INDUSTRIAL EXPERIENCE ON PROCESS TRANSITION MONITORING FOR CONTINUOUS STEEL CASTING OPERATION

Yale Zhang* **and Michael S. Dudzic**

Process Automation, Dofasco Inc.
Box 2460, Hamilton, Ontario, Canada, L8N 3J5

Abstract: Process transitions are common in the iron and steel industry. Our investigation shows that more than 50% of catastrophic process failures in continuous steel casting operation are related to abnormal operations during the process transition period. As a multivariate statistical (MVS) analysis tool, Multi-way PCA (MPCA) is applied in this paper to monitor one important process transition in the continuous casting process: submerged entry nozzle (SEN) change. A novel scheme is proposed for synchronizing process trajectories over the SEN change and the missing data existing in the synchronized trajectories are handled subsequently in both modeling and monitoring parts. The monitoring results are demonstrated by an industrial example. It is shown to provide good detectability of various process abnormalities. The proposed scheme can be further extended to monitor other process transitions in continuous casting process such as flying tundish change and product grade change.

Keywords: process transition; multivariate statistics; process monitoring; continuous caster; breakout.

1. INTRODUCTION

There are many process transitions in the iron and steel industry. Some common examples include process start-up, shutdown, product grade change and so forth. Since process transitions are not operating in a steady state, they are extremely difficult to control. During these transition periods, some process sensors or automatic control systems may be disabled which require operators taking a large amount of manual control actions. They are required to follow a series of predetermined standard operating procedures (SOP) to ensure the process stays within the safe operating zone. Any lapse from such procedures may lead to accidents or other process abnormalities. Our plant experiences show that catastrophic process failures often occur in the transition period, which not only create substantial profit loss due to non-productivity but also pose a significant safety risk to operation personnel. Therefore it is crucial to monitor process transitions in real-time to avert such abnormalities.

With the rapid development in advanced instrumentation technology and data acquisition systems, steel industries are currently storing massive volumes of plant data. To uncover useful process knowledge, MVS technology, including principal component analysis (PCA) and projection to latent structures (PLS), has been widely used for modeling and monitoring of complex industrial processes. This technology was introduced to the iron and steel industry in the mid 1990's and several online applications have been successfully implemented in various process units (Zhang, *et al.*, 2003a and Quinn, *et al*., 2003).

Although there have been considerable efforts for applying MVS technology for process modeling and monitoring, most applications are limited to continuous, steady-state processes. Modeling and monitoring of process transitions have received very little attention. Some recent work in this area include: (1) Duchesne *et al.* (2002) reported a PLS-based transition monitoring scheme applied to re-start process of an industrial polymer reactor. (2) Zhang *et al.* (2003b) developed a real-time monitoring system for caster start-up operation in order to prevent start-cast breakouts. This system has been implemented at Dofasco's No.2 continuous caster and demonstrated very good predictability to start-cast breakouts. In this paper, our previous work has been further extended to monitor another important process transition in the continuous casting operation: SEN change where a novel scheme is proposed for synchronizing process trajectories over the SEN change and the missing data existing in the synchronized trajectories are handled subsequently in both modeling and monitoring parts. The monitoring results are demonstrated by one industrial example from Dofasco's No.2 continuous caster.

* Author to whom correspondence should be addressed. Tel.: +1(905)548-7200 ext. 3888. E-mail: yale_zhang@dofasco.ca.

2. MOTIVATION AND PROBLEM DESCRIPTION

Continuous casting is a key process in the steel-making industry whereby molten steel is solidified to produce solid steel slabs for subsequent rolling operations. A typical slab casting process is illustrated in Fig. 1. In this process, molten steel is poured into a tundish and then into a water-cooled copper mold through a device at the bottom of tundish to allow the flow of steel into the mold. This device is a submerged entry nozzle (SEN) with a stopper-rod that opens and closes to regulate the flow of steel into the mould to provide precise control of the steel level in the mould. Within the mold, the outer shell of the steel becomes solidified to form a steel strand with the liquid steel inside. The solidifying strand is continuously withdrawn from the mold into additional cooling chambers to promote solidification. Once the strand is fully solidified, it is cut to the steel slabs in various lengths to meet downstream product specifications.

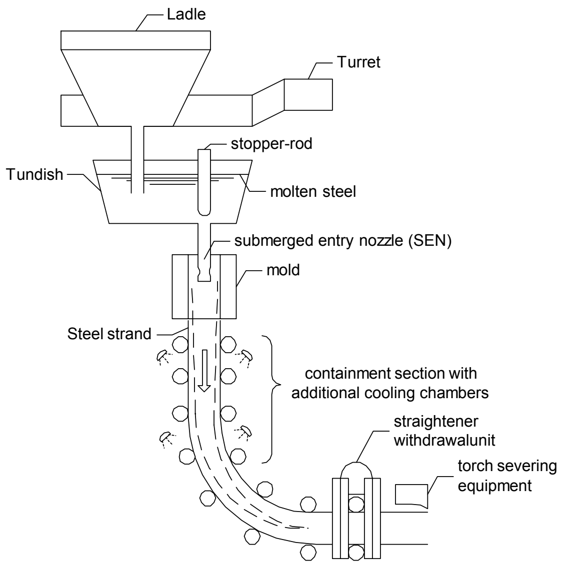

Fig. 1. Schematic diagram of continuous caster.

A typical sequence of a casting operation consists of a brief start-up operation (this is also referred to as start-cast), followed by a prolonged continuous, run-time production operation, and then a shutdown operation. Three types of process transitions in continuous casting operation are defined as follows: (1) start-up operation; (2) shutdown operation; and (3) special transitions during the continuous, run-time production operation, including SEN change and flying tundish change (FTC). These special transitions are critical in ensuring a long continuous, run-time operation. However, the nature of these transitions makes them particularly sensitive to process failures.

One of the most catastrophic process failures in the continuous casting operation is a *breakout*, which occurs when the solidifying strand shell ruptures or tears, leading to the molten steel pouring out beneath the mold. The direct economic loss of one breakout can be significant due to a large amount of process downtime, and the substantial cost associated with equipment damage. More seriously, breakouts may pose significant safety hazards to plant operators. Breakouts can be avoided by reducing the casting speed thereby providing more residence time in the mold for the steel to solidify. To avoid the occurrence of a breakout, it is critical to detect improper solidification of the steel shell in advance with enough lead-time to appropriately slow down the caster. A number of approaches have been proposed to predict breakouts in the continuous casting process. For example, the sticker detection method develops comprehensive rules to characterize patterns in the mold temperatures prior to the incidence of a sticker type breakout. If such patterns have been recognized in the current casting operation, then there is a high likelihood that a breakout will occur. MVS method has also been applied to develop a Caster Stable Operation Supervisory (SOS) system at Dofasco for breakout detection (Dudzic *et al*., 2002). In this system, a PCA model is built using selected process measurements to model the normal operation of casting processes; certain hypothesis tests are then performed to detect abnormal operations including breakouts. With the aid of the Caster SOS system and continuously process improvements, the number of breakouts at Dofasco has been significantly reduced. Our plant experiences show that, in the current small number of breakouts, more than 50% of them are related to the abnormal operation of start-cast, SEN change, FTC and other process transitions (Rasmussen and Strobl, 2003). Such breakouts in process transitions cannot be detected by either a sticker detection system or the Caster SOS system. Our previous work proposed a novel method that is able to successfully detect the start-cast breakouts using MPCA algorithm (Zhang *et al*., 2003b). In this paper, this work has been further extended to monitor the caster SEN change.

3. BATCH PROCESS MONITORING USING MULTI-WAY PCA

Prior to discussing SEN change monitoring in continuous casting operation, the fundamental concepts of MPCA is introduced in this section. More details can be found in Nomikos and MacGregor, (1994, 1995) and the recent published paper (Kourti, 2003).

MPCA is an extension of the standard PCA algorithm, which was developed for online monitoring of batch processes. Essentially, every batch process is a dynamic process. The process dynamics are shown in the process trajectories over the batch duration. In addition, batch process measurements are highly auto-correlated, which will violate the assumption for standard PCA that measurement samples are independent and process statistics are stationary over time. Therefore, standard PCA cannot be directly used to monitor a batch process. As shown in Fig. 2, batch process data can be organized into a 3-dimensional data block: there are a number of batch operations; for each operation, various process variables are measured at each sampling interval over time (these measurements are also referred to as observations). Batch processes often exhibit variable time duration. As illustrated in Fig. 2, they may end sooner or later depending on operating conditions.

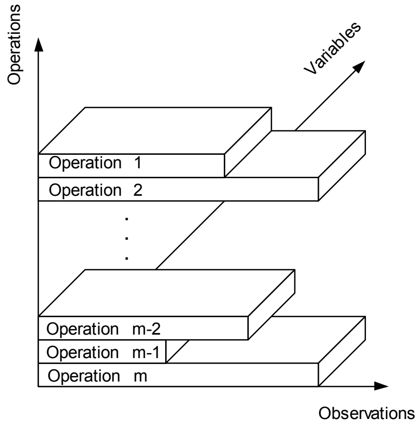

Fig. 2. 3-dimensional batch process data over various batch durations

The core concept of MPCA is to handle this 3-dimensional, dynamic data to monitor batch operation through the following four steps. (1) *Process trajectory synchronizing:* synchronization is performed to align all process trajectories such that the similarity of process dynamics of batch operations can be revealed. Our experiences show that the indicator variable method (Nomikos and MacGregor, 1995) works well for this purpose. In this method, a monotonically increasing variable that has the same value at the beginning and end of each batch is selected as the indicator variable. All process trajectories are then interpolated themselves upon the constant intervals in the indicator variable. After synchronization, each batch operation will have the same number of observations, as illustrated by the data block (**W**) in Fig. 3. (2) *Batch-wise unfolding*: the synchronized, 3-dimensional data block (**W**) was unfolded to a 2-dimensional data matrix (**X**) in Fig. 3. **W** is sliced vertically along the observation direction. The obtained slices are then juxtaposed to build the data **X** with a large column dimension such that each row corresponds to a batch operation. (3) *Modeling batch-to-batch variance*: a standard PCA algorithm is applied to **X** to build a statistical model to benchmark the normal batch operation. The data in **X** are projected to a new latent variable space defined by a loading matrix **P**, where most of the batch-to-batch variance contained in **X** is captured by only a few latent variables (*i.e.*, principal components). The values of principal components for each batch operation are called scores (denoted by **T**). *Squared Prediction Error* (SPE) and *Hotelling T^2* statistic (HT) are defined at each observation such that they are able to describe how the process trajectories in a new batch operation are coincided with the normal operation. (4) *Monitoring a new batch*: as a new batch operation evolves, the real-time measurements of process variables are collected online. The process trajectories of these measurements from the beginning of the batch operation to the current time become known. The future trajectories are predicted based on the assumption that the current deviation from the average trajectory remains constant over the rest of the batch duration (Nomikos and MacGregor, 1995). The complete trajectories are then synchronized and unfolded in the same way in step (1) and (2). Their deviation from the normal batch operation is examined by SPE and HT statistic. Any difference that cannot be statistically attributed to common process variation indicates that the new batch operation is abnormal and an alarm will be generated.

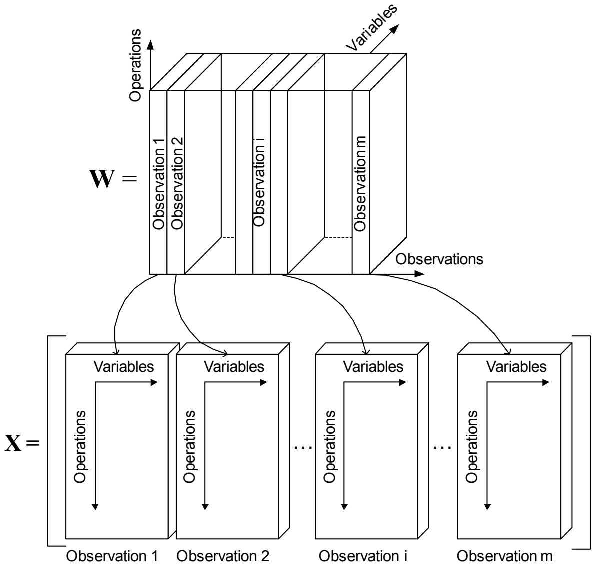

Fig. 3. 3-dimensional synchronized batch process data being unfolded to a 2-dimensoinal matrix to preserve the direction of batch operation.

4. ONLINE MONITORING OF PROCESS TRANSITION IN CASTER OPERATION

MPCA can be used to monitor a SEN change transition in the casting process by clearly defining the start and the end point of each transition. A SEN change is usually executed every 3 or 4 hours during the continuous casting production. Simply speaking, a SEN change consists of three operational steps as shown in Fig. 4: (1) Point A to B: slowing down the caster from the initial casting speed (at Point A) to approximately 0.6 meters per minute. (2) Point B to C: manually replacing the old SEN with the new one while the casting speed remains unchanged (the casting speed between B and C is also referred to as holding speed). (3) Point C to E: ramping up the casting speed to the desired normal operating condition (at Point E). Due to the changing operating conditions, the casting speed profile for each SEN change is very different. For example, the initial speed at Point A can be varying from 1.0 to 1.7 meters per minute, and the time duration between Point B and C can also be varying depending on how long it takes for operators to manually change a SEN.

Synchronization of SEN change Data. In order to monitor a SEN change using MPCA, all process trajectories during SEN change transition must be synchronized in such way that they progress similarly and have the same number of observations. As previously described, the indicator variable method is well-known for this purpose. To be the indicator variable, the selected process variable must satisfy two conditions simultaneously: it increase (or decrease) monotonically and have same values at the beginning and the end of each process transition. Unfortunately, there is no such a variable that can act as the indicator variable in a SEN change because of the varied operating conditions and inconsistent operators' behavior in a SEN change. The following procedures are applied to solve this problem.

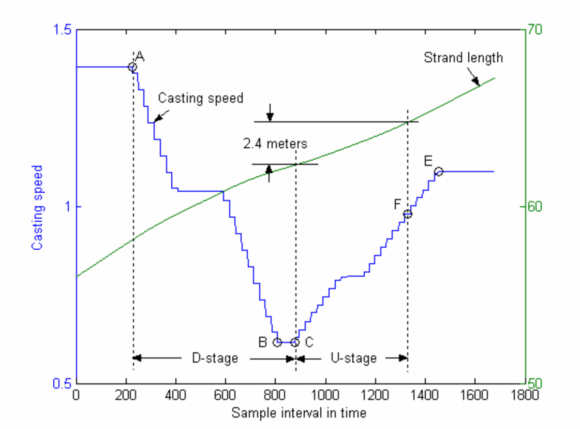

Fig. 4. Typical SEN change operation.

The entire SEN change operation is divided into two stages. The first stage (denoted by D-stage) starts from Point A and ends at Point C, in which the casting speed is continuously decreasing and therefore is chosen as the indicator variable. The second stage (denoted by U-stage) is from point C to F, where F is determined in such way that the strand length from C to F is equal to 2.4 meters[1]. Although the strand length is not measured, it can be calculated by the integral of the casting speed over time. In the U-stage, the strand length is chosen as the indicator variable. As a result, all process trajectories in U-stage are aligned by interpolating themselves based on the pre-defined synchronization scales in the strand length, which is illustrated in Fig. 5. It is worth noting that the non-uniform synchronization scales are used so that it possesses finer resolution of monitoring the beginning of the U-stage, where the process is changing fast and typical process failures often occur at that moment.

One issue of the casting speed being the indicator variable in D-stage is that the casting speed at the beginning and the end of D-stage are very different for each SEN change, which implies that the second condition for indicator variable is not satisfied. One method proposed by Garcia-Munoz (2003) can be used to deal with this situation: assume D-stage is 0% completed at Point A and it is 100% completed at Point C; then process trajectories can be synchronized based on the percentage of completeness of D-stage. Unfortunately, synchronization in this method can only be performed at the end of the stage when the casting speed at Point C becomes known. Obviously, this method is only good for offline process analysis and not suitable for online monitoring. In this paper, an alternative method is proposed for D-stage synchronization. Through process knowledge and all available historical process data, we know the maximum and minimum casting speed within D-stage, denoted by S_{max} and S_{min}, respectively. It is assumed that each D-stage starts at S_{max} and ends at S_{min}. Thus, all process trajectories can be resampled on m synchronization scales pre-defined by:

$$s(i) = S_{\max} - i \times \left(\frac{S_{\max} - S_{\min}}{m-1} \right) \quad i = 0, \ldots, m \quad \text{(eq.1)}$$

As shown in Fig. 6-a, the casting speed profile during a SEN change is very different due to various operating conditions. Compared with the raw process trajectories over time (Fig. 6-b), the resulting *synchronized* trajectories of a certain thermocouple temperature in both D-stage and U-stage are demonstrated in Fig. 6-c. Note that, in U-stage, all trajectories are synchronized with the same number of observations along the increasing strand length; whereas, the trajectories in D-stage show the different start and end value of casting speed for each SEN change. Apparently, some data are missing in D-stage due to the applied synchronization method. These missing data will be handled subsequently for both modeling and monitoring.

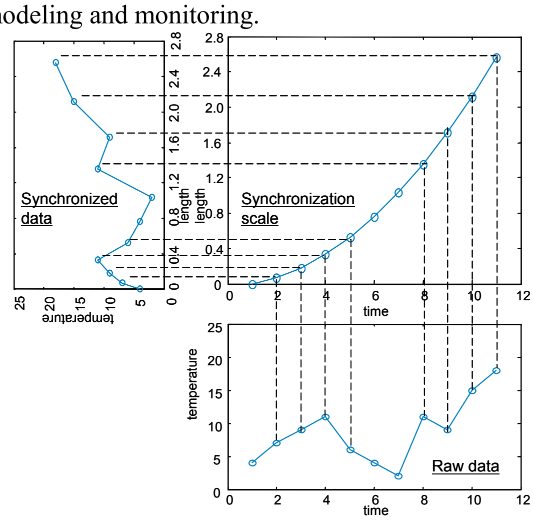

Fig. 5. Trajectory synchronization in U-stage.

Missing data handling. In a real industrial environment, process data can be missing due to various reasons, for instance, sensor failures, digital communication errors, *etc*. Missing data handling is a very important feature in an MVS-based online monitoring system. In this particular application of SEN change monitoring, a large portion of missing data is actually created by the synchronization method applied in D-stage. Fig. 7 gives an example of missing data pattern in one modeling set. In this synchronized, unfolded 2-dimensional matrix, any SEN change with the initial casting speed less than S_{max} or the holding casting speed greater than S_{min} may contain missing data blocks (illustrated by the

[1] This value is initially determined by prior process knowledge and then verified by the steady-state detection to ensure the casting operation reaches a pseudo steady-state at the end of the SEN change.

light grey color). Since the casting speed profile during SEN change is largely depending on the changing operating conditions and operators' preferences, we can assume that, in a large modeling set that includes sufficient number of SEN change operations to cover the entire operating region, these data are *randomly* missing.

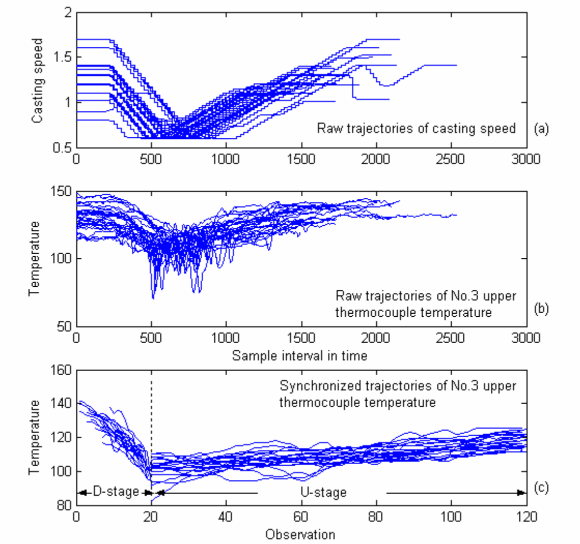

Fig. 6. Example of trajectory synchronization during SEN change.

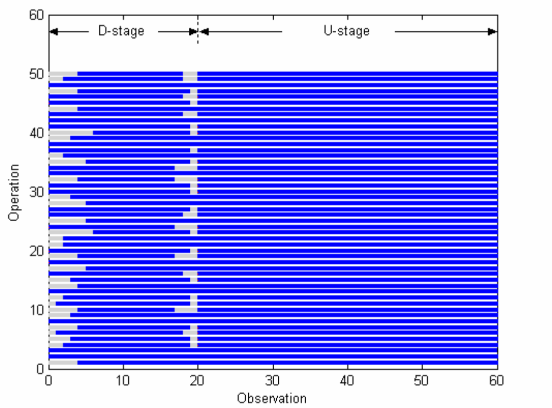

Fig. 7. Missing data pattern (only the first 60 observations during SEN change are shown).

The modeling set contains more than 700 normal SEN change operations, with 60 selected process variables and over 120 observations. To build a MPCA model based on the above modeling set with missing data, H. Wold's NIPALS algorithm (Geladi and Kowalski, 1986) is adopted. In this algorithm, linear regressions between the columns (or rows) of modeling data and the score (or loading) vectors are performed iteratively to obtain the converged scores **T** and loading matrix **P**. When data in any column or row of the modeling set are missing, the linear regressions are performed simply by ignoring the missing points. This algorithm has been proven very efficient to handle the missing data in PCA/MPCA model development. Moreover, missing data may also occur in observations of a new SEN change being monitored. If this is the case, the *Project to Model Plane* method proposed by Nelson *et al.* (1996) is used to estimate the scores from an existing MPCA model such that the available observations can be best explained by the scores. Thus, SPE and HT statistic can be calculated to determine if the new SEN change coincides with the normal operation.

Contribution plot of current observations. When an alarm is generated, it is important to quickly inform operators what may be causing the alarm. Such process diagnosis information is normally derived from contribution plots. The traditional PCA contribution plot includes all process variables involved in model calculation and the most likely process variables causing the alarms are identified by their largest contributions. However, as shown in Fig. 8-a, such a plot may suffer from a huge number of process variables and their observations over time in the MPCA model and won't provide helpful operating guidance to operators in a quick and clear manner. In the monitoring scheme of SEN change, a modified contribution plot is used, where only the observations that describe the current operating conditions are presented to operators. It is expected that, at current observation, a certain process variable with a high contribution to SPE or HT statistic in all normal SEN change within the modeling set should also have a high contribution in a new SEN change. Thus, under an alarming situation, if one process variable has a higher contribution at the current observation than what it usually has in the normal operation, it is the most likely process variable that caused the alarm. Under the above assumption, the contribution control limits at each observation can be determined based on the historical data in the modeling set. The process variables that most likely caused the alarms during a SEN change are then identified by the highest ratio of contributions at the current observation to their corresponding control limit, as illustrated in Fig. 8-b.

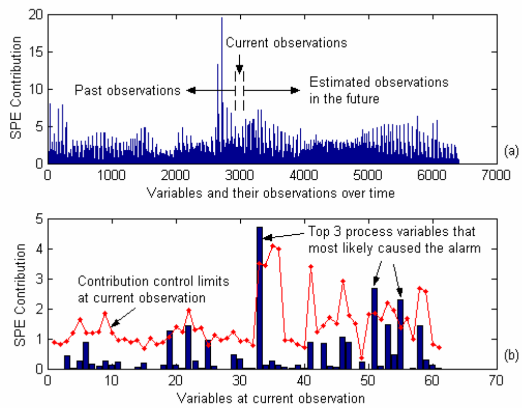

Fig. 8. (a) Traditional contribution plot in MPCA; (b) Contribution plot of current observations.

The scheme described in this section has been applied to monitor SEN changes at Dofasco's No.2 Caster. Industrial results show that the proposed methods provide continuous indication of process normality of a SEN change and some selected process failures such as sensor failures and equipment problems can be correctly detected.

5. INDUSTRIAL EXAMPLES

In this section, an industrial example is described, focusing on abnormal operation detection during SEN change. Since this monitoring scheme is still in a preliminary testing stage, all monitoring information is not made available to operators. There are no actions taken by operators to respond to the generated alarms.

This particular example occurred in April 2003. After a SEN change, operators found that there was a hole developing in the north-west side of the SEN. This ruptured SEN may have lead to some quality issues, even a breakout. Fig. 9-a shows the monitoring results calculated based on the historical data of this SEN change. Significant HT alarms were generated in D-stage, where the ruptured SEN was used in operation. The HT contribution plot of current observations is shown in Fig. 9-b, where most mold thermocouple temperatures and their differences on both north and south face exceeded their contribution control limits. It implied that the process fault was not isolated to a specific mold location but was globally distributed across the entire mold. Such observations are very consistent with our previous experience of SEN failures. After a new SEN was changed, the process was back to its normal operation and HT alarm was not observed in the U-stage.

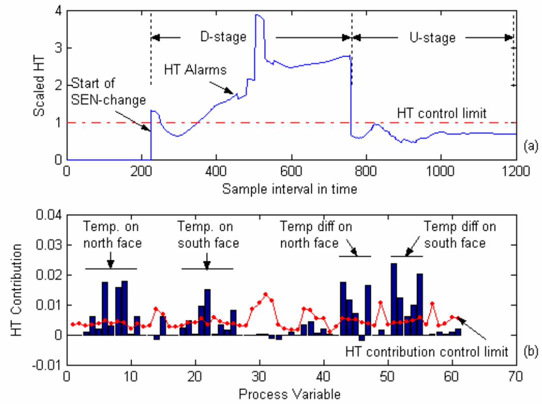

Fig. 9. HT alarms caused by a ruptured SEN in D-stage.

A background test was performed to monitor 101 SEN changes operated in July 2003 where 6% of SEN changes showed significant alarms, indicating certain abnormal situation occurred due to either process upsets or inappropriate operations. It is expected that, with the aid of an online monitoring scheme being commissioned to operators, the percentage number of abnormal operations can be significantly reduced.

6. SUMMARY AND CONCLUSIONS

In continuous steel casting processing, stable process transitions are very crucial for achieving excellent casting performance. The work presented in this paper focuses on developing an online monitoring scheme for one important process transition in the continuous casting process: SEN change. Some benefits of the monitoring scheme can be summarized as follows. (1) Severe process failures including breakouts can occur during SEN change. The online monitoring scheme is able to detect these process upsets such that the correct actions can be taken in advance by operators to avoid the occurrence of a catastrophic event. (2) Online monitoring scheme can provide a consistent indication on how SEN changes are executed. Some plant experiences have shown that stricter adherence to the SOP during SEN change or other process transitions may reduce the number of breakouts or other process failures. In summary, the proposed monitoring scheme for SEN change in continuous casting process has shown good detectability of various process abnormalities. Future work may include online commissioning this monitoring scheme to operation and extending it to monitor other process transitions in casting process.

REFERENCES

Duchesne C, T. Kourti and J.F. MacGregor (2002), Multivariate SPC for start-ups, and grade transitions, *AICHE J.* **48**, pp.2890-2901

Dudzic M. and I. Miletic (2002), Multivariate statistical monitoring of a continuous caster. In: *Proceeding of American Control Conference 2002*, pp. 600-601

Garcia-Munoz S., T. Kourti, J.F. MacGregor (2003), Troubleshooting of an industrial batch process using multivariate methods, *Ind. Eng. Chem. Res.*, **42**, pp.3592-3601

Geladi P. and B.R. Kowalski (1986), Partial least squares regression: a tutorial, *Analtica Chemica Acta*, **85**, pp. 1-17

Kourti T. (2003), Multivariate dynamic data modeling for analysis and statistical process control of batch processes, start-ups and grade transitions, *J. Chemometrics*, **17**, pp.93-109

Nelson P.R.C., P.A. Taylor and J.F. MacGregor (1996), Missing data methods in PCA and PLS: score calculations with incomplete observations, *Chemometric Intell. Lab. Syst.*, **35**, pp.45-65

Nomikos P and J.F. MacGregor (1994), Monitoring of batch processes using multi-way principal component analysis, *AICHE J.*, **40**, pp.1361-1375

Nomikos P and J.F. MacGregor (1995), Multivariate SPC charts for monitoring batch processes, *Technometrics*, **37**, pp.41-59

Quinn S. and V. Vaculik (2002), Improving the desulfurization process using adaptive multivariate statistical modeling, *AISE Steel Technology*, **10**, pp.37-41

Rasmussen P. and N.A. Strobl (2003), personal communication

Zhang Y. M. Dudzic and V. Vaculik (2003), Integrated monitoring solution to start-up and run-time operations for continuous casting, *Annual Reviews in Control*, **27**, pp.141-149

Zhang Y., V. Vaculik, M. Dudzic, I. Miletic, A. Smyth, and T. Holek (2003), Start cast breakouts preventative prediction using multi-way PCA technology, In: *IFAC workshop on new technologies for automation of metallurgical industry*, Shanghai, China, October 11-13, pp.97-102