Condition Monitoring of Casting Process using Multivariate Statistical Method

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***Abstract*—Growing demand for higher performance, safety and reliability of industrial systems has increased the need for condition monitoring and fault diagnosis. A wide variety of techniques were used for process monitoring. This study will mainly investigate a technique based on principal component analysis in order to improve the accuracy for fault diagnosis of casting process. The process faults are identified using the following statistical parameters: Q-statistic, also called squared prediction error, and Q-residual contribution. The proposed method is evaluated using real sensor measurements from a pilot scale. The monitoring results indicate that the principal component analysis method can diagnose the abnormal change in the measured data.**

Keywords-fault diagnosis*; *process monitoring; principal component analysis*; *Q-statistic*; *Q-residual contribution

I. INTRODUCTION

The fault detection and diagnosis is an extremely important task in process monitoring. It provides operators with the process operating information, which helps monitor the process and quickly detect and diagnose the fault.

Investment casting process has known a great development due to its wide use in automotive industry. It can be used to create complex castings at a high production rate and low cost. Even in a controlled process, defects in the output can occur.

One critical process step is filling the mold with molten metal. Significant research has been performed to link factors like pouring temperature, metal velocity, sand and refractory coating, to the filling process and defect formation [1][2][3].

Casting defects are often very difficult to characterize. They will fall into one or more of the established seven categories of casting defects: metallic projections, cavities, discontinuities, defective surface, incomplete casting and incorrect dimensions or shape [4][5].

In a controlled process, defects do not just happen, they are caused. If a defect occurs, measures must be adopted to eliminate its cause and prevent its repetition. It is the purpose of this paper to diagnose process faults that can cause casting defects. Casting process fault diagnosis is an important research domain, and gotten large attention by a number of researchers. Several methods have been proposed to identify possible causes for reducing or eliminating casting defects, e.g., Abdelrahman et al. [6] presented a methodology for monitoring the metal filling process. In order to achieve this, a data collector and sensors were designed. An electrostatic simulation package was used to interpret signature obtained from the sensors during the metal filling. An artificial neural network was trained to indicate the metal filling profile based on the results of the electrostatic simulations. The results were verified by comparing the metal filling profile inferred from the neural network to the actual metal filling profile captured by an infrared camera. Similarly, a novel approach based on a fuzzy inference system was applied by Deabes et al. [7] for obtaining the profile of the liquid metal to monitor the filling process. Dobrzański et al. [8] developed a computer code based on the X-ray imaging and the artificial intelligence tools. The proposed method was used to ensure the automatic identification and classification of possible defects in cast aluminum alloys in order to reduce and even eliminate them. To quickly detect process faults, a monitoring method of the metal filling profile was proposed by Okaro et al. [9]. This method makes use of an array of capacitive sensors to detect the position and amount of the molten metal as it displaces into the mold. An iterative algorithm for the estimation of metal filling time was also used to provide a good prediction of the filling time. A recent study [10] has been carried out by Jafari et al. on the effects of some important casting process parameters on the quality and the properties of castings using full-factorial design of experiment. These methods usually adopt measurements as the essential basis and provide aid in early detection and diagnosis of process faults by extracting useful information from measured data.

The accuracy of diagnosing process faults from measured data can be improved using Principal Component Analysis (PCA) method [11]. The PCA is a data compression method; it produces a lower dimensional representation in a way that preserves the correlation structure among the original data. The PCA method has received a great deal of attention in recent years for their ability to successfully determine when a fault has occurred, a large number of applications have been reviewed [12][13][14][15].

This paper presents the PCA method for fault detection and diagnosis with application to low pressure lost foam casting process. The PCA is used to establish the statistical correlation among the measured data to detect and diagnose

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the abnormal situations and to provide information about the process state by using the statistical parameters; Q-statistic, also called SPE (Squared Prediction Error), and Q-residual contribution. The main goal of this method is to obtain more detailed information contained in the measured data.

The paper is organized as follows. Section II presents a brief overview of the low pressure lost foam casting process and the proposed method for its monitoring. The PCA method and process fault diagnosis using PCA, along with its formulations, are described in Section III. The monitoring results are discussed in Section IV. Finally, Section V concludes our contributions.

II. MATERIALS AND METHOD

In this section, the experimental setup and the proposed method used to monitor the casting process are presented.

A. Casting Process

The low pressure lost foam casting process was developed by Lang [16]; it is used to create complex castings. The casting process uses air pressure to push liquid metal up into a flask containing the foam pattern and unbounded sand. Fig. 1 illustrates the schematic of the low pressure lost foam casting process.

The casting machine employs a resistance furnace capable of melting standard aluminium base alloys. The components contacting the liquid metal, like the tube and the adapter, are made of cast iron with a refractory coating. A thin sheet of aluminium foil is used to protect the foam from thermal radiation of the liquid metal before the beginning of the mold filling process. Air pressure is applied to the chamber containing the crucible to raise the liquid metal into the mold.

B. Data Acquisition

The foam pattern was supported in the flask. The thermocouples were wired to the data acquisition unit. When the vessel is pressurized, the liquid metal rises through a steel pipe into the flask. All test parts were cast using AlSi12 alloy at temperatures between 730°C and 750°C, as presented in Table I.

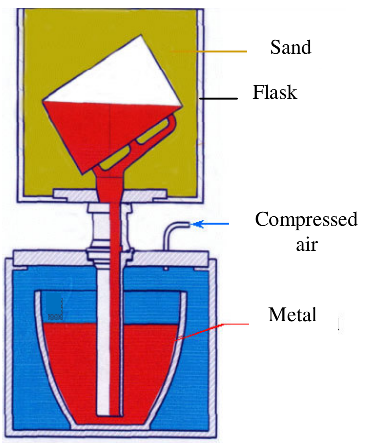

Figure 1. Schematic of low pressure lost foam casting process.

TABLE I. MEASUREMENT CONDITIONS

Test n°	Pouring Temperat-ure (°C)	measured Temperatu-re (°C)	Holding Pressure (bar)	Mold Filling time (s)	Holding time (s)
1	735	711	0.24	6	90
2	750	705	0.24	6	90
3	750	700	0.24	6	90
4	730	711	0.24	6	90

Five temperature transducers were used to acquire data by five thermocouples for temperature input. These sensors were implemented in the process. Both the pressure and temperature inputs were wired to a National Instruments data acquisition board. Other signals are also included as well as the ability to drive outputs as needed. National Instruments DASY Lab software was used to collect and analyze the signals from the temperature sensors. The measured variables are listed in Table II and presented in Fig. 2.

TABLE II. PROCESS VARIABLES

Variables	Description	unit
T	Temperature	°C
P	Pressure	Bar
S	Rise (height of filling)	M
T1	Temperature 1	°C
T2	Temperature 2	°C
T3	Temperature 3	°C
T4	Temperature 4	°C
T5	Temperature 5	°C

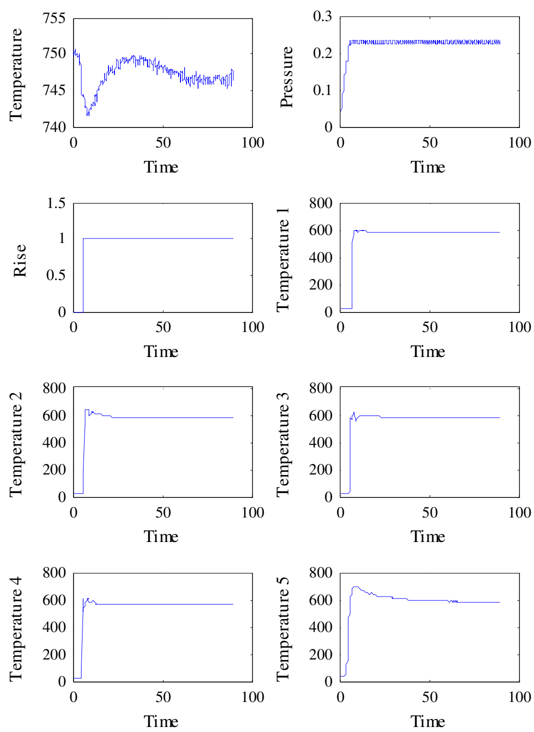

Figure 2. Measures of the process variables.

C. Method

Casting defects will generally fall into one or more of the established seven categories of defects. Generally, a casting defect is defined as all observable and unplanned variation. When defects exist, the possible causes can be examined and the corrective action can be taken.

In the casting industry, there is little and inconsistent data about the conditions that cause casting defects. There is a temptation to attempt to diagnose a process fault by the possible causes. The proper identification of a fault is required to correct and control the quality of castings.

The requirements of productivity and quality impose the application of advanced monitoring methods. In this work, the PCA method is used for casting process monitoring with surface defect. The PCA model is trained with input matrix X that contains the eight variables presented in Table II; the matrix $X \in R^{m \times 8}$ represents m observations or samples of these variables.

In the next section, the PCA algorithm that is in charge of the identification of abnormal situations in the behavior of the process is presented.

III. Principal Component Analysis

The PCA [11][17] is a multivariate analysis technique and also a dimension reduction technique. It reduces the dimensionality of the original data by projecting the data set onto a subspace of lower dimensionality including a series of new variables to protect the main original data information.

For a given data matrix $X \in \Re^{m \times n}$, which contains m observations and n variables, the PCA actually relies on eigenvalue/eigenvector decomposition of the covariance or correlation matrix C given by:

$$C = \frac{1}{n-1} X^T X = V D V^T \tag{1}$$

where $D = diag(\lambda_1 \ldots \lambda_n)$ is a diagonal matrix with diagonal elements in decreasing magnitude order and V contains the eigenvectors.

The PCA determines an optimal linear transformation of the data matrix X in terms of capturing the variation in the data as follows:

$$T = XP \tag{2}$$

$$\hat{X} = TP^T \tag{3}$$

where T is the principal component matrix and the matrix P contains the principal vectors which are the eigenvectors associated to the eigenvalues λ_i of the covariance matrix.

The difference between X and $\hat{X}$ is the residual matrix E (4). This residual captures the variations in the observation space, and it is the basis for fault detection and diagnosis.

$$E = X - \hat{X} = X(I - PP^T) \tag{4}$$

where I is the unit matrix.

The identification of the PCA model thus consists in estimating its parameters by an eigenvalue/eigenvector decomposition of the matrix C, and determining the number of Principal Components (PCs) k to retain. A key issue to develop a PCA model is to choose the adequate number of PCs. Many procedures have been proposed for selecting the number of the PCs to be retained [18]. In this paper, the experiential method [19] is used, which judges that the cumulative sum contribution of the anterior k PCs is higher than 0.85, as follows:

$$100 \times \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i} > 85\% \tag{5}$$

where k is the index of the PCs, n is the number of process variables and λ_i is the eigenvalue.

A. Fault Detection and Diagnosis

The PCA is used to establish the normal statistical correlation among the coefficients of the multivariate process data. To perform process fault detection, a PCA model of the normal operating conditions must be built. When a new observation data is subject to faults, these new data can be compared to the PCA model. The correlation of the new data is detected by Q-statistic:

$$Q - statistic = SPE = e^T e = (x - \hat{x})^T (x - \hat{x}) \tag{6}$$

The process is considered normal if

$$Q - statistic \le \delta_Q^2 \tag{7}$$

where δ_Q^2 denote the confidence limit or threshold. It can be calculated from its approximate distribution [20]:

$$\delta_Q^2 = \theta_1 \left[\frac{C_\alpha \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right]^{\frac{1}{h_0}} \tag{8}$$

where $\theta_i = \sum_{j=k+1}^{n} \lambda_j^i \quad i = 1,2,3$ and $h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2^2}$

where C_α is the critical value of the normal distribution.

The δ_Q^2 is used to determine whether the data is within range of the model. To compare the test set to the model using the Q-statistic, a plot of test data must be created with a confidence limit. A confidence limit of α=95% is used throughout this work. Any point below the confidence line is considered normal variance from the selected number of PCs, and any point above this line is considered to have an abnormally high level of variance.

In order to diagnose the process fault, a contribution plot is necessary. The contribution plots are bar graphs of the Q-residual contribution of each variable calculated as in (9) [21]. Variables having the largest residuals produce the worst compliance to the PCA model, and indicate the source of the fault.

$$Q - contribution = cont_i = \frac{\|e_i\|^2}{Q - statistic} \tag{9}$$

where e_i presents the i^{th} element of the residual vector e and $cont_i$ is the contribution of the i^{th} variable to the total sum of variations in the residual space.

IV. Monitoring Results

The PCA algorithm implies two parts: the first one is the development and training of the PCA model, the second is the test of the process fault based on the trained model. The process data used in training represent the measurements in normal operation conditions.

The sets of representative normal and fault process data are gained through the experimental measurements, including two normal data sets: test1 and test2, and two fault data sets: test3 and test4. Each data set includes eight measurement variables. The sampling interval is 0.1s and data length is 900 observations or samples for each data set.

The eight process variables are used as input to the PCA algorithm. In total, 900 data points at different times were collected for training the PCA model. The variables are of different units, so the data are scaled to zero mean and unit variance.

The eigenvalues of the covariance matrix, which are the variances of PCs, are listed in Table III. Through the PCA, the anterior 2 principal components' accumulation sum contribution rate is 92.96%. As shown in Table III, the best monitoring performance is achieved when two PCs are used. The PCA model is established by using them, and then the fault detection with the process is progressed.

TABLE III. PCs Values

Variables	Eigenvalues	Variance (%)
1	**6.4323**	**80,40**
2	**1.0049**	**12,56**
3	0.2905	03,63
4	0.1222	01,53
5	0.0729	0,91
6	0.0415	0,52
7	0.0262	0,33
8	0.0095	0,12

The results in the training phase are shown in Fig. 3. The detection threshold is calculated according to (8), which is 1.5192; this is also shown in this figure with a dashed red line. To evaluate fault detection method, the detection ratio is used. It is defined as the number of samples whose Q-statistic values go beyond the threshold to the total number of samples. When the detection ratio is less than 20%, the faults are not detected successfully [21]. As shown in Fig. 3, only 13.66% of the total samples were above the threshold value. It implies that the model has captured the major correlation and variance among the process variables.

During the testing phase, the new data sets can be compared to the PCA model and its threshold. These new data has been scaled to zero mean and unit variance of the model. The fault detection results of the test data sets including test3 and test4 are presented in Figs. 4 and 5. As illustrated in these figures, all samples of Q-statistic violated the threshold. The model has not captured the majority of the variance; therefore, the PCA model does not describe the data adequately, the data are considered faulty.

After the fault is detected, the diagnosis is determined by the contribution plot. The bar graph of each variable is presented in Figs. 6 and 7. The process fault is produced through the 8th variable (temperature 5) for the test3 and 4th variable (temperature 1) for the test4.

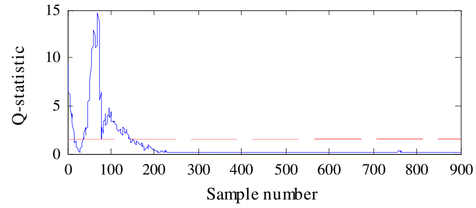

Figure 3. Q-statistic of training data (test2).

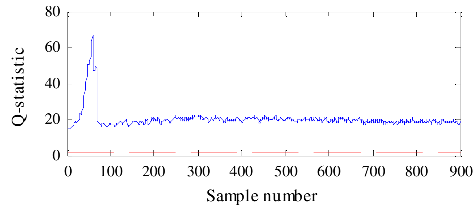

Figure 4. Q-statistic of test3.

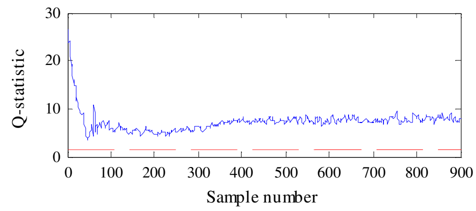

Figure 5. Q-statistic of test4.

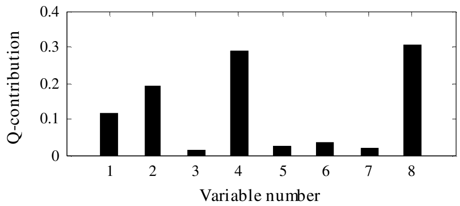

Figure 6. Q-contribution of test3.

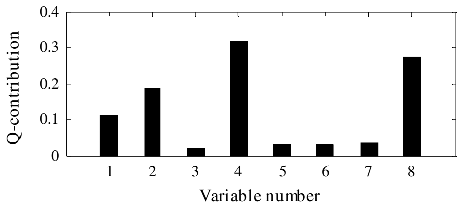

Figure 7. Q-contribution of test4.

The obtained results allow us to identify the pouring temperature as the main cause for the occurrence of the surface defect. Another possibility is that a surface defect may be formed because the thermocouple has to be embedded into the foam.

V. CONCLUSION AND FUTURE WORK

In this paper, the PCA method is applied to improve the performance of casting process monitoring by using the statistical parameters; Q-statistic and Q-residual contribution. The aim of this application is to detect casting defects occurring at different stages of the process, and also to identify their causes. The obtained results demonstrate that the normal running state and the state with fault of the process can be clearly identified; the fault can be given by using the proposed method.

The PCA method used in this work is accurate in fault detection and diagnosis of low pressure lost foam casting process. The operator can combine the results obtained by the multivariate statistical analysis with the process knowledge, and easily find out the reasons that arouse the faults. The future work will be focused on the application of condition monitoring on other types of casting defects.

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