# Design and Implementation of a Process Monitoring System in a Just in time PIMS Platform

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Abstract: Process monitoring in complex multivariate systems is challenging due to numerous influencing factors, making it difficult to track process specifications or expected error rates. These systems often exhibit non-stationary behavior and operational modes with constant changes in key performance variables, complicating the use of Multivariate Statistical Process Control (MSPC) techniques, which require process stationarity. Here it's proposed a methodology for designing PCA, $T^2$, SPE, and combined index control charts to handle small mean fluctuations. The methodology considers the quasi-stationary mean and variance estimated from typical operating data for each set point or operating region, enabling distinct designs for each. A first-order filter with a slow time constant estimates the mean of non-stationary process variables, allowing work with residuals that reflect true common-cause variability. The implementation of this methodology in a commercial PIMS platform for real-time monitoring of a thermoelectric power plant is discussed. Experimental results show that the control charts perform better during the monitoring phase, frequently alarming in the presence of special causes.

*Keywords*: Multivariate Statistical Process Control; Process Monitoring; PCA-Principal Component Analysis; Hotelling's $T^2$ Control Chart; Thermoelectric Power Plant; PIMS Platform.

## 1. INTRODUCTION

World Class Manufacturing demands new perspectives on product quality and just-in-time production. Key features include performance measurements and process monitoring for agile problem detection and continuous improvement. There is a strong demand for automated tools to support industrial plant maintenance and operation, maximizing performance and minimizing air pollution. Monitoring systems should detect both common and special causes of process variation.

Monitoring systems have been referred in the literature as *industrial process monitoring* and, when based on data-driven techniques, *statistical process monitoring* (Sousa et all. 2015, Mason and Young 2002, Qin 2012). However, some researchers have been nominating systems with specific monitoring functionalities and applications, e.g. structural health monitoring (Kullaa 2011) and machine health monitoring (Li and He 2012) as *health monitoring system*, as a healthy system is the one whose operating conditions closely matches expectations, or usual behavior. The ability to monitor the health of an entire system, using adequate techniques, can help operating and maintenance teams to know about changes detected in process behavior in relation to the usual and expected behavior, indicating a performance degradation or an increasing possibility of faults.

Statistical techniques, based on process operation data, have rich information about process operation conditions. This approach has been investigated and significant results have been published, (R. L. Mason and J. C. Young 2002, S. J. Qin 2012). Based on PCA and Hotelling's $T^2$chart, Zhu and Braatz (2014) propose the application of a two-dimensional contribution map for identifying faults in multivariate process and obtained positive results with the application over Tennessee Eastman Process data. Qin (2016) discusses the use of Hotelling's $T^2$ chart together with PCA and other multivariate methods for detection, identification, and diagnosis of faults. Hu et al (2014) present an adaptive fault detection scheme based on recursive PCA, while Alkaya and Eker (2011) propose a PCA method based on a variance sensitive adaptive threshold to overcome false alarms during the transient states according to changes in process conditions.

However, some processes have specific operating conditions with variations in key variable set points, limiting the straightforward application of classical statistical process control schemes that require process-wide stationarity (Mason and Young 2002). Additionally, faults or degradation in components and systems can simultaneously impact multiple

process variables. Therefore, a scheme that can handle a set of variables concurrently, considering their correlations and non-stationary trends, is essential.

Given that process variables are dynamic and often feedback-controlled, residual variations can cause the process means to fluctuate within a specific operating region, leading to non-stationary conditions due to autocorrelations. To monitor such processes, MSPC techniques that handle multiple set points and small mean fluctuations are proposed. These techniques aim to determine if the process is operating normally or to detect abnormal conditions, distinguishing them from intentional or expected changes.

However, addressing non-stationarity only during monitoring is insufficient. Ignoring small mean fluctuations during the design phase results in an overestimated variance, as low-frequency variations are included. Therefore, it is suggested to model these mean fluctuations dynamically, using a first-order filter, for instance, to obtain residuals that reflect the true data variance for designing PCA and multivariate control charts. The use of PCA combined with $T^2$ charts is analyzed under both fixed and moving average conditions. This comprehensive methodology for designing and monitoring processes with multiple set points and quasi-stationary means is illustrated with a case study of a boiler in a thermoelectric power plant.

Additionally, it is essential to use industrial-grade hardware and software infrastructure with robust and efficient implementation to run applications online. This setup provides real-time health information for the entire system, enabling timely operational and maintenance actions. The implementation of the monitoring system, using the proposed methodology, on a commercial PIMS platform is also presented. The primary objective is to detect changes in the operational conditions of the boiler unit, which is critical for the power plant due to its significant impact on overall performance. It is also desirable to assist in fault tracking using the PCA technique.

The three-step MSPC-PCA methodology, capable of handling multiple operating set points and mean fluctuations, including the design step, is discussed in section 2. Section 3 covers the monitoring system implementation on the PIMS platform. Section 4 discusses an experimental case study applying the proposed methodology to the boiler unit of a thermoelectric power plant. Finally, section 5 presents concluding remarks.

## 2. MSPC-PCA METHODOLOGY FOR STEPWISE SETPOINT AND MOVING AVERAGE

The MSPC-PCA methodology that deals with nonstationarity and stepwise quasi-stationarity conditions consists of three steps: (i) data pre-filtering, fixing of gap samples and selection of design data set assumed as reference or nominal; (ii) computation of principal components and design of the Hotelling's $T^2$ chart and (iii) design validation by monitoring a test data set. The following subsections detail these procedures.

### 2.1 Primary Data Treatment and Design Data Set Selection

The first step of the design is to verify data files and data set consistency. The data set must be scanned to remove outliers, fix data gaps and remove sporadic fault message codes. The Hotelling's $T^2$ chart design requires regular sample intervals, and the data used in this work was obtained from a PIMS (Process Information Management System) with a sample rate of 1 Hz. After pre-filtering and sample time regularization, the main variables of interest for each unit, according to a consensus of opinions of operators and process engineers, are plotted and decimated after proper antialiasing filtering. A trial-and-error interactive approach is used with visual inspection of the plotted data to reduce the number of samples, without degrading dominant dynamics and pertinent (e.g. operator commands) abrupt changes. The data decimation is important to setup an adequate statistical control horizon for a given process dynamics allowing a mitigation of excessive alarm rates with the control chart in the monitoring stage. Following the decimation step, a visual inspection is carried out to determine segments of the main variables that represent distinct operating points. Operators and process engineers are called to classify the operating points as reference or nominal operating conditions. As an example from a case study, four operating points for the overheated steam flow rate were identified and they are shown in section 3, Figure 4. The variable Overheated Steam flowrate was established as a main variable of interest in the boiler unit since the boiler is set up to produce steam with the least cost and consumption of fuel.

### 2.2 On designing MSPC-PCA charts.

The traditional multivariate control charts do not account for autocorrelation and assume that the processes are serially independent. But, in fact, there are fluctuations on process variables means, as they are dynamic. The proposed methodology calculates the moving average present on this data using a first order filter model, to obtain a sequence of residues that represents the real data variance for the design of PCA and the control charts limits, as shown on Figure 1.

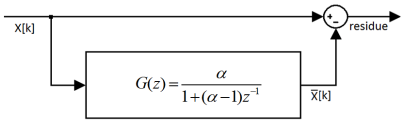


Figure 1: Online Residue calculation of process data.

The design step of the PCA and T2 control charts, as well of the SPE and combined index charts, considers data obtained from an in-control process to calculate the means vector ($\bar{\boldsymbol{X}}$) and the covariance matrix (S), compute the principal components, obtain the eigenvectors matrix (U), define the number of retained components (k) and, finally, calculate the control limits for T2 charts. The design of traditional T2 control charts assumes that data are normally distributed [4]. This assumption has limited the use of T2 control charts in non-normal situations found in many systems, as the case of a boiler and a turbine-generator.

A segment of active power data is shown in Figure **2** (a) and (b), with fixed and moving average calculations, for the use in PCA and control charts design. It's possible to observe the presence of small mean fluctuations, showing that the average is not fixed. The standard deviations calculated for the residues of this segment confirms that using residues of moving average

allows more appropriate design of the control limits for the control charts.

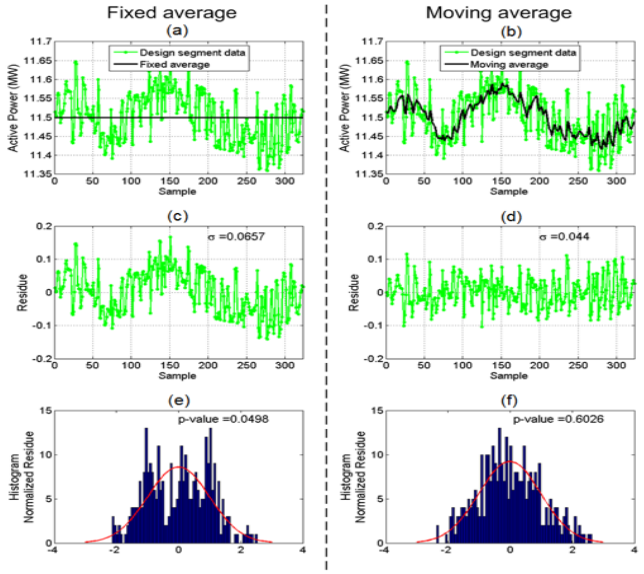


Figure 2: Active power with fixed and moving average. Residues and Histogram for both conditions.

Another segment of active power data is shown in Figure **2** (c) and (d), with residues calculated using fixed and moving average respectively. It also shows a histogram for both situations, from which it is possible to understand the effect of using moving average to obtain the residues: the data set approach closely a normal distribution. Figure **2** (e) clearly illustrates that the residue considering a fixed mean in not a good normal distribution, but Figure 2 (f) nicely fits a normal distribution when the moving average is considered. The Kolmogorov-Smirnov test for Gaussian data resulted in a *p*-value of 0.6026, with a significance level of 5% for this last case. Therefore, designing control charts using residues from moving average guarantees the assumption of data normality in this case and provides better adjusted control limits.

Following the calculation of the residues with moving average for all process variables considered, their residues are normalized using the respective standard deviation for each segment, transforming them into variables with zero mean and unit standard deviation. Normalized variables are crucial for PCA analysis since scale differences can obscure relative variability contribution in a multivariate system.

2.3 Principal Component Analysis, Hotelling's T² Chart, SPE and Combined index charts Project

Monitoring with Hotelling's $T^2$ is based on representing information from a set of correlated variables in a single statistical index, the $T^2$. This index is calculated by Sousa et all (2015) where $\bar{\boldsymbol{X}}$ and $\boldsymbol{S}$ are the vector of means and the estimation of the covariance matrix of the process in state of statistical control, respectively. $\boldsymbol{X}$ is the sample vector with unit observations.

$$T^2 = (\boldsymbol{X} - \bar{\boldsymbol{X}})' \boldsymbol{S}^{-1} (\boldsymbol{X} - \bar{\boldsymbol{X}}) \qquad (1)$$

As the efficiency of this multivariate method decreases with an increasing number of variables (Montgomery, 2009), changes in the means vector can become diluted in a p-dimensional space. PCA is often used to reduce the variable space, generating uncorrelated principal components without significant information loss. The main components typically contain most of the total data variability, allowing the application of T² over the k retained components to represent a metric for the system's global performance, where k < p (Mason and Young, 2002). Monitoring this metric at each sampling period of relevant process variables aims to detect possible system changes, indicated by points plotted over the control limit of Hotelling's T² chart. Additionally, each coefficient in a principal component's computation is proportional to the influence of the corresponding variable. This aspect of PCA aids in fault identification and diagnosis, as identifying the scores with greater influence on the alarm indicates which variables likely caused the process to shift to an undesirable state. The score vector $\boldsymbol{z}$ of principal components for a multivariate sample of $p$ variables, $\boldsymbol{X}$, is calculated as:

$$\boldsymbol{z} = \boldsymbol{U}'\boldsymbol{X}, \qquad (2)$$

where $\boldsymbol{U}$ is a matrix, whose columns are the eigenvectors of the system's correlation matrix. These eigenvectors forming $\boldsymbol{U}$ point to the main directions of variability of the original data set $\boldsymbol{X}$. PCA technique is expected to reduce, in a systematic way, the space dimensionality of the original data set, retaining the relevant transformed variables that explain the majority (e.g. 95%) of the data variability (Montgomery 2009, Mason and Young 2002).

In the case study illustrated in section 4, for each segment representative of each operating set-point for the boiler, a correlation matrix $\boldsymbol{U}$ is computed. A quasi-stationarity condition is assumed, as required for the correct application of PCA algorithm. In the design step of the Hotelling's chart, the T² index is computed with the scores of the principal components that explain most of the variability of the system:

$$T^2 = (\boldsymbol{z}_r - \bar{\boldsymbol{z}})' \boldsymbol{S}_z^{-1} (\boldsymbol{z}_r - \bar{\boldsymbol{z}}), \qquad (3)$$

where $\boldsymbol{z}_r$ and $\bar{\boldsymbol{z}}$ are, respectively, the score vector and the average-scores vector of the retained components. $\boldsymbol{S}_z$ is the covariance matrix of the scores in the correspondent segment. The upper control limits (UCL) calculated for each step of the use of the control chart (design and monitoring) are given by (4) and (5), where $n$ is the number of samples and $k$ the number of retained principal components (Mason and Young, 2002):

Design-step Limits:

$$UCL = \frac{(n-1)^2}{n} \beta_{\alpha,k/2,(n-k-1)/2}, \qquad (4)$$

Monitoring-step Limits:

$$UCL = \frac{p(n+1)(n-1)}{n^2 - nk} F_{\alpha,k,(n-k)}, \qquad (5)$$

where $\beta$ and $F$ are statistical distribution functions [3].

The SPE and the combined index are also used to improve the capacity of the monitoring system to detect and to isolate root cause of changes, which may be a fault. The squared prediction

error, also known as Q statistic (Jackson, 2003), represents the deviation between the data vector and its approximation made from the principal components retained, and is also a measure of the variability not captured by the retained components. The SPE is computed by

$$SPE = (\boldsymbol{x} - \hat{\boldsymbol{x}})^T(\boldsymbol{x} - \hat{\boldsymbol{x}}), \qquad (6)$$

where $\boldsymbol{x}$ is the multivariate sample and $\hat{\boldsymbol{x}}$ is its prediction based on the first $k$ retained principal components. The upper control limit is calculated as proposed by Jackson (2003).

The combined index $\varphi$ is the sum of these two statistics, $T^2$ and SPE, balanced by their respective control limits, as proposed by Yue and Qin *apud* Qin (2003):

$$\varphi = \frac{SPE}{Q_\alpha} + \frac{T^2}{T_\alpha^2} \qquad (7)$$

The upper control limit for this chart is, also, calculated as proposed in Qin (2003).

Contribution plots, as proposed by Alcala and Qin (2009), are also used to support fault isolation and validate the proposed change detection technique in complex processes. These plots are based on the idea that variables with the largest contributions to the fault detection index are most likely the faulty ones. They are constructed by determining each variable's contribution to the change detection indices, such as $T^2$, SPE, and φ, as described by Alcala and Qin (2009).

### 2.4 The monitoring stage

In the monitoring stage, each new sample of a process variable at a given time instant $k$, $x_p(k)$, is normalized by

$$x_{p_n}(k) = \frac{x_{p_{in}}(k) - x_{p_{out}}(k-1)}{s_p}, \qquad (8)$$

where p is the index of the variable tag, $x_{p_{in}}(k)$ is the input to an adaptive filter shown in Figure 3, $x_{p_{out}}(k-1)$ is the previous estimated mean with a slow update time constant and sp is the standard deviation. The sample of each variable (X_in) is the input for two arithmetic recursive mean filters: a fast filter, which follows the variations of the original data; and a slow filter, that has a much slower dynamic (e.g. 100 times) than the original signal. The filters are based on a recursive first order mean filter. An abrupt change is detected by a CuSum filter applied to a residue computed between a slow and a fast mean estimator filter as shown in Figure 3. The slow mean estimation is switched to the fast estimated value when an abrupt change is detected, providing a fast adaptation mechanism during set point changes or operator commands. The slow estimated mean, $x_{p_{out}}(k)$, is used to select the standard deviation reference value designed for the set point segment that is closer to the current estimated mean (Sousa et all. 2015). In this way, the MSPC-PCA algorithm can focus on the variability for each segment considering that the process is stepwise quasi-stationary. The normalized variable $x_{p_n}(k)$ in equation (8) is then mapped by (2) and the T2 index computed as given in (3), SPE index as given in (6) and combined index as given in (7). Note that $\bar{z} = 0$ and that $S_z$ is a diagonal matrix with the ranked score eigenvalues computed from the chosen segments of the design data sets. The retained variables of the principal components are used to monitor 95% of the process variability with a confidence interval of 99%. The dataflow and procedures are shown on the block diagram of the MSPC-PCA algorithm in Figure 4, where the normalized variable $Y$, corresponds to $x_{p_n}(k)$ in equation (8).

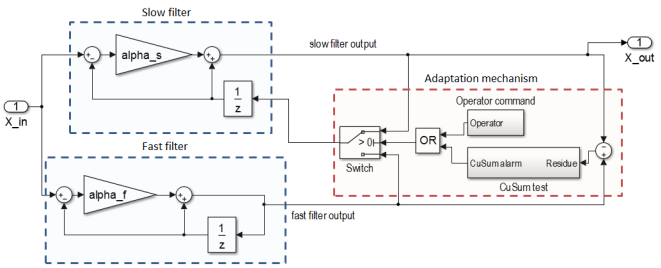


Figure 3: Adaptive mean estimation filter with two cascaded sections, a slow and a fast dynamic and an accelerating switch.

## 3. JUST IN TIME IMPLEMENTATION ON A PIMS PLATFORM

The monitoring system was implemented using the existing automation architecture in the thermoelectric power plant, based on a Distributed Control System (DCS). Two cabinets collect process data and execute control laws, communicating with two workstations that run the supervisory system via a proprietary network, VL-Net. A dedicated workstation running Microsoft Windows Server 2008 was used to implement the monitoring system. This machine stores all process data using a database managed by a PIMS platform, specifically the PI System from OSIsoft™, which obtains data via an OPC client interface that communicates with the OPC server on one of the supervisory workstations.

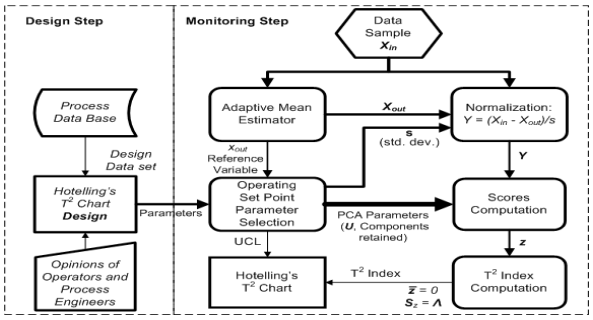


Figure 4: Block diagram of the MSPC-PCA algorithm with adaptive mean estimator (Sousa et all. 2015).

A PIMS platform can handle large volumes of data from an entire plant or organization, integrating data from various sources. It serves as a software data infrastructure that collects, stores, and distributes operational data and information. This data can be mined to help optimize plant operations. The specific PIMS platform, software PI System, contains three layers of capabilities that are jointly used: i) the PI System Tools, which provide configurable visualization and analytical tools that delivers data access to users for just-in-time and historical information of the process; ii) the PI Server, responsible for handles the storage, aggregation, integration, processing, and delivery of data throughout all machines interconnected; and iii) the PI System Connections, which connect and integrate data from different systems using interfaces. A powerful tool is the PI ACE (Advanced

Calculation Engine), which is an environment for the development and execution of more elaborate calculations over process data stored in the database.

In a PIMS environment, all operations are mediated by a database. An algorithm retrieves data from the database, performs calculations, and saves the results back into the database. The IHM (Human-Machine Interface) then displays this data and the calculation results for process monitoring. This setup is considered a just-in-time operating mode. However, if the workstation has high processing capacity, the execution time for just-in-time operations is very close to real-time processing, where data is processed directly without database intermediation. Given the PIMS's vast potential to collect, store, handle, and provide data, the PI System resources were chosen to implement the adaptive MSPC-PCA algorithm for process monitoring. The functions related to this technique were implemented in the PI ACE module, using Microsoft Visual Studio® as the development environment and VB.Net® as the programming language.

As shown in Figure 4, the parameters of Hotelling's T2 chart, calculated at the design step, are used in the monitoring step, and each segment has a specific set of parameters (eigenvalues and eigenvectors matrix, control limits of the $T^2$ chart, number of retained PCs). To make calculations dynamic and parameters easy to be categorized, edited and read, they were organized into an xml (eXtensible Markup Language) file extension. Thus, before the online monitoring, the xml file with parameters configurations is read and available for use in calculations.

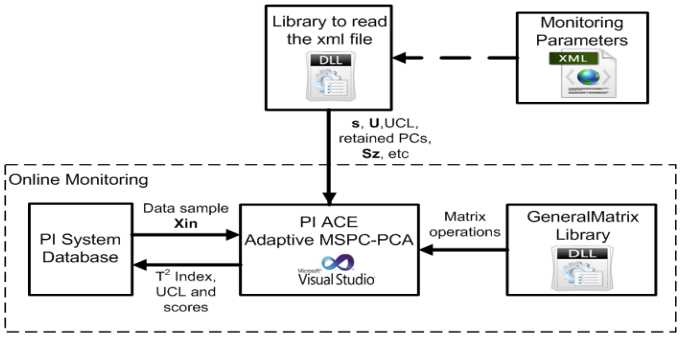


Figure 5: Software structure for the adaptive MSPC-PCA algorithms in a *PI System* platform (Fonseca et. all, 2016).

Figure 5 illustrates the methodology for implementing adaptive MSPC-PCA algorithms on a PI System platform. These techniques frequently use matrix operations (inversion, multiplication, addition, subtraction, transpositions, etc.), but VB.Net lacks native support for these operations. To address this, the *GeneralMatrix* external library is used for basic linear algebra operations during online monitoring in the PI ACE application. This library provides all necessary functions for the proposed algorithms. Additionally, a class library was developed to read and structure monitoring parameters from an XML file, making them available to the main program.

## 4. CASE STUDY

The just-in-time results of the proposed technique implemented for a boiler unit in a thermoelectric power plant in Brazil, illustrate the ability to deal with the quasi-stationary and frequent changes in set point behaviors observed in complex industrial systems.

### 4.1 Barreiro Thermoelectric Power Plant

The thermoelectric power plant, located within a steel company site, operates on three fuel sources: blast furnace gas, natural gas, and tar. These fuels have varying Lower Calorific Values (LCV), affecting the plant's efficiency and controlled variables. Operators must balance fuel availability and costs, with natural gas being more expensive but always available. The LCV variations necessitate manual set point adjustments to optimize efficiency. Despite the challenges posed by non-stationary processes and multiple operating set points, the plant can be effectively supervised using MSPC-PCA tools. This scenario highlights the limitations of classical statistical process control schemes and the need for methodologies that handle stepwise quasi-stationary processes.

### 4.2 The Boiler Unit Monitoring

The boiler is a water-tube type with an overheated steam generation capacity of 60 tons per hour, operating at 60 bar pressure and 450°C (Wang et al., 2013). It has several critical process variables, such as boiler-drum pressure and water level, which are tightly regulated to prevent equipment damage. Fuel burning control in the furnace is also crucial and significantly impacts overall performance, especially when using a mixture of fuels with varying uniformity. The selection of process variables to be monitored was based on a preliminary study of the process operation and variables (classified as regulated, disturbance, and manipulated), project design goals, and a consensus of operators and process engineers. They ranked the process variables according to recommended operation practices and maintenance procedures. Table 1 lists the ranked process variables for the boiler.

Table 1: Boiler ranked variables for process monitoring.

| | |
|---|---|
| FIQ101 | Blast furnace gas flow rate in the burner inlet |
| FIQ313 | Pressured water flow rate to the drum-boiler |
| FIT301 | Output flow rate of overheated steam |
| PI343 | Steam pressure in the drum-boiler |
| PIC322 | Overheated steam pressure |
| TIC327 | Overheated steam temperature |
| TI323 | Temperature of the inlet water |
| TI329 | Temperature of fumes (exhaust gases) |
| TI343 | Temperature of blast furnace gas |
| FIQ311 | Flow rate of combustion air |
| AIC301 | Oxygen analysis of exhaust gases |
| POT | Active power generated by the power plant |

The data set used for designing the Hotelling's chart spans a continuous period of 18 days. Changes in operating set points were made according to real-time power demands by the federal agency regulating the Brazilian National Power Grid. Active power serves as a reference for each typical nominal segment identified. Figure 6 shows stepwise active power data, decimated with a sample time of 60 seconds.

The four segments of data highlighted in Figure 6 were used for the Hotelling's chart design. These segments were assumed to be representative of a state of statistical control for the process. The sets of retained principal components were

selected to explain about 95% of the variability of the data segment used in the design step. Table 2 summarizes the number of retained components and the percentage of variability explained for each segment illustrated in Figure 6. Thermoelectric Power Plant considered, according to the procedures used for mean calculation in the design step.

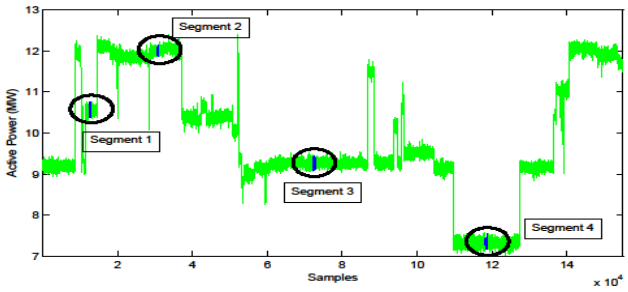


Figure 6: Stepwise active power for a period of 18 days and indication of data segments of the Hotelling's chart design.

Table 2: Number of retained components and percentage of variability explained in each segment, for each method.

| | Number of retained principal components | | % Variability explained | |
|---|---|---|---|---|
| **Segment** | **Fixed average** | **Moving average** | **Fixed average** | **Moving average** |
| Segment 1 | 8 | 9 | 95.41 % | 94.68 % |
| Segment 2 | 8 | 9 | 95.57 % | 93.77 % |
| Segment 3 | 8 | 9 | 95.55 % | 95.43 % |
| Segment 4 | 8 | 9 | 96.67 % | 96.08 % |

Table 3: Standard deviation (sd) of residues calculated with fixed and moving average.

| Variable | sd of res. calculated with fixed average | sd of res. calculated with moving average |
|---|---|---|
| FIQ101 | 607.3914 | 525.8729 |
| FIQ313 | 412.7495 | 288.3126 |
| FIT301 | 291.8193 | 214.4800 |
| TIC327 | 0.8061 | 0.1269 |

Taking residuals from the moving average directly impacts data variability, resulting in smaller standard deviations for some variables, as shown in Table 3. This method removes slight mean fluctuations, making the remaining variability more representative of natural cause variations. Using moving average residuals in the design step increases Hotelling's $T^2$ chart sensitivity to detect abnormal situations. Figure 7 compares $T^2$ results in just-in-time monitoring for these methodologies, showing a better fit for the 99% confidence interval using moving average. Two fault situations are detectable around samples 25200 and 25700. Analyzing the principal component scores helps identify that the out-of-control points in Figure 7, near sample 25700, correspond to variations in overheated steam pressure and temperature. These variables significantly influence the first and ninth principal components, respectively. This conclusion was supported by loading vector analysis, which inspects the variables contributing most to each principal component. This methodology for the design step is compatible with the proposed adaptation of means in the monitoring step, effectively handling small fluctuations and multiple operating set points. As illustrated in Figure 8, during a transient caused by an intentional operator command, the $T^2$, SPE, and $\varphi$ control chart alarms are silenced for about 150 samples. This duration is determined through trial and error, based on the typical time scale of a dynamic transient in the process.

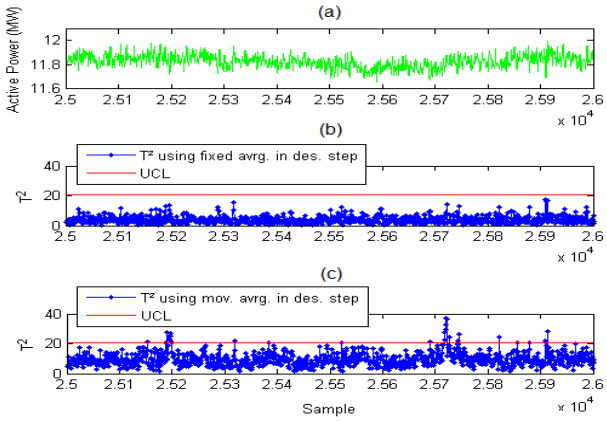


Figure 7: Effect of the design step made with residuals from moving average on $T^2$ chart monitoring.

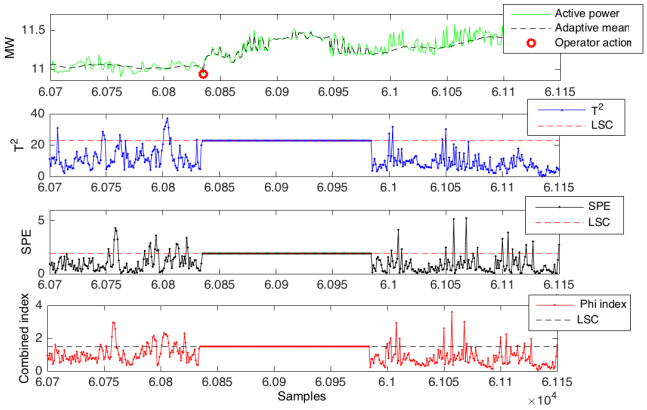


Figure 8: Boiler Hotelling's $T^2$, SPE, and Combined index; alarm silenced post-change in power setpoint for 150 samples.

Figure 9 shows a period in the process monitoring system where three detection indexes indicated a change in process behavior, particularly between samples 11800 and 11900. To investigate the root cause of these alarms, contribution plots for the change detection indexes are used. The $T^2$ index plots reveal that PIC 322 (superheated steam pressure) is the first variable to contribute over the mean, followed by FIQ313 (water flow to the drum boiler) and TI329 (exhaust gas temperature). For the SPE index, PI343 (drum boiler steam pressure) is the first to contribute over the mean, with other significant variables being FIQ101 (burner inlet GAF flowrate), FIQ311 (combustion air flowrate), AIC301 (oxygen analysis of exhaust gases), and LIC302 (drum boiler water level). Figures 10 and 11 show the changes in these six variables identified as the cause of the alarms in Figure 9.

An analysis of the observed changes starts with the slight increase, followed by a sudden fall, in the superheated steam pressure. This behavior is mirrored in the drum boiler steam pressure due to the direct connection of the steam pipe outlet. The sudden pressure drop in the drum boiler causes an immediate rise in the apparent water level, as the vapor bubbles expand. However, as the lower pressure promotes

water vaporization, the water level soon declines. This reduction triggers an increase in feed water and fuel flow to rebalance the water level and the main steam's pressure and temperature. Finally, disturbances in the combustion system and related variables affect the exhaust gas temperature. Correctly diagnosing the vapor pressure imbalance, involving this sequence of changes, requires collaboration with plant operators, technicians, and engineers. The monitoring system's information greatly aids in quickly understanding process behavior and taking appropriate actions to restore normal operation.

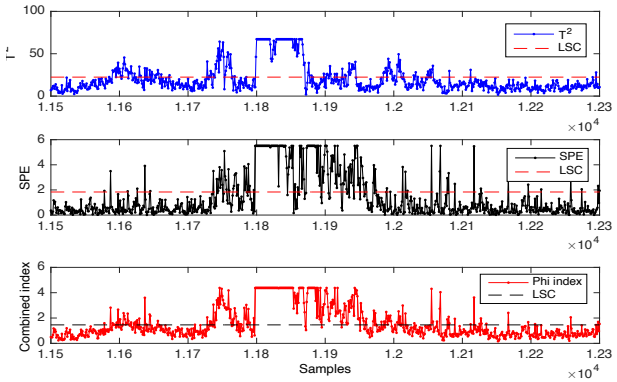


Figure 9: T2 (a), SPE (b) and $\boldsymbol{\varphi}$ (c) behavior change between the samples 11800 and 11900.

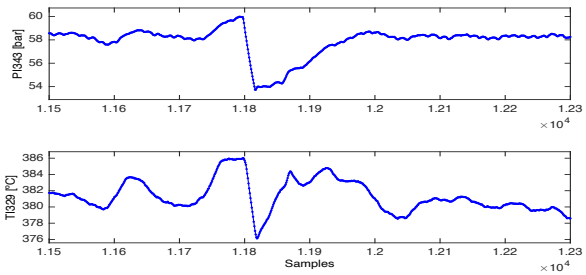


Figure 10: Changes in PI343 and in TI329.

## 6. CONCLUSIONS

The proposed MSPC technique, which includes a design step based on moving average normalization and a monitoring step with a mean adaptation scheme, effectively handles stepwise set points and nonstationary conditions. This methodology was applied to a real case involving a Boiler unit, using Hotelling's T² chart coupled with PCA, and SPE and φ indexes for design and monitoring stages. The benefits of this approach include fault origin location, recurring faults analysis, and tracking equipment degradation and operation modes. The technique is valuable for converting process data into actionable information for plant-wide performance assessment. Results from online monitoring on the PIMS platform in a Thermoelectric Power Plant highlight the importance of proper implementation for just-in-time monitoring, aiding in detecting changes in operating conditions and identifying the causes of alarms. This systematic analysis helps the maintenance engineering team proactively plan interventions to prevent serious failures.

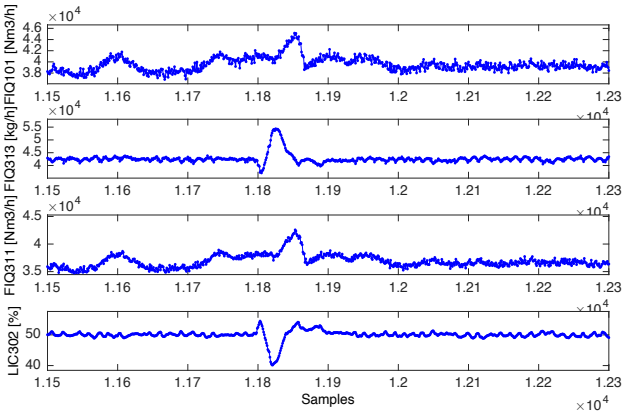


Figure 11: Changes in FIQ101(a), FIQ313(b), FIQ311(c) and LIC302(d) for the period of change detected analyzed.

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