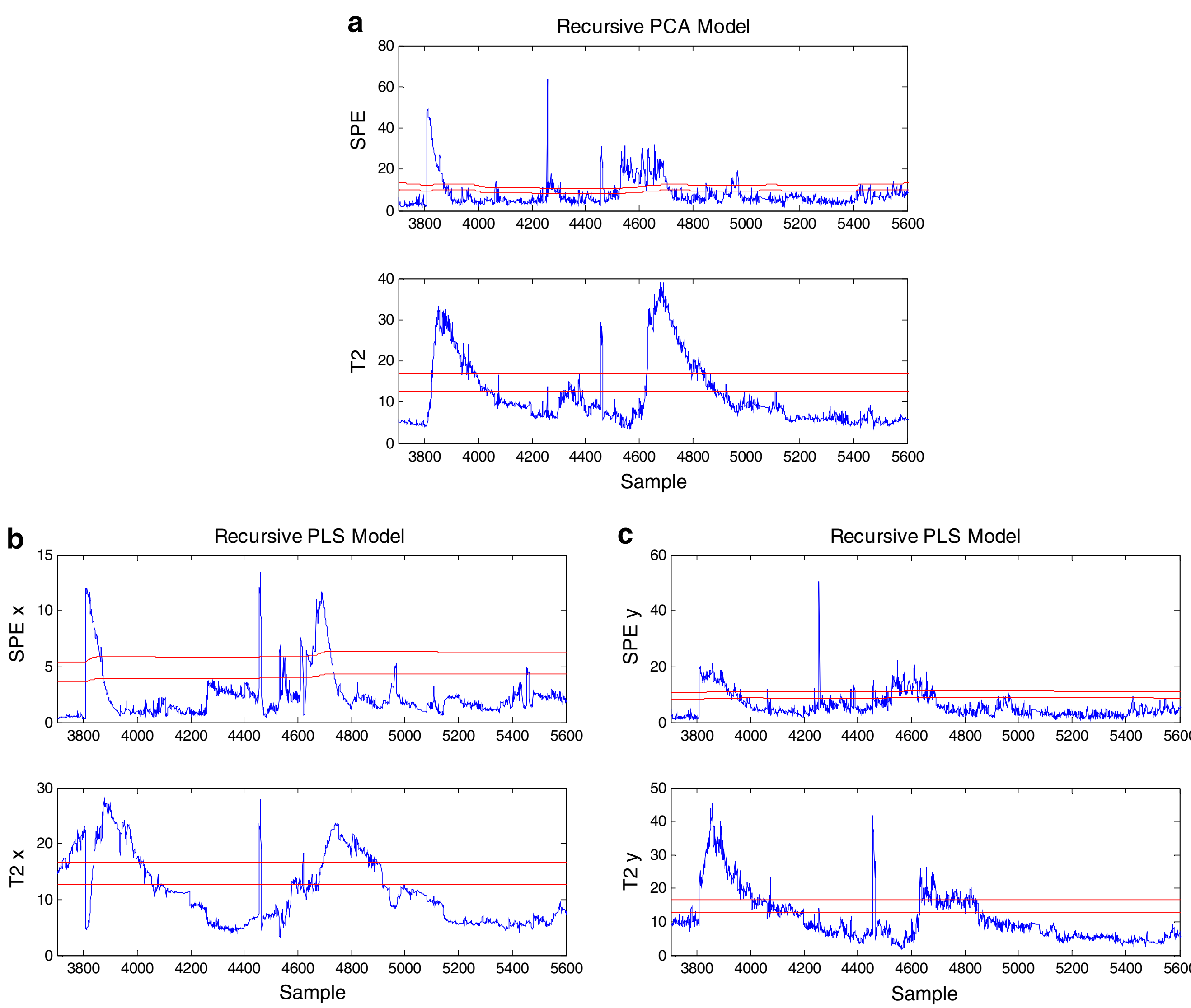

Fig. 10. Recursive models monitoring charts (a) recursive PCA T^2 and SPE charts, (b) recursive PLS input variables T^2 and SPE charts, (c) recursive PLS output variables T^2 and SPE charts.

as the condensate process under test. Furthermore, the recursive models performance was tested for its ability to handle changes in controller configuration. In the data set used in this study, a period where several changes to the controller tuning parameters were made as well as major changes in three soft-sensors, which were defined as CVs in the MPC system. All three soft-sensors are critical controller variables representing key product specifications. Several recursive MSPC algorithms have been proposed in the literature in recent years to cater for the time varying nature of many process systems [35,22]. In this paper a relatively simple approach to recursive MSPC was applied, which identified a new PCA model at each sampling instant using a moving window of process data. For the recursive PLS modelling, the approach proposed by Qin [31] was employed. Similar to the recursive PCA algorithm, this method involved updating the PLS coefficients using a moving window of data at each sampling instant. The window size selected in this study was 3000, which represented around four months of operating data. The selection was made based on considerations of process modes of operation and is thought to be consistent with the rate at which the feed stock and other disturbances to the process occur.

Fig. 8 shows the T^2 and SPE charts for the recursive PCA and PLS (RPCA/RPLS) models. Similar to the results from the static PCA/PLS models, both RPCA and RPLS were able to identify the poor control behaviour between samples 3300 and 3400 in Fig. 9. The abnormality was clearly shown in both RPCA and RPLS output variables SPE charts, and the same contributing variable were highlighted by both models. All major excursions identified in the static models developed in the previous section were identified also by the recursive technique. Two major abnormalities however in the recursive models were highlighted that were not clearly visible in the static models at approximately samples numbers 3900 and 4700; Fig. 10 shows the RPCA/RPLS T^2 and SPE charts around these two segments of the MPC operating data.

The process abnormality shown in Fig. 10 at approximately sample number 3900 is attributed to the portion of data representing the period where the MPC controller was revamped by changing a number of tuning parameters as well as adjustment the coefficients and models of three of the soft-sensors. The changes in the soft-sensors are shown in Fig. 11, where it is shown that for the first sensor, the magnitude of change is considerable since the sensor was reconfigured to predict a different product property from the one previously computed. The tuning parameter changes primarily affects the controller dynamic performance and is unlikely to contribute to the steady state analysis shown here. The charts shown in Fig. 10 shows that despite the changed made in the controller configuration the recursive models have adapted quickly to this new data.

An interesting observation from the recursive results was noted at sample number 4690, where a clear abnormality was detected

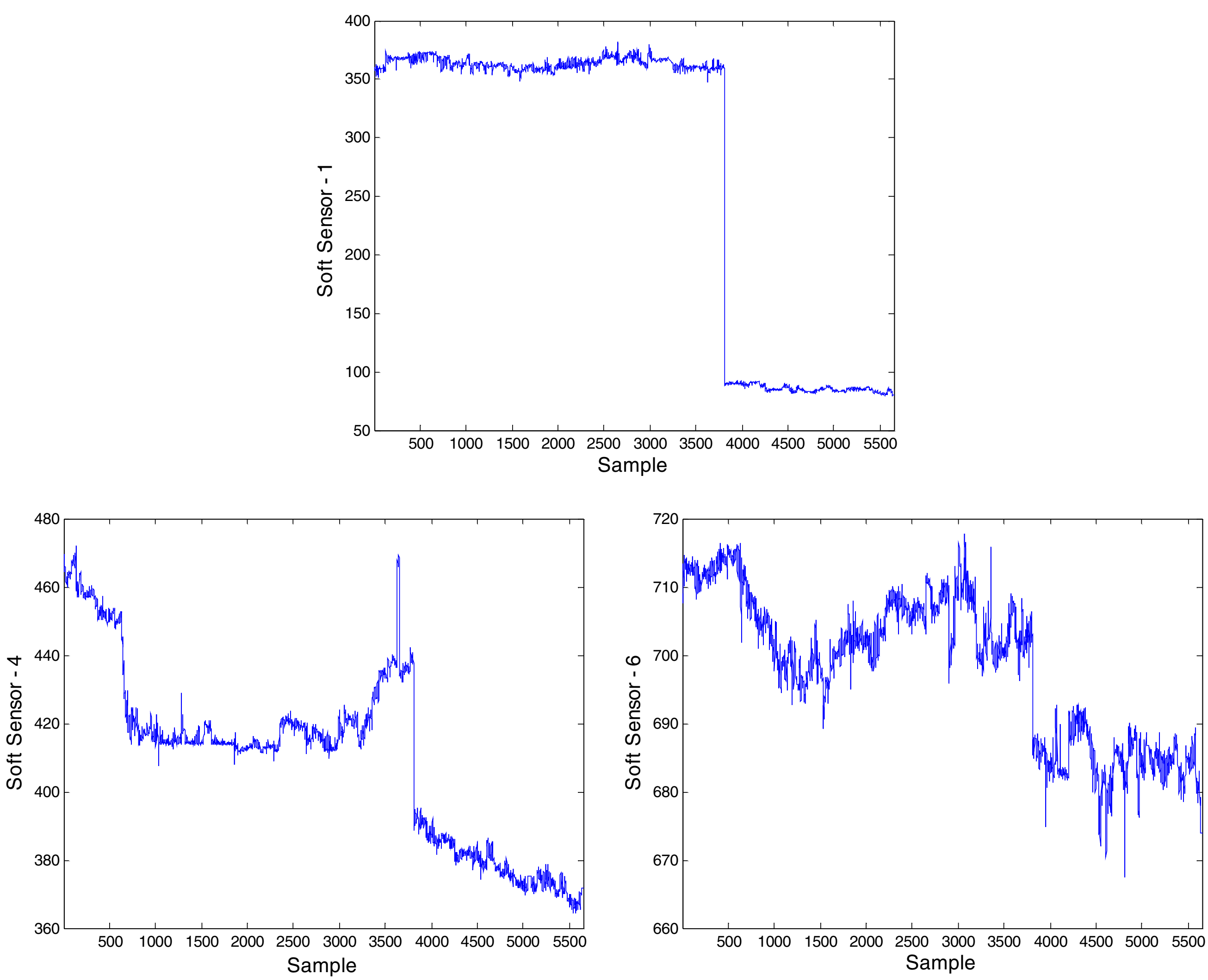

Fig. 11. Soft-sensors raw data.

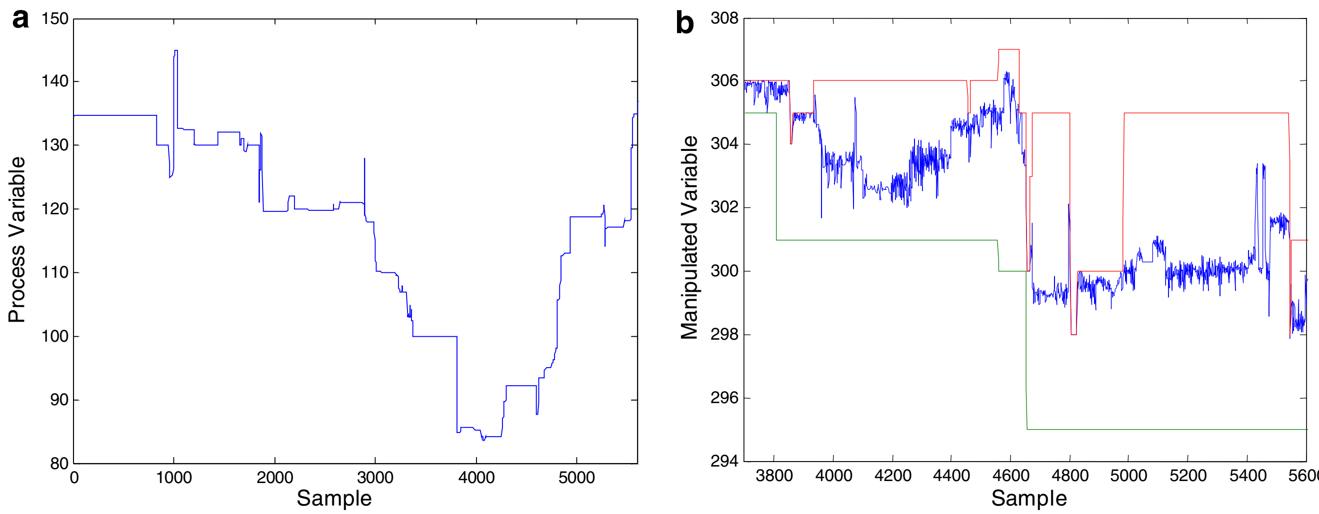

Fig. 12. Contributing process variables to the abnormality in RPLS input variables charts at Sample 4690 (a) raw data for process variable most contributing to the abnormality, (b) raw data for process data for another contributing variable.

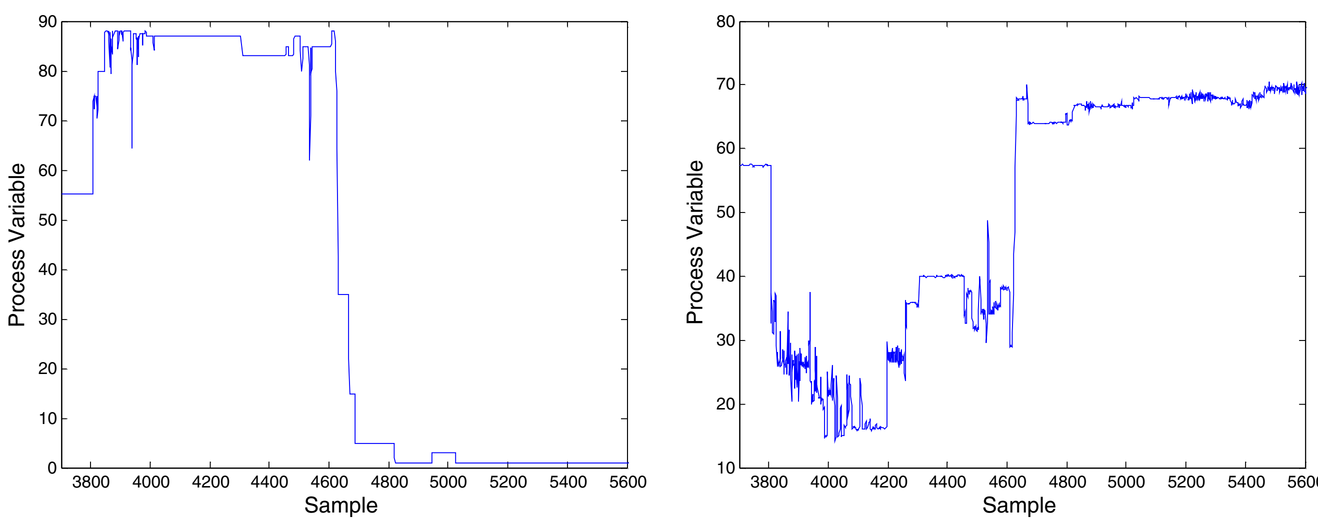

Fig. 13. Contributing process variables to the abnormality in RPCA charts at sample 4750.

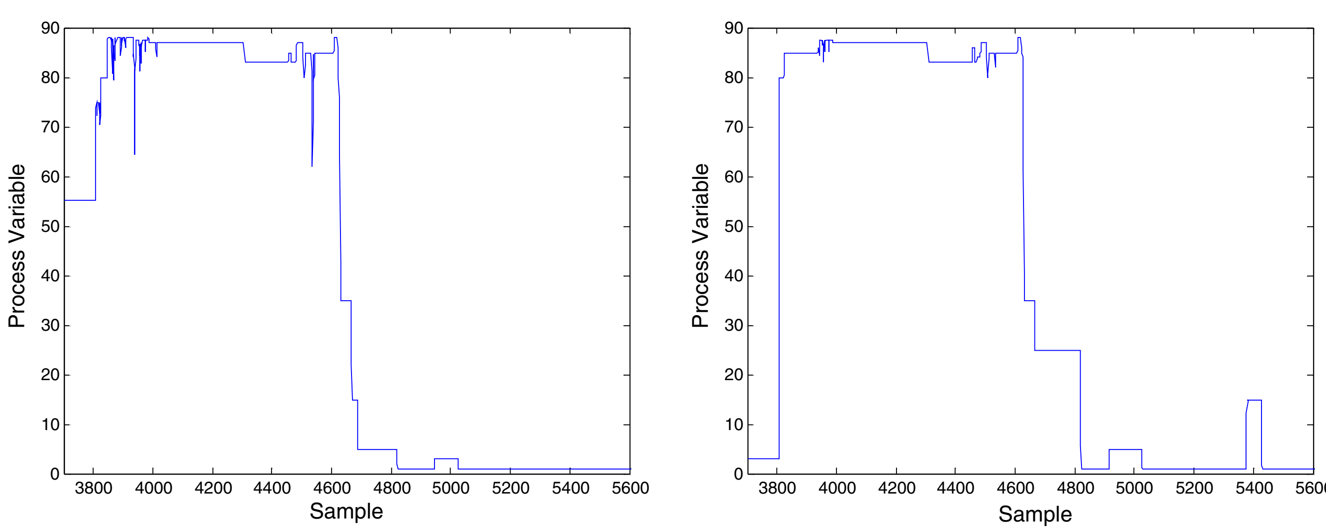

Fig. 14. Contributing process variables to the abnormality in RPLS charts at sample 4750.

by the RPLS input variables SPE charts, as seen in Fig. 10b. The contribution charts during this period revealed that the variables shown in Fig. 12 are the primary contributors to the SPE limit violations. Although there is nothing peculiar about the raw data of the process variable shown in Fig. 12a, other than it appearing to be at the lowest operating point of the eight months periods, the main contributor of the abnormality was in fact the variable displayed in Fig. 12b which is shown with its upper and lower control limits. The identified variable was a controller MV that had been restricted from moving by closing the upper and lower limits, thus clamping the variable from moving freely to control its relevant CV. It is shown in the figure that operators eventually took notice and relaxed the limits on this variable. This result showed that in this particular case, RPLS gave better information to isolate the cause of the abnormality.

Finally, the abnormality at sample 4750, identified by both RPCA and RPLS charts was investigated. The RPCA charts contribution plots identified the variable displayed in Fig. 13, which shows one variable moving to a lower than normal operating point, while the other variable is moving to a higher operating point. One of the contributing variables was also identified by the RPLS contribution charts as shown in Fig. 14.

The use of recursive MSPC models was studied in this section, and showed potential for practical applications involving time-varying processes, and presence of MPC design changes. Furthermore, results in this section showed an example where RPLS gave more information on the cause of a process abnormality, while in all other cases, both techniques gave comparable results.

7. Conclusion

This paper presented results from a comprehensive study on the use of MSPC methods, namely PCA and PLS in developing MPC condition monitoring applications for practical applications involving industrial MPC systems. Results from both static and recursive PCA/PLS techniques showed that MSPC methods offer great potential for developing effective MPC condition monitoring tools that would help casual users monitor the performance of MPC systems and take appropriate actions to resolve abnormalities when necessary. The developed static and recursive techniques use intuitive user friendly charts to help users quickly identify any process anomaly and isolate probable causes. The developed tool complements current commercially available MPC condition tools that assist expert MPC users and support engineers in diagnosing more complex MPC abnormalities.

Results from this study showed that the developed prototypes were able to identify abnormalities attributed to poor control performance, process upsets and disturbances, as well as inappropriate interference from process operators. Both PCA and PLS models gave comparable results, however in at least one case, PLS helped identify the root cause of an abnormal condition more clearly. The use of recursive PCA/PLS models highlighted the benefits that these techniques offer with their ability to withstand time-varying processes and MPC changes; which will significantly enhance the robustness of the condition monitoring tool in a practical application.

On a final note, although the developed tool helped identify abnormalities and possible causes, it was evident that process knowledge and experience is necessary to analyse MPC or process abnormality.

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