

# Advanced Online Monitoring of Fars Province Gas Pressure Reduction Stations Based on Distributed Control System of PCS7

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## Abstract

**Monitoring is an essential and inseparable tool for every industrial automation system. In advanced monitoring, in addition to representation of the process conditions, fast identification and removing of the faults in different critical parts of the system is indispensable. Distributed Control Systems (DCS) are an integral part of the current automation systems and hence, advanced monitoring techniques need to be effectively adapted and implemented in these control systems.**

**This paper presents a novel method for implementation of the advanced online monitoring on the PCS7. Model of the gas station is first developed. The effectiveness of the model is evaluated using the model data of a real gas pressure reduction station under various operating conditions. Advanced monitoring is then implemented for this station. The real-life results demonstrates that the presented method can effectively detect the system faults.**

**Keywords:** *Advanced monitoring, Gas pressure reduction station, PCA, PCS7.*

## 1.Introduction

The Industrial automation is facing increasing challenges. Nowadays, different tools and new control systems are being added to industrial processes to increase the system flexibility, modularity and reliability and to facilitate the implementation of the recently developed control methods. Besides, due to the non-linear and time-varying dynamic nature of the processes, the system modelling may be more complicated than before.

The proper operations of many different industries such as petrochemical, chemical, and power plants essentially depend on efficient monitoring of their processes. As the size and complexity of the process increases, the need for an effective monitoring tool increases as well. The conventional monitoring methods which are usually utilized by different

industries and are implemented through the HMI software are based on the single-variate techniques. In the conventional single-variate monitoring, the data collected from different units of an industrial plant, are merely used to display and record the instantaneous conditions of the process variables. Moreover, the fault identification and alarming can be achieved through comparing the current value of the process variable to the minimum and maximum thresholds. Therefore, the abnormal conditions of the process is only identified when the process variable exceeds these thresholds. For many reasons, the conventional monitoring method, is found to be inefficient and that it cannot meet the industrial demands. Dependability of the measured variables of the process and multiplicity of the sensors are some of these reasons. Additionally, the single-variate methods may fail to identify the faulty condition. Hence, in the conventional monitoring method, the fault condition cannot be properly identified in most cases. On the other hand, implementing advanced monitoring algorithms, eliminates the need for observation of all the process variables. Even if a great number of variables exist in the process, after analyzing all the variables, the advanced monitoring algorithms easily present the process conditions through one graphical figure. The system users and operators can readily be informed of the process conditions. The conventional and dominant automation systems in the industry such as DCSs do not offer advanced monitoring. Likewise, DCSs monitoring tools such as WinCC [1] and Citect [2] are only designed to record and display different incidents and they usually have no ability for execution of advanced monitoring techniques. Consequently, developing the methods to implement and adapt the advanced monitoring techniques to DCSs seems to be essential. In this paper, the widely used PCS7 system is invoked for implementing of the aforementioned methods.

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$T^2$  Hotelling statistics is one of the statistical process control (SPC) methods. This statistic investigates the dependability of the process variables. Due to the prominent features of this statistic, it is increasingly being used by many engineers and operators. However, as the system dimension increases, the direct utilization of the  $T^2$  statistic can bring about ill-conditioning or co-linearity problems. Hence, dimension reduction methods are often used to improve the performance of the statistic. Principal Component Analysis (PCA) is one of the outstanding methods among the dimension reduction methods. The PCA was first developed by Hotelling [3]. It is considered as an advanced multivariate technique as well. The main function of PCA is to convert a set of dependable process variables to a decreased set of independent variables. PCA is considered as a static analysis method which could be improper for some dynamic processes. Hence, the Dynamic Principal Component Analysis was proposed to overcome the foregoing defect [4]. Likewise, Recursive Principal Component Analysis (RPCA) and Nonlinear Principal Component Analysis (NPCA) were also presented by [5] and [6] respectively.

In [7], a density estimation technique was developed to address the fault detection issue. The technique was used to estimate the density of the chemical process (CSTR) data. The results was used to determine a normal region for process so that abnormal changes could be detected. In [8] an enhanced neural network-based fault detection is presented. 10 simulated events data from a VVER-1000 simulator (VVER nuclear power plant) was used to evaluate the performance of the method. An easy fault diagnosis technique which is based on PCA was also proposed by [9].

By far, many efforts have been done to improve the advanced monitoring techniques so that the abnormal conditions of the process can be more effectively detected. However, the advanced monitoring algorithms based on PCA, RPCA, etc. are utilized neither in DCSs such as PCS7 nor in the common monitoring software like Citect and InTouch [10].

This paper investigates a method to implement the advanced monitoring in PCS7. The implemented monitoring tool in then applied to monitor the process conditions of a real gas pressure reduction station in Fars province. Despite the outstanding features and capabilities of PCS7, there exists some software restrictions which makes the execution of the advanced arithmetical algorithms more difficult. Due to the need for implementation of various algorithms of advanced monitoring in automation systems on one hand, and the implementation limitations on the other hand, a comprehensive structure is proposed to address this issue. Based on the abovementioned structure, a PCA-based advanced monitoring

algorithm is executed for a real industrial process.

Different scenarios and conditions need to be applied to the station to evaluate the performance of the monitoring method. However, these conditions could not be directly applied to the real process since it may lead to process instability and physical damages. A comprehensive model of the station is proposed by [11] which completely coincides the real data gathered from the Fars province gas pressure reduction station and precisely tracks the process behavior. The advanced monitoring algorithm is successfully applied to the station model and it is to be implemented in the real station in the near future.

After the introduction, in this paper, in Section II, the gas pressure reduction stations are introduced and basic needs for the advanced monitoring are also discussed. Additionally, the PCA-based monitoring method is investigated and PCS7 is briefly introduced. Sections III introduces the proposed method. Finally, the implementation and evaluation of the proposed method is performed according to the model data of the Fars province gas pressure reduction station.

## II. Concepts Review

### A. An Introduction to Gas Pressure Reduction Stations

The natural gas is extracted from deep oil wells in the first step. It is then collected by a network of the gas pipelines and is conducted to the filtration and purification units. In the third step, the purified gas is conducted to the distribution network and passes through the gas pressure reduction stations when it is to be used by the industrial and home user clients [11].

A large number of these stations are usually built in the countryside which makes the continuous accessibility more difficult. Moreover, due to the high gas pressure of the input pipelines, they are under serious risk of damage or even explosion. In addition, the behavior of these gas stations is strongly dynamic, nonlinear and time-varying. The abovementioned discussions, invoke the need for efficient advanced monitoring methods in which the safety and security of the process can be properly guaranteed.

In this paper, the advanced monitoring method is implemented on the dynamic model of the Fars province gas pressure reduction station. The station dynamic model includes the main three parts of heater, first, and second regulators, respectively.

### B. The PCA-based Monitoring Method

In PCA [14], the principal components which are a linear combination of the main data  $X_i$ , are defined as a new set of variables  $Z_i$ .

$$z = U^T x \quad (1)$$

The observations vector  $x \in R^n$ , should be properly scaled. The new data vector is  $z \in R^a$ . The transformer matrix  $U$  is composed of the eigenvectors of covariance matrix  $S$ .

$$U^T S U = \Lambda$$

(2)

In Eq. 2, the diagonal matrix  $\Lambda \in R^{n \times n}$  includes the eigenvalues of the covariance matrix  $S$ . Matrix  $U$  is an orthonormal matrix. The matrixes  $U$  and  $\Lambda$  are obtained using eigenvalue decomposition of matrix  $S$  or singular value decomposition of matrix  $X \in R^{m \times n}$ ,  $x(i) \in R^n$ .

Using the singular value decomposition one can obtain:

$$\frac{1}{\sqrt{m-1}} X = V \Sigma U^T$$

(3)

$$\Lambda = \Sigma^T \Sigma$$

(4)

In Eq. 3 and Eq. 4,  $V \in R^{m \times m}$  and  $U \in R^{n \times n}$  are unitary matrices and the diagonal matrix  $\Sigma \in R^{m \times n}$  contains the non-negative real eigenvalues of decreasing magnitude. Loading vectors are orthogonal column vectors in matrix  $U$  [12].

One selects the columns of the loading matrix  $P \in R^{n \times a}$  to correspond to the loading vectors associated with the first  $a$  singular values of diagonal matrix  $\Sigma \in R^{m \times n}$ .

The projections of the observations in  $X \in R^{m \times n}$  into the lower-dimensional space are contained in the score matrix  $T \in R^{m \times a}$ :

$$T = X P$$

(5)

The projection of  $T$  back into the  $m$ -dimensional observation space is  $\hat{X}$ :

$$\hat{X} = T P^T$$

(6)

The residual matrix which is defined as  $E = X - \hat{X}$ , describes the variations in the observation space spanned by the loading vectors associated with the  $n - a$  smallest singular values. Hence, by implementing PCA, only  $a$  variables are necessary for process monitoring which are to be investigated. The monitoring uses the  $T^2$  statistic, which is based on the first  $a$  principal components, can show the variations of the quality variables in the space of the first  $a$  principal components in the "In-control" and the PCA model building state. For  $i$ th observation which is a vector in space  $R^{n \times 1}$ , Hotelling  $T^2$  is defined as below:

$$T^2(i) = x_i^T U (\Lambda^{-1/2} \Lambda^{-1/2}) U^T x_i$$

(7)

The abnormal condition can be obtained by observation of the points which exceed the threshold. The threshold can be represented to be:

$$T_a^2 = \frac{(m^2 - 1)n}{m(m - n)} F_a(n, m - n)$$

(8)

In 8,  $m$  is the numbers of samples in the data set and  $n$  is the variable numbers of process.  $F_a$  is the fisher distribution with  $m$  and  $n$  degrees of freedom [13].

Since the  $T^2$  statistic directly measures the variation along with each of the loading vectors, it is significantly sensitive to inaccuracies in the PCA space corresponding to the smaller singular values and hence, directly measures the scores corresponding to the smaller singular values. The portion of the observation space which corresponds to the  $n - a$  smallest singular values can be robustly monitored using the  $Q$  statistic. Since the  $Q$  statistic indirectly measures the variations along each loading vector but measures the total sum of variations in the residual space, the  $Q$  statistic would not suffer from an over-sensitivity to inaccuracies in the smaller singular values [14].  $Q$  statistic is defined as below:

$$Q = (X - \hat{X})^T (X - \hat{X}) = \sum_{j=a+1}^n t_j^2$$

(9)

The upper confidence limit of the  $Q$  statistic can be computed as below:

$$Q_a = q_1 \left[ \frac{c_a \sqrt{2q_2 h_0^2}}{q_1} + 1 + \frac{q_2 h_0 (h_0 - 1)}{q_1} \right]^{1/h_0}$$

(10)

$$q_i = \sum_{j=a+1}^n l_j$$

(11)

$$h_0 = 1 - \frac{2q_1 q_3}{3q_2^2}$$

(12)

Where  $c_a$  is the standard normal deviate corresponding to the upper  $1 - \alpha$  percentile [15].

One important stage in dimension-reduction techniques is to determine the reduction order. Various methods are yet proposed to determine the number of principal components cumulative percentage variance, average eigenvalues, variance of the reconstruction error, imbedded error function and etc. are some of these methods.

### C. PCS7 Distributed Control System

DCS-PCS7 was proposed by SIMENS Corporation in 1996. PCS7 is able to fulfil various automation levels and can establish an integrated structure of the system available tools as well. PCS7 software is being used by many industries all around the world. It offers many programing features which facilitates the remote supervision and control of many complicated industrial processes. Another prominent feature of PCS7 is Enterprise Resource Planning (ERP) in which the process parameter can be transmitted from the field level to upper levels and even managing system levels.

Due to the integration of the facilities in the automation system PCS7, many system designers and engineers prefer to incorporate PCS7 instead of normal PLCs to facilitate the monitoring and control of the process. SIMATIC WinCC is one of the PCS7 most important and useful tools which is utilized for HMI graphical designing in the monitoring system

PCS7-DCS. The software is equipped with various graphical designing tools. Creating reports, alarm logging, data archiving, process trend display, faceplate design and other programs in *C* and *VB* are other features of the foregoing software which makes it ideal for process monitoring.

D. OPC Communication Protocol

The OPC protocol is a standard interface which provides the connection between different data sources such as the equipment installed in different levels of a factory, laboratory equipment and databases. For many reasons, including elimination of the incompatibility of the devices, presenting support for hardware characteristics variations and preventing incompatibilities when accessing the industrial control systems, a set of standard interfaces are defined which enables every system client to access every device compatible with OPC. The control and data acquisition equipment, such as Programmable Logic Controllers (PLCs) and Programmable Automation Controllers (PACs) produced by most of the manufacturers, are designed to operate based on OPC standard [16].

Table 1. Classification of the advanced monitoring algorithms

		Calculations level	Implementation method
Advanced Monitoring Algorithm	Simple	Programming and direct implementation of the algorithms in PCS7	
	Complicated	Computations are executed in an interface software and are then transferred to PCS7	

III. Implementation

This section presents the proposed method for the implementation of the conventional algorithms along with the complicated algorithms of the advanced monitoring. The structure of the proposed method is shown in Table. I. The first solution is to use the capabilities of PCS7 for implementation of the algorithms. In this way, all the processes are executed using the PCS7 tools. The second solution is suitable for advanced monitoring algorithms in which the whole or part of algorithm calculations are executed through an interface software and the obtained results are then transferred to PCS7. This paper utilizes the second method to implement the advanced monitoring

algorithms. The algorithm calculation parts are executed in MATLAB and the results are transferred to PCS7 to fulfil the advanced online monitoring which is discussed in Section A. In order to transfer the results (generated by MATLAB) to PCS7, the OPC communication protocol is proposed. The KEPServerEx server is used to implement the OPC communication protocol. The block diagram of the proposed method is shown in Fig. 1.

Implementation of the algorithms are performed on the data gathered from the Fars province gas pressure reduction station and the results are presented in Section B.

A. Implementing the advanced monitoring algorithm in MATLAB & PCS7

The PCA-based monitoring method is programmed and implemented into MATLAB. Cumulative Percentage Variance (CPV) and Average eigenvalues (AE) methods are used to determine the number of the principal components. This number is found to be 2 according to the both methods. Hence, one can conclude that the system dimension which was initially 4 has been reduced to 2. In order to detect the normal and abnormal conditions of the system, two  $T^2$  and  $Q$  statistics are taken into account.

The disturbances that cause interferences in the principal components subspace are identified though the  $T^2$  statistics. Moreover, the disturbances that affect residual subspace are detected via the  $Q$  statistics. In other words, these two statistics are complementary indices which can cover and analyze the whole measurement space.

A method for process conditions display and fault identification is implemented. In this method, at first the PCA algorithm is applied to the data extracted from the process. Secondly, two of the principal components are chosen to build the PCA model. The resulted principal components are then plotted versus one another. Hence, the process conditions is shown as a point in a two dimensional display during the time. After the principal components of the normal data are plotted, the region in which the system operation is normal can be determined. The outside of this region is considered as the abnormal process conditions. In accordance to the direction in which the data are leaving the normal region, the fault diagnosis can be easily achieved.

After the algorithm is implemented in MATLAB, the OPC server named KEPServerEX is utilized to transfer the results into PCS7 online. The communication link necessary settings are chosen in the MATLAB as well as KEPServer. The communication settings need to be chosen for linking the PCS7 and KEPServer as well. Moreover, the graphical pages and plots needs to be created in PCS7 to display the advanced monitoring algorithms. At the



Fig. 1. The block diagram of the proposed advanced

same time, the conventional monitoring method is also implemented to ease the comparison of the two methods.

### B. Implementation results

In order to analyze the performance of the proposed PCA-based advanced monitoring method, the gas station data under different normal and abnormal conditions are required. The station model is utilized to obtain the required station data under abnormal conditions. The station model contains three input variables including heat generated by the heater and the input gas flow and pressure. The output variables include the temperature of the heater output water and gas as well as the temperature and the pressure of the output gas. The abnormal conditions of the process is imposed through the sudden disturbance occurrence in the heater input. The input and output waveforms after applying the disturbance are shown in Fig. 2 and Fig. 3 respectively.

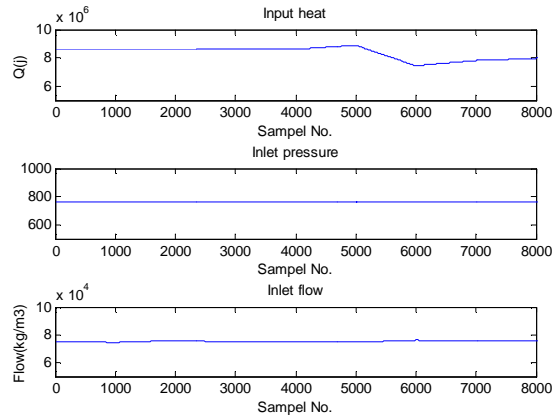


Fig. 2. The process input waveforms after imposing the external disturbance.

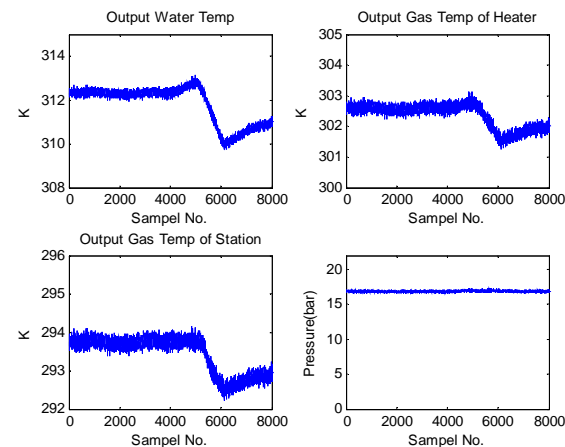


Fig. 3. The process output waveforms after imposing the external disturbance.

The advanced monitoring algorithm is applied to the data gathered from the model and the results are shown in Fig. 4. As can be seen in Fig. 4, after around

4000 samples, the process parameters are influenced and the advanced monitoring algorithm has successfully detected the imposed faulty conditions. The severity of the fault in the station conditions can be observed as well.

As we pointed out in Section III.A, two-dimensional display of the station conditions is also presented which is shown in Fig. 5.

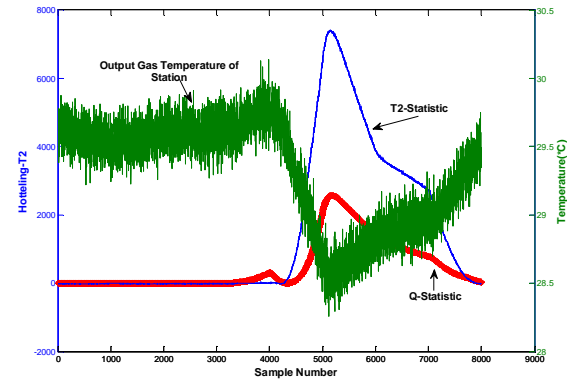


Fig. 4: The advanced monitoring algorithm results executed in MATLAB

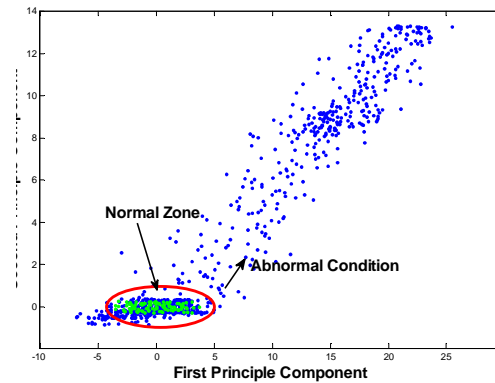


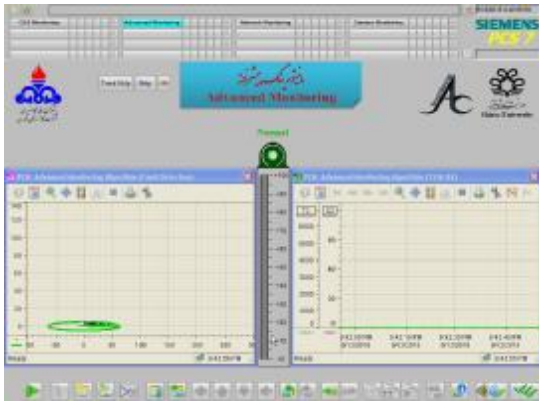
Fig. 5: Fault diagnosis and identification plot

In this figure, the principal components are plotted versus one another. Whereas inside of the ellipsoid shows the system normal region, the outside of the ellipsoid depicts the abnormal conditions of the system. The direction in which the data are leaving the ellipsoid exhibits the fault source. Here, for example, the fault origin is found to be the reduction of the heater input heat.

After working out the calculations in MATLAB, the processed outputs are transferred to the PCS7 software and the results are presented in Fig. 6. Both the Hotelling statistic and the  $Q$  statistic are shown in the right hand side plot in Fig. 6. The system fault is discriminated based on the value of these plots. If the curves rise above zero, the fault is detected. The left hand side figure, shows the process conditions in two dimensions under the environment of PCS7 which is

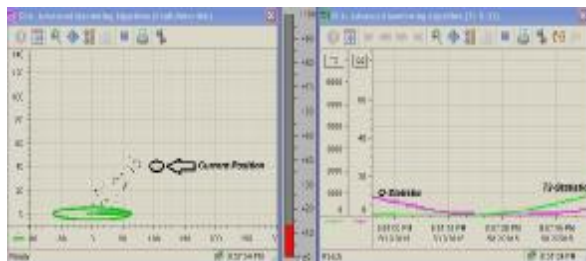


obtained by implementing the PCA algorithm on the system data.



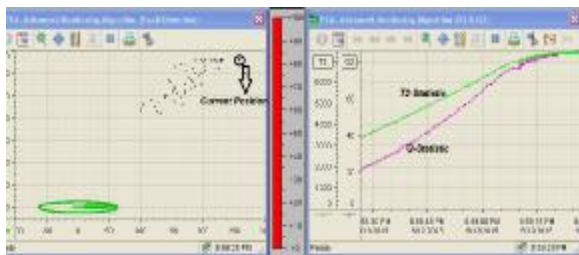
**Fig. 6:** An overview of the implementation of the advanced monitoring algorithm in PCS7

In this figure, the ellipsoid shows the normal conditions of the process. After the disturbance is applied, the advanced monitoring algorithm detects the imposed fault online. At the instance of the fault occurrence, the plots of  $T^2$  and  $Q$  in Fig. 7, rises above zero and hence, the current conditions of the station is not within the normal region. The bar graph in Fig. 7 shows the severity of the system fault.



**Fig. 7:** Fault occurrence identification according to the implemented advanced monitoring algorithm in PCS7.

Fig. 8 shows that as the effect of the fault is more severe, the value of the statistics increase and the station conditions moves away from the normal region of the ellipsoid.

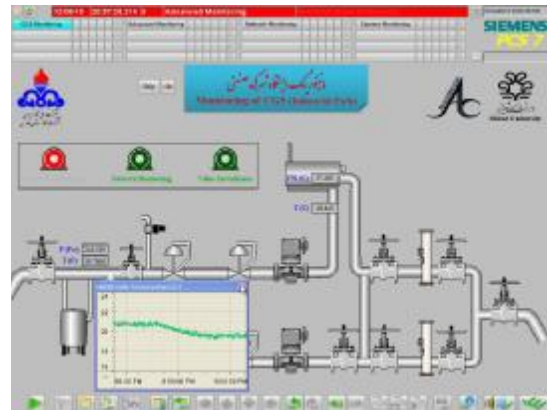


**Fig. 8:** Fault increment identification according to the advanced monitoring algorithm implemented in PCS7

In accordance to Fig. 7 and Fig. 8, it can be observed that the  $Q$ -plot has quickly detected the fault. After several samples, the  $T^2$ -plot strongly discloses the fault. Based on the above results, one

can conclude that the imposed disturbance of the system input has initially influenced residual subspace. Consequently, the error is quickly detected through the  $Q$ -plot. The disturbance is then influenced the principal components. Since the principal components significantly affect the process behavior, the resulted variations are accordingly greater. As a result,  $T^2$  statistics which shows the variability of the subspace of the principal components, can better describe the fault occurrence.

Besides the advanced monitoring, this paper has also implemented the conventional monitoring which is shown in Fig.9. In the conventional monitoring method, every single variable of the process is necessary to be controlled and supervised which makes it complicated when employing the method for large processes. On the other hand, the parameters variations at the fault events are negligible in most cases and the user may fail to discriminate these changes. Fig. 9, shows the conventional monitoring for gas pressure reduction station when a fault arises. According to Fig. 9 one can observe that the temperature of the station and the heater output gas is decreased by two centigrade at the fault event. The conventional monitoring has failed to properly detect the system fault and its severity.



**Fig. 9:** The implementation of the conventional monitoring method in PCS7

## V. Conclusion

Nowadays, with the advancement of industries, monitoring is considered as an indispensable part of every industrial process. In a typical process, there exists large number of variables which should be supervised. These variables are sampled hundred times each day. In the conventional monitoring methods, this large number of variables do not provide sufficient information of the process conditions to the system user. Through the intelligent analysis of the data, the advanced monitoring can detect the system behavior and process conditions online which significantly improves the effectiveness of the process control. This paper investigated the

design and implementation of the advanced monitoring techniques based on the Distributed Control System (DCS), PCS7. The viability of the proposed method was evaluated using the real-life data of the Fars province gas pressure reduction station. The proposed method is applied for PCA-based advanced monitoring of the foregoing process. The method is capable for implementation on the other DCSs as well.

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