Final Scientific Report

SQA™: Surface Quality Assured Steel Bar Program

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EXECUTIVE SUMMARY

OG Technologies, Inc. (OGT) has led this SQA (Surface Quality Assured Steel Bar) program to solve the major surface quality problems plaguing the US special quality steel bars and rods industry and their customers, based on crosscutting sensors and controls technologies. Surface defects in steel formed in a hot rolling process are one of the most common quality issues faced by the American steel industry, accounting for roughly 50% of the rejects or 2.5% of the total shipment. Unlike other problems such as the mechanical properties of the steel product, most surface defects are sporadic and cannot be addressed based on sampling techniques. This issue hurts the rolling industry and their customers in their process efficiency and operational costs.

The need of the industry is well documented. The Steel Technology Roadmap has identified process efficiency as one of the four critical areas (targets of opportunities) that require continuous improvement for the industry to be competitive. The Roadmap further identified in-line hot surface defect detection and classification and on-line non-destructive evaluation technology as the major R&D needs and opportunities for rolling and finishing. Supplied material is one of the key issues in the Forging Industry Technology Roadmap. The forging Roadmap specifically states that “Joint research or quality management initiatives between (forging) companies and (raw material) vendors could go a long way to improving the overall utilization of raw materials.” More than 50% domestic special quality bar producers and the largest US special quality bar buyers supported this SQA program.

The goal of this program is to develop and demonstrate an SQA prototype, with synergy of HotEye® and other innovations, that enables effective rolling process control and efficient quality control. HotEye®, OGT’s invention, delivers high definition images of workpieces at or exceeding 1,450°C while the workpieces travel at 100 m/s. The SQA technology is expected to eliminate ALL the surface quality related rejects, resulting in improved product quality, improved efficiency, reduced operational costs and enhanced competitiveness for both the steel industry and their customers. The elimination of surface defect rejects will be achieved through the integration of imaging-based quality assessment, advanced signal processing, predictive process controls and the integration with other quality control tools. The SQA program will use HotEye® to detect surface defects, combine that information with information from other process sensors, apply advanced diagnostic methodologies to analyze the data, and predictively control the rolling process and systematically track the defects along with other quality information.

The SQA program team, composed of entities capable of and experienced in (1) research, (2) technology manufacturing, (3) technology sales and marketing, and (4) technology end users, is very strong. There were 5 core participants: OGT, Georgia Institute of Technology (GIT), University of Wisconsin (UW), Charter Steel (Charter) and ArcelorMittal Indiana Harbor (Inland). OGT served as the project coordinator. OGT participated in both research and commercialization. GIT and UW provided significant technical inputs to this SQA project. The steel mills provided access to their rolling lines for data collection, design of experiments, host of technology test and verification, and first-hand knowledge of the most advanced rolling line operation in the US.

This project lasted 5 years with 5 major tasks. The team successfully worked through the tasks with deliverables in detection, data analysis and process control. Technologies developed in this

project were commercialized as soon as they were ready. For instance, the advanced surface defect detection algorithms were integrated into OGT's HotEye® RSB systems late 2005, resulting in a more matured product serving the steel industry.

In addition to the commercialization results, the SQA team delivered 7 papers and 1 patent. OGT was also recognized by two prestigious awards, including the R&D100 Award in 2006.

To date, this SQA project has started to make an impact in the special bar quality industry. The resulted product, HotEye® RSB systems have been accepted by quality steel mills worldwide. Over 16 installations were completed, including 1 in Argentina, 2 in Canada, 2 in China, 2 in Germany, 2 in Japan, and 7 in the U.S. Documented savings in reduced internal rejects, improved customer satisfaction and simplified processes were reported from various mills. In one case, the mill reported over 50% reduction in its scrap, reflecting a significant saving in energy and reduction in emission.

There exist additional applications in the steel industry where the developed technologies can be used. OGT is working toward bringing the developed technologies to more applications. Examples are: in-line inspection and process control for continuous casting, steel rails, and seamless tube manufacturing.

INTRODUCTION

The goal of this program is to develop and demonstrate an SQA (Surface Quality Assured Steel Bar) prototype, with synergy of HotEye® and other innovations, that enables effective rolling process control and efficient quality control. HotEye®, OGT's invention, delivers high definition images of workpieces at or exceeding 1,450°C while the workpieces travel at 100 m/s. The SQA technology is expected to eliminate ALL the surface quality related rejects, resulting in improved product quality, improved efficiency, reduced operational costs and enhanced competitiveness for both the steel industry and their customers. The elimination of surface defect rejects will be achieved through the integration of imaging-based quality assessment, advanced signal processing, predictive process controls and the integration with other quality control tools. The SQA program will use HotEye® to detect surface defects, combine that information with information from other process sensors, apply advanced diagnostic methodologies to analyze the data, and predictively control the rolling process and systematically track the defects along with other quality information.

This SQA program to solve the major surface quality problems plaguing the US special quality steel bars and rods industry and their customers as well as the US forging industry, based on crosscutting sensors and controls technologies. Surface defects in steel formed in a hot rolling process are one of the most common quality issues faced by the American steel industry, accounting for roughly 50% of the rejects or 2.5% of the total shipment. Unlike other problems such as the mechanical properties of the steel product, most surface defects are sporadic and cannot be addressed based on sampling techniques. This issue hurts both the rolling and forging industry in their process efficiency and operational costs. The SQA program is expected to result in a product that includes a HotEye® surface inspection system, a sensor fusion system, and a rolling line monitoring station (with software). For the US special quality bar rolling industry alone, the SQA program, as documented in the proposal, has the potential to directly reduce their operational cost by 2.5%, or over $200M per year and their energy consumption by 6 Trillion Btu per year. OGT has accomplished 16 installations to date, to major steel mills in the U.S., Argentina, Canada, China, Germany, and Japan. OGT expects to deliver another 10 to 15 by the end of 2010, despite the economic downturn. OGT has also set up sales channels in North America, China, Japan and South Korea. It is actively interviewing candidates for the sales services in Europe. To date, the cumulative HotEye® related sales revenue has exceeded $10 million. In 2008, the HotEye® RSB sales revenue was over $4 million.

Technologies developed in this SQA program can also benefit other applications. OGT is working with steel mills to apply the newly developed technologies to the manufacturing process of seamless steel tubes, steel rails and continuously cast slabs.

BACKGROUND

State of the Art

Prior to this Project, the rolling force and dimensional control (width, thickness, and flatness, etc.) technologies were quite mature. However, the understanding of the physics of the root causes of the surface defects in hot rolled process was very limited. The reason for this limited understanding was insufficient data on surface defects.

Eddy-current based sensing systems were and still are widely used in industry for non-destructive testing [1,2]. The data is more qualitative than quantitative. According to the American Iron and Steel Institute (AISI) [1,3], eddy-based devices are sensitive to temperature and vibration and cannot detect long and uniform defects, such as seams. Spinning eddy current heads are only used in moderate temperature conditions. Its migration to hot surface detection has not been demonstrated. Several companies, such as Foester, supply eddy-based systems. Attempts in vision-based surface inspection existed [4]. However, these systems were in their early (evaluation) stage. They were limited to flat sheets, which had a simple geometry and a moderate rolling speed.

Because of the limits, the temperature, geometry and speed of the hot rolled long products were beyond their working scope. Due to a lack of inspection capability, little research had been done on the surface defects analysis and elimination. The British Iron and Steel Research Association [5] and AISI [1] provided a qualitative classification of the surface defects of the hot rolled surfaces. Only some preliminary research on automatic classification of surface defects on the hot rolled steel was reported [6,7,8]. Nevertheless, the technology was immature and not used much in real-world practice. No systematic quantitative research on the relationships among the process variables and product surface quality has been reported. The statistical process control (SPC) [9] has been widely used in industry to monitor the product quality. However, conventional SPC methods assume uniformly distributed quality problems across different streams and are not directly applicable for monitoring the occurrence of surface defects in hot rolling processes.

Existing quality control and quality associated process control in the hot rolled long and merchant mill product industry is reactive and typically involves long time delays**.** Often, the scope and magnitude of the surface defects are unknown to the steel makers until they receive complaints or stock returns from their customers. Defects with complex causes, such as seams, may require months to track down and eliminate.

Overseas steel makers such as Daido Steel cope with the surface quality issue by paying a very heavy premium in their processes. A bigger bloom is cast and reduced to a billet. To assure surface quality, about 30% of the billet surface material is removed before rolling.

To date, there are some new developments.

In order to untie the limit imposed by the probe rotating speed, Daido Steel (Japan) tested an approach of a multi-coil eddy current probe [10]. In this approach, eddy current coils made in the form of printed circuit boards are embedded into a non-moving probe. With the multi-coil design, the coils can be activated in a sequence electronically, simulating a rotating coil. According to the report, this new probe is capable of detecting a slit that is 0.5 mm to 1.5 mm in width on a hot rolled flat bar with a 5 mm working distance. The coil size is designed to be 9 mm or larger. This may limit its ability to detect finer defects.

Infrared based in-line surface inspection is reported. The application is limited to the roughing mill. This is due to the limits imposed by the optical resolution and scanning speed of infrared imaging.

There are a few attempts in the long product area [11][12] with imaging based approach. The earliest report was made by OGT in 2000. The R&D work emerged in 2003, with its first commercial prototype successfully installed. With the support of this SQA project, OGT's effort with the imaging based surface inspection has emerged into a matured product accepted by the bar and rod industry worldwide. The two known attempts [11][12] are still in the early stage.

Area of Interest

The technical areas of interest in this project are the combination of advanced ***imaging***, ***process control*** and ***quality control***, in order to address the surface quality issues faced by the bar and rod mills.

Project Objective

The goal of this program is to develop and demonstrate an SQA prototype, with synergy of HotEye® and other innovations, that enables effective process control and effective quality control for bar and rod mills.

Approaches

To achieve the goal, OGT employed the approaches with the following components.

- In-line, real-time imaging based inspection for surface defects on hot rolled steel bars;
- Advanced data rendering, statistics and analysis for process signatures and root cause identification;
- Predictive process control to prevent surface defects;
- Integration with quality information from other mills instruments for a total quality control.

Project Team

The SQA team that consists of technical staff from **OGT**, Georgia Institute of Technology (**GIT**), University of Wisconsin (**UW**), ArcelorMittal Indiana Harbor (**Inland**), and Charter Steel (**Charter**) was very strong.

The SQA program team was composed of entities capable of and experienced in

(1) *research* (GIT, UW and OGT);

(2) *manufacturing* of the technology proposed (OGT);

(3) bringing the technology to the end user through *sales* and *marketing* (OGT); and

(4) serving as an industrial *end user* of the technology proposed (Inland and Charter)

OGT served as the project coordinator and participated in both research and commercialization. ***GIT*** and ***UW*** provided significant technical inputs to this SQA project. GIT brought to the team their well-recognized expertise in advanced in-line process control. UW contributed their expertise in signal processing and process identification.

The steel mills provided access to their rolling lines for data collection, Design of Experiments, host of technology test and verification, and first-hand knowledge of the most advanced rolling line operation in the US.

The technical expertise of the team members is a combination of imaging, sensing, signal processing, statistical analysis, process controls, automation, systems integration, and steel rolling. Dr. T.S. Chang led the project with his expertise in systems integration, as well as imaging and optics. Dr. J. Shi brought to the team his expertise in process control, feature extraction, and statistical analysis. Dr. S. Zhou contributed with his expertise and experiences in advanced signal processing, pattern recognition and automation.

The industrial experts from the steel mills also contributed with process knowledge and the constraints of applying new technologies into the real-world manufacturing processes. Inputs about business models in the industries from the participating experts ensured the final feasibility, commercializability and acceptability of the developed technologies.

SNAPSHOTS OF DEVELOPMENT WORK

Through out this project, the SQA team has:

- Demonstrated the inspection of small bars to ϕ5.5 mm.Improved the surface detection accuracy of the in-line surface detection system with false positive rate down to 2%.
- Built and tested the prototype of the vibration suppression device with 5.5 mm wire rods.
- Completed the tests on the speed measurement device and achieved the desired accuracy of 0.02%.
- Improved the robustness for pattern analysis on two types of defects, Flutter Overfills and Roll Cracks.
- Developed the methodologies for surface defect oriented process control and demonstrated the off-line process control for one surface defect case with result verified by the mill.
- Demonstrated the statistical approach in identifying potential sources of sporadic surface defects via off-line process diagnosis.
- Developed real-time patterns for real-time process control in bar rolling
- Demonstrated the result of the near-line process control
- Started the Beta test of the process control software at a site.
- Started the Beta test of the quality control software.
- Implemented at the "module" level for an integrated rolling mill inference model.

In this report, snapshots of several development works are documented.

A. Advanced Detection Algorithms

The development is illustrated by the detection of seams. A seam is a thin deep crack along the longitudinal direction of a rolling bar. It is one of the most critical defect types on the hot rolled products. It shows as a nearly-vertical thin dark strip with a constant width of 2~3 pixels in the sensing-image. Figure 1 is a seam-containing sub-image and the cross-section grayscale projections (the blue traces) at 3 horizontal lines.

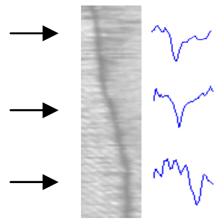

Fig. 1. A seam sub-image

The most dominant feature for a seam image is its long, narrow vertical pattern. However, there are two types of mill acceptable anomalies that bear the similar long narrow feature: ridge-based and mark-based, as shown in Fig. 2. A ridge-based false positive is a longitudinal ridge on the surface caused by material overfills. It is usually pictured as a thin bright strip with one or two dark strips on its sides depending on the angle of the lighting source, where the bright and the dark strips are the ridge and its shadow(s), respectively. A mark-based false positive is a longitudinal mark on the surface, usually characterized by a dark strip of varying width. Note that although the false positives have different physical forms and image patterns, they each have a dark strip in the sub-images, which could be misidentified as a seam. However, in the ridge-based false positive, the dark strip is paralleled by a bright strip (i.e., the ridge); and in the mark-based false positive, the width of the dark strip (i.e., the mark) varies. These two characteristics form the fundamental difference between false positives and seams.

Fig. 2. (a) Two ridge-based false positive sub-images (left: containing two dark strips; right: containing one dark strip)

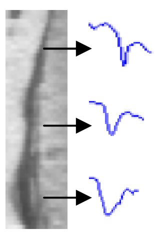

Fig 2. (b) A mark-based false positive sub-image

The snake-projection-wavelet algorithm, developed in the program, is applied to capture the differences between a true seam and these two types of false positives, as shown in Fig. 3. The sub-images are first converted to 1-D sequences by a feature-preserving snake-projection method. Discrete Wavelet Transform is then performed on the sequences for feature extraction. Finally a T^2 control chart[1] is constructed based on the features to distinguish seams from false positives.

[1] When there are multiple related quality characteristics (recorded in several variables), one can produce a simultaneous plot for all means based on Hotelling multivariate T^2 statistic (first proposed by Hotelling, 1947); such a plot is known as the T^2 control chart.

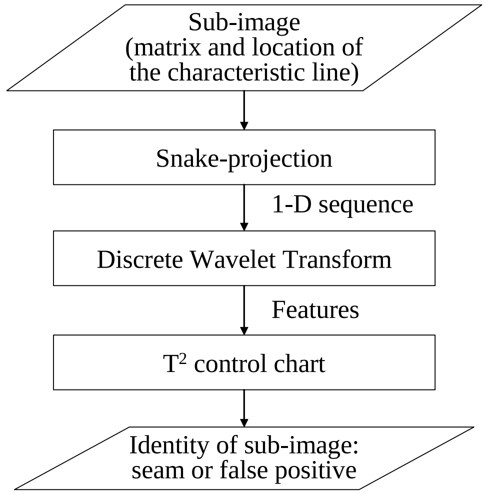

Fig. 4 Procedure of the snake-projection-wavelet algorithm

B. Basic Pattern Identification

Examples of basic pattern identification are the detection of flutter overfill and horizontal roll cracks on the rolling bar based on the HotEye® images. Not only the detecting algorithms were developed, the reliability was improved with a novel algorithm that could handle the uncertainties embedded in the rolling process. Such uncertainties include the signal strength variation, the signal repeatability variations, the signal period variations, and so forth. While a full 2-D auto-correlation may be a good tool to detect repeating signals, its application to the rolling process is not intuitive. First, there is not time for a full 2D auto-correlation for a real-time detection. Second, the signals may be distorted, as the bar is twisting along the rolling line. Some repeating marks may be rolled (deformed) in subsequent stands while some may not. A robust algorithm that can reduce the computing requirement for real-time detection and survive all the potential variations is a must for the success.

In addition to the methodologies for repeating patterns on images, the team also worked on a generic pattern analysis methodology for root cause identification purpose. Two approaches were tested. One is a statistic regression approach and the other is a Bayesian network.

B1. Regression Model of the relationship between process variables, chemical components and surface quality measurements

First, a model is established to link the relationship between the process variables, chemical components and quality feedback from the imaging sensor. Regression technique is used to model the relationship.

A new variable, π, the severity of a billet's quality, is introduced. It is defined as follows,

π=1, if there is at least one checking type of defect on the final product

0, if there is no checking on the final product

Logistic regression model is applied to model the relationship between the predictors and the response variable as follows,

$$\log\frac{\pi}{1-\pi}=\beta_0+\beta_1 x_1+\ldots+\beta_p x_p+\varepsilon \quad \text{or equivalently,} \quad \pi=\frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\ldots+\beta_p x_p)+\varepsilon}}$$

Further, we use the backward deletion method (by AIC criteria) to reduce the insignificant predictors from the model. The final subsets that are identified as significant predictors to the severity π is presented in Figure 5.

Predictors	Estimate	Std Error	P value
(intercept)	-1.496	0.099	<2e-16
barDiameter	-0.245	0.106	0.0209
vpntm1_waterbox_flow	0.419	0.135	0.0018
mpntm2_waterbox_flow	0.376	0.131	0.0042
vpntm2_waterbox_flow	-0.529	0.157	0.0007
vstand_26_speed	0.565	0.127	8.68E-06
Aluminum_Total	-0.897	0.220	4.72E-05
Lead	0.458	0.135	0.00067
Tellurium	0.450	0.094	1.77E-06
Bismuth	0.626	0.094	2.94E-11
Boron	0.858	0.183	2.66E-06

Fig. 5. Significant predictors identified by logistic regression model

The significant predictors in Figure 5 include the variables (barDiameter, Lead) that conform to the industrial experience. Other variables are to be verified. However, since this model is based on simplified assumptions, it should be cautious when using the model for interpretation. Experimental verification would be necessary.

However, regression model approach can only support semi-real-time process control, given the fact that enough data must be collected for the model. Therefore, cheaper and faster alternative was tested.

Bayesian Network Approach

The Bayesian appraoch has certain amount of self-adjusting. The K2 Bayesian network structure learning algorithm is used and combined with the background knowledge. The Bayesian network is used to map a set of process variables such as reheat temperature, rolling speed, etc. to the response variables, the surface quality indications, such as the #defects, frequency (tempero and spatial) of defects, etc. Once the network is established, the Bayesian network provides a tool to estimate the probability of each process variable (the process variable patterns) for a given response variable pattern. This pattern can be used for root cause diagnosis, as the probability table associated with a certain patterns of the response variables in the Bayesian network forms the bases for control strategy. This probability table can be used to trace the most likely (high probability) root causes if a pattern of the response variables is observed. A response variable pattern could be that seams are ~6” long, ~5 seams per bar and so forth. This pattern could be mapped to a probability table that “tonnage at the 3rd stand” is, say, 62% likely, “temperature variation at the reheat furnace exit” is, say, 47% likely, etc. A case study was performed to test this theory. Table 1 documents the process variables and the response variable used in this case. According to the configuration of the manufacturing process, we can have the following variable ordering from the casting process to the rolling process.

$\mathit{EMSAmpsAvg} \prec \mathit{SpeedAvg} \prec \mathit{TundTemp1} \prec \mathit{NozzleSize} \prec \mathit{ArgonFlow} \prec \mathit{ArgonPressure} \prec \mathit{MoldLevel} \prec \mathit{MoldLubeFlow} \prec \mathit{MoldWtrInletTemp} \prec \mathit{SprayWtrInletTemp} \prec \mathit{SprayWaterZone1} \prec \mathit{SprayWaterZone2} \prec \mathit{SprayWaterZone3} \prec \mathit{DeltaTemp} \prec \mathit{Strand} \prec \mathit{bardiam} \prec \mathit{speed} \prec \mathit{defects}$

Assume we want to find the top three candidates of the root cause process variables for the seam defect, applying the K2 learning algorithm with the maximum parent nodes number equals 3, we have following Bayesian network in Figure 6. We have three root cause candidates for the defect, EMSAmpsAvg, Bardiam and speed.

Table 1. Process and quality variables and their physical meanings

Variable category		Variable name	Variable physical meaning
Process variables	Casting process	EMSAmpsAvg (amp)	Electromagnetic stirring amps
		SpeedAvg (feet/min)	Average casting speed
		TundTemp1 (F)	Absolute temperature of the steel in the tundish
		NozzleSize (inches)	The size of the diameter of the tundish nozzle
		ArgonFlow (feet^3/min)	Flow of argon into the mold shroud
		ArgonPressure (inches of water column)	Pressure of argon in the shroud
		MoldLevel (feet)	Distance of liquid steel level from top of mold
		MoldLubeFlow (ml/min)	Mold lube flow
		MoldWtrInletTemp (F)	Mold cooling water temp
		SprayWtrInletTemp (F)	Spray water inlet temperature
		SprayWaterZone1 (Gallon/min)	Spray water zone 1 flow
		SprayWaterZone2 (Gallon/min)	Spray water zone 2 flow
		SprayWaterZone3 (Gallon/min)	Spray water zone 3 flow
		DeltaTemp (F)	Mold water temperature change from entry to exit
		Strand (#)	Strand of continuous caster
	Rolling process	Bardiam (in)	Diameter of rolling product
		Speed (ft/min)	Speed of the rolling product
Quality variable		Defect (#)	Number of defects (seam) on each rolling product

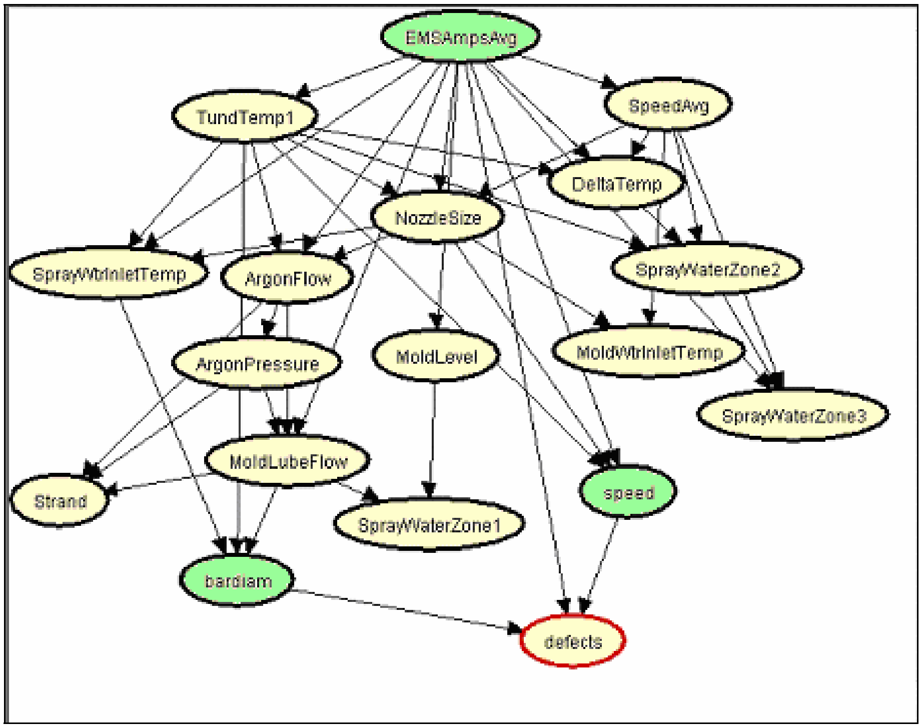

Fig. 6. Bayesian network based on K2 algorithm given variable ordering #1

After that, we change the process variable ordering to the following, and see its influence for the defect root cause candidates from the Bayesian network.

SprayWaterZone1 ≺ *EMSAmpsAvg* ≺ *speed* ≺ *ArgonPressure* ≺ *SpeedAvg* ≺ *SprayWaterZone2* ≺ *TundTemp1* ≺ *NozzleSize* ≺ *SprayWaterZone3* ≺ *Strand* ≺ *MoldWtrInletTemp* ≺ *bardiam* ≺ *ArgonFlow* ≺ *MoldLevel* ≺ *MoldLubeFlow* ≺ *SprayWtrInletTemp* ≺ *DeltaTemp* ≺ *defects*

The second ordering also results in the same candidate process variables that are responsible for the defect generation, as in Figure 7. Five different ordering of the process variables were tested and all of them have the same three candidates root cause for the defects: EMSAmpsAvg, speed and bardiam. Therefore, we can simplify the Bayesian network by deleting those non-root cause process variables. By searching all the ordering of this three variables and picking the network that best fits the data, we have following final network in Figure 8. The root cause diagnosis will be based on this simplified network.

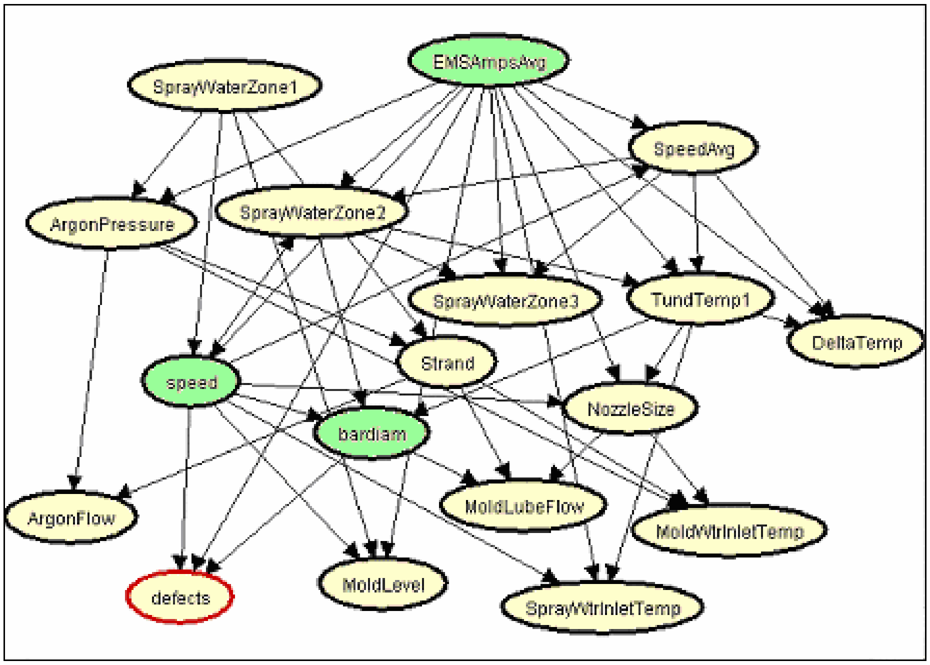

Fig. 7. Bayesian network based on K2 algorithm given variable ordering #2

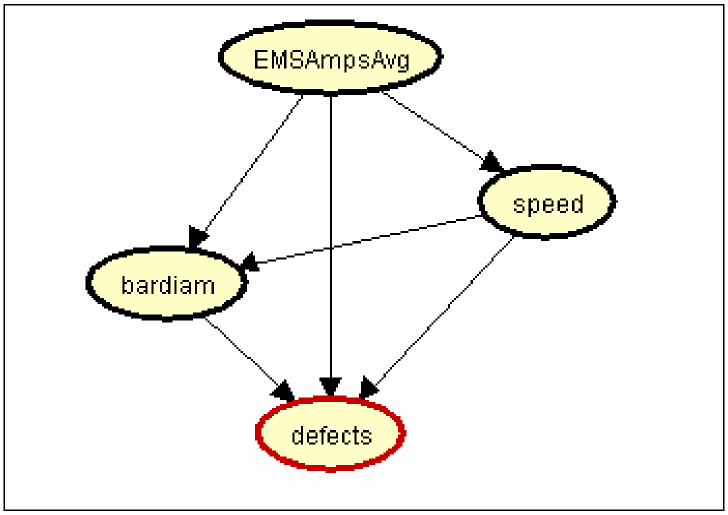

Fig. 8. Simplified Bayesian network

Experiments

A Design of Experiments was conducted in December 2005. A mill charged 17 billets with several control variables such as the billet dimension, billet condition, reheat temperature, and breakdown mill charging speed. Data was analyzed and revealed interesting information such as the impact of the billet sizes and billet surface conditions to the focused response variable for surface quality. Based on the success of the first run of experiments, the mill hosted the second run of experiments, focusing on the "critical" process variables identified from the regression and Bayesian models.

C. Advanced Data Extraction

In addition, the team also extended the analysis in basic pattern identification. The following figures show some work of this area. For instance, principal component analysis was applied to different mill variables with two classes of data, bars with "checking marks" and bars without "checking marks", given the same material grades and same final diameters. The team also investigated the functionals, such as the derivatives of the temporal history of the mill variables, in an attempt to separate the two classes. The results show the functional data of the process variables could provide better separation of the two classes. However, with the additional of functional data, the total numbers of the potential control target increase exponentially. Therefore, an automatic search method would be required for commercialization.

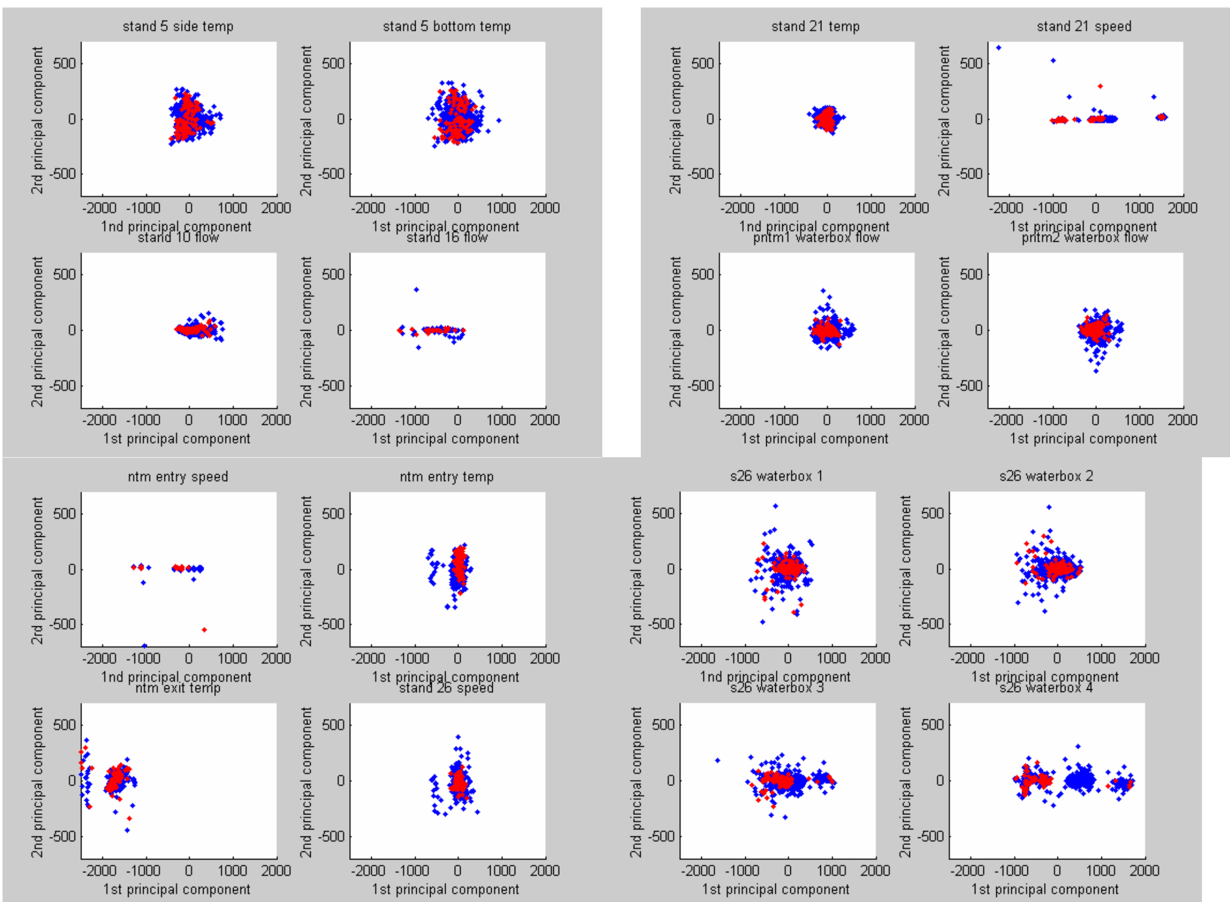

Fig. 9. 2-D principal component plots for major process variables

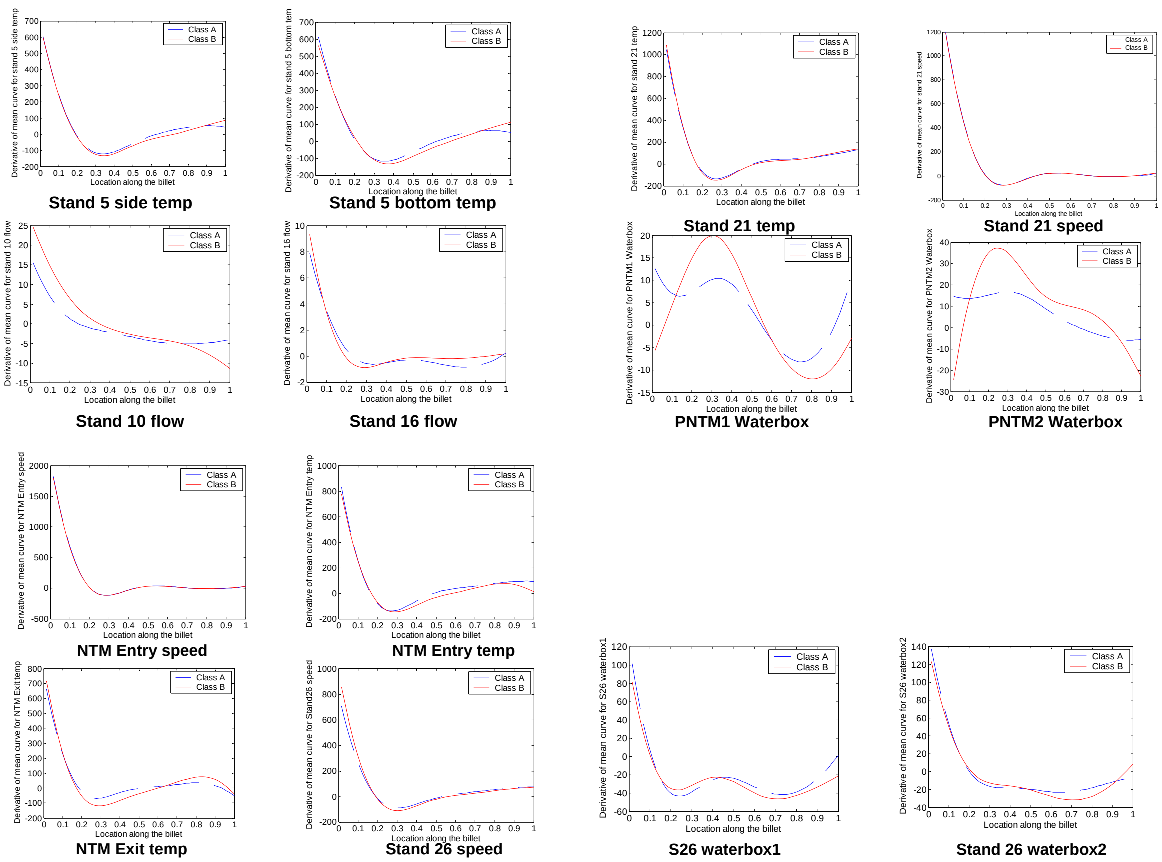

Fig. 10. Derivative curves of mean curves for both classes of each process variable

D. Predictive Control Model

The team designed the software application that could facilitate the predictive process control based on the strategy and the real-time pattern recognition. The frame work design is developed to support the process control system, which is illustrated below:

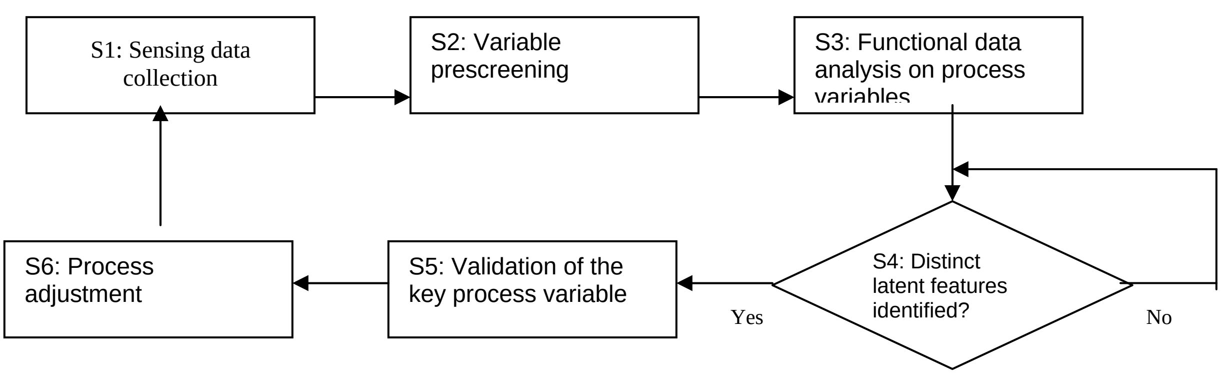

Figure 11. Frame work of the Predicitve Control model.

The whole procedure includes six steps.

S1: Sensing data collection. In the hot rolling process, many process variables are monitored by sensors. Steel mills have comprehensive databases to keep track of the historical production records.

S2: Variable prescreening. A logistic regression technique is used to filter out the effects of the melting operation variables on surface quality.

S3: Functional data analysis on the functional variables in the rolling operation. For each functional variable, FDA will estimate a smooth curve to approximate the actual functional variable.

S4: Latent feature extraction. The derivative of the mean curve will be used as the latent feature of each functional variable. The steel billets are grouped into two classes: the steel billets with and without surface defects. The influence that a particular functional variable has on the surface quality will be calculated by comparing the latent features for both classes. If the functional variables are similar then the functional variable has little influence on the surface quality; if they appear to be different, then the process will continue to S5 for further validation.

S5: Validation of key functional variables. An evaluation criterion based on the Pearson $\chi 2$ method[2] will be used to quantify these feature differences and to conclude if the functional variable is indeed influential to the surface quality.

S6: Process adjustment. Based on the latent feature identified in step S4, the key functional variables validated by S5 will be adjusted to improve the surface quality of the steel billet. The whole procedure can be repeated to monitor and improve the surface quality of the steel billets in the hot rolling process.

The team tested on-site, to incorporate the link to the database of the testing site with the software. With this linkage, the implementation of control charts and on-site tests were made possible. The SQA demonstrated the software packaging on site. A new software package "Rolling Process Imformatics (RPI)" is developed. Following are some samples of its user interfaces.

Query Interface: RPI provides a streamlined interface for multiple databases in the mill storing process, business and/or quality data. For example, to perform a Hoteye (Quality) Query, the user simply selects 'Hoteye Query' from the Database Menu at the top of the RPI user interface, and the dialog shown in Figure 12 will be displayed.

From here, the user can select the constraints from which to perform the query. Constraints are the variable parameters that must be met for each bar record that is retrieved. Available constraint variables include: any bar record variable, total # of defects on a bar, and total # of a specific defect type on a bar. Once the data is retrieved, it can be exported to a 3rd party software such as Excel for further analysis or individually examined from within the RPI interface.

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[2] Pearson $\chi 2$ method is a statistical procedure first investigated by Karl Pearson for testing hypothsis on the frequency distribution of certain events.

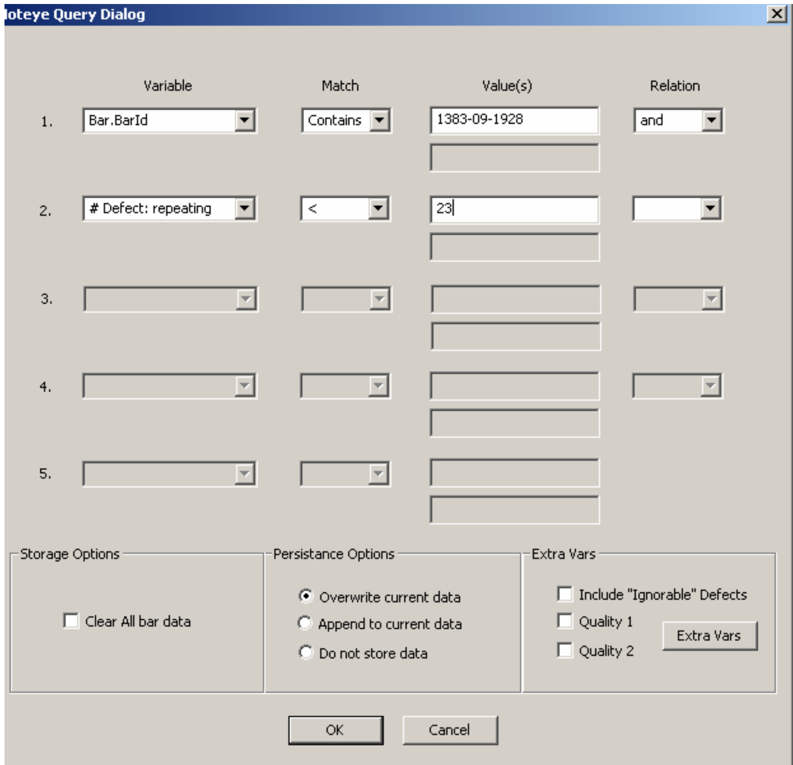


Figure 12. Hoteye Query Dialog

Control Chart GUI: The system can monitor any real-time and archived data. To setup the control chart interface, the user selects 'Watch Configuration' from the Control Chart Tab at the top of the user interface and set up the charts as shown below:

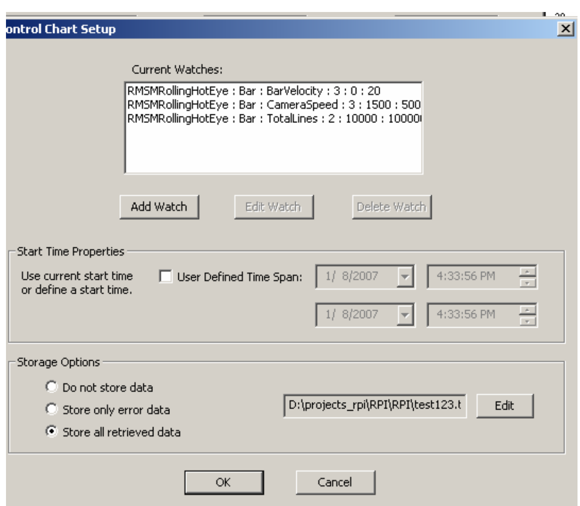


Figure 13. Control Chart Setup Dialog

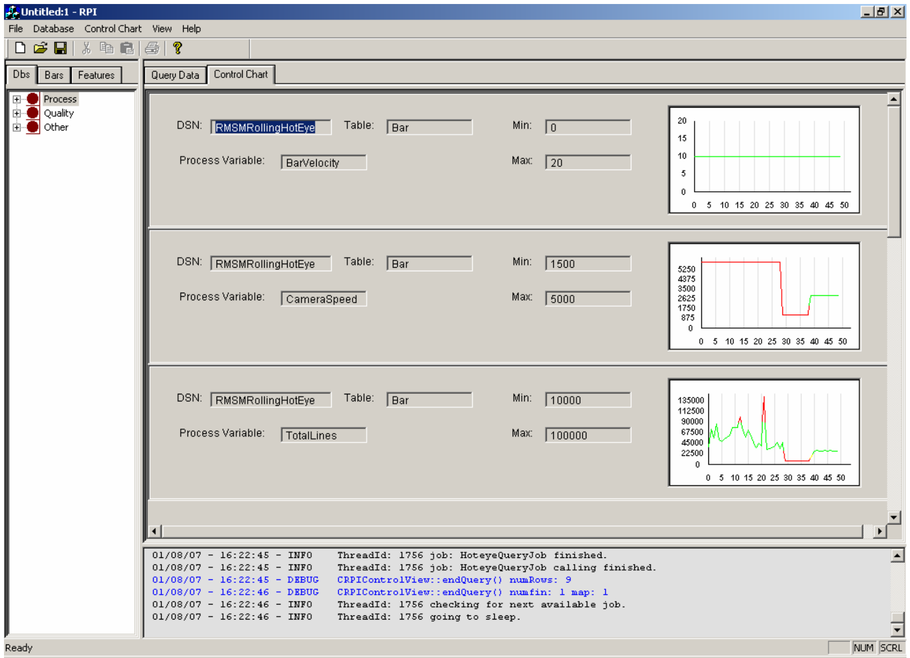


Figure 14. Sample retrieving data to the RPI Control Chart Interface

Control charts on different variables can be created with various algorithms. The following two samples illustrate the implementation while being site tested. Various algorithms are designed to handle different types of data. For instance, the algorithms/distribution to monitor a continuous variable (such as the cooling water flow rate at Stand X) and to monitor a discrete variable (such as the total number of defects per coil) would be different.

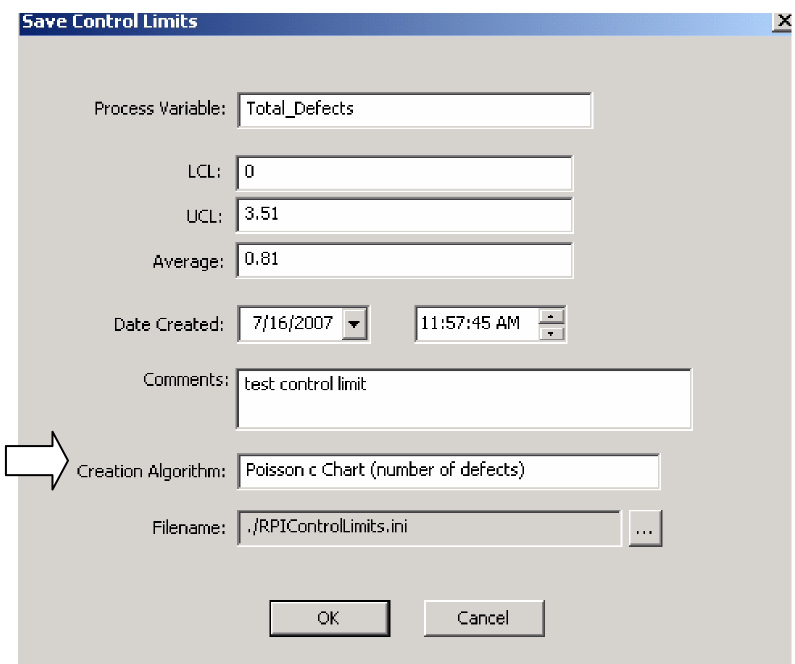


Fig. 15. Save Control Limits Dialog

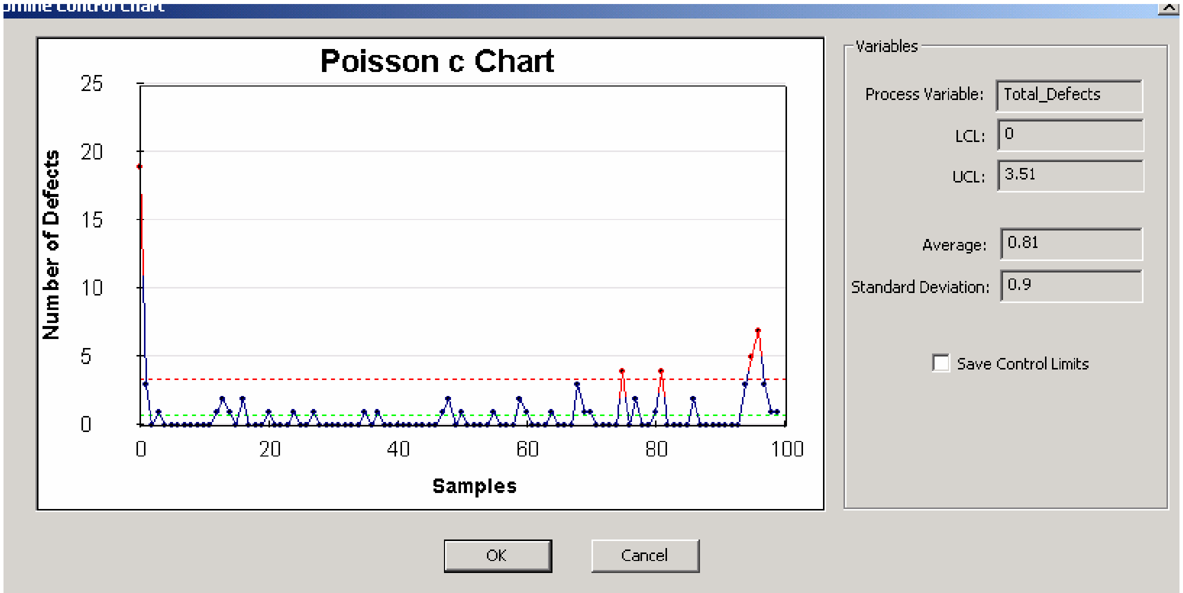
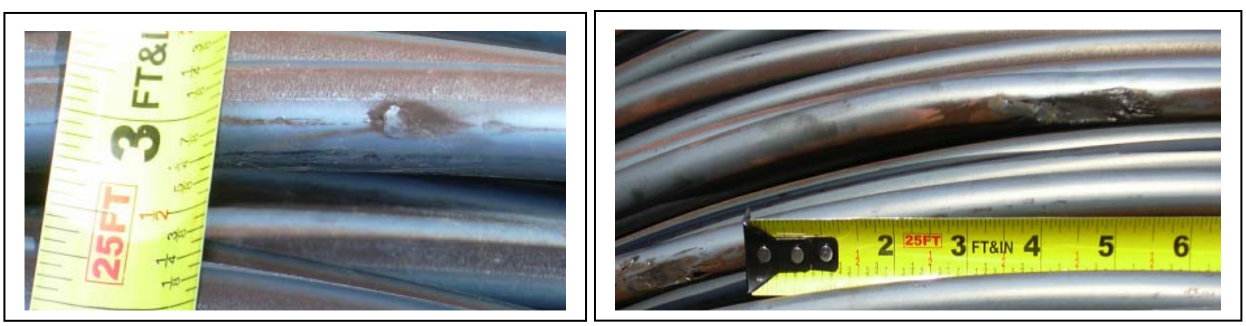


Fig. 16. Sample Poisson C-control chart (# defects)

E. Data for Quality Control

When applying inspection data against process control, the most important factor is what is being produced. When applying inspection data for quality control, not only what kind of defect is important, but also where it is. The team further tested the position accuracy on normal production coils. An experiment was conducted at the testing site. Seven coils were tracked, among which 5 with transverse marks, 1 with overfills, and 1 with broken roll marks. In these coils, actual defects were found in the coils with locations within +/- 6 inches of the HotEye® RSB reported locations. Some tracked defects are pictured as following.



****Only transverse defects are shown here because it is very difficult to picture longitudinal defects on a cold coils*

Figure 17. Detected samples on steel bars.

In addition to the defect location tracking, the testing site has also studied the correlation between their "customer complaints" and the defect data for over 12 months. Whenever the testing site received a customer complaint, the defect image records for that coil would be reviewed. A very strong correlation has been established.

An additional data review center is cooperated in the quality inspection station at the testing site. A procedure to link HotEye® inspection result to the final quality control decision making, such as hold the coil from shipment and/or trim the coil for partial shipment is under development.

F. System Integration

The integration work started at the "component level" of parameterization, in order to build up a software system that can capture a rolling mill, as well as be re-configured to each individual mill.

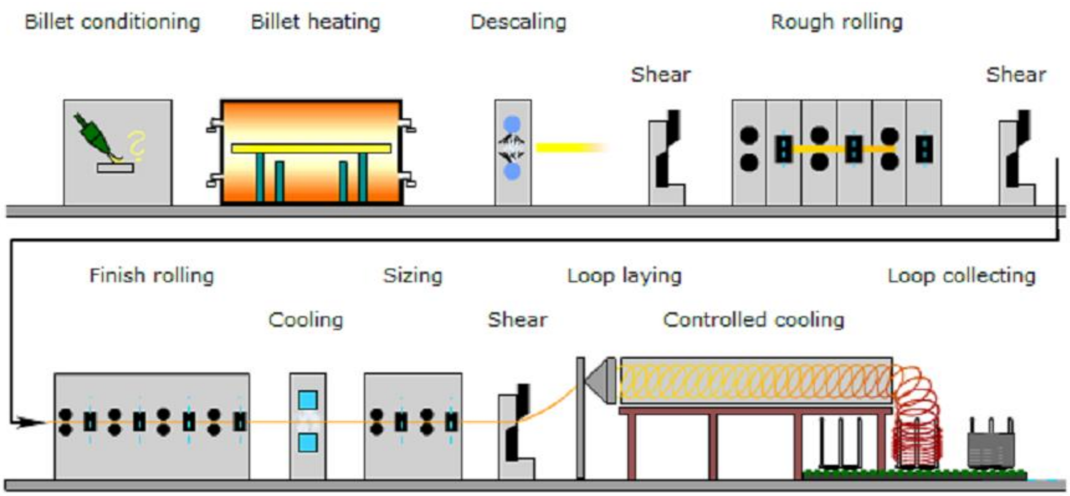


Fig. 18. A schematic mill implementation that has all basic mill elements.

The figure above illustrates the work. Each element, such as the reheat furnace, the cooling tubes and the shear, is being established with key input parameters (such as power input) and key output parameters (such as bar temperature), as well as key internal parameters (such as forming force and rpm). With the element set, a user will be able to drag multiple elements in place, to build a mill of his or her own. Once the mill is constructed, each element will be calibrated based on the actual mill data. The work developed in S4 provides the platform to properly extract the mill data. The data which includes data for good coils and bad coils will be used to establish the relationship among all the parameters of an element, such as roughing mill.

To date, the team has establish the element models for the reheat furnace, roughing mill, water descaling, intermediate mill, finish mill, Kocks mill, Tekisun mill, no-twist mill, runout table (Stelmor), and cooling bed. Each element has been verified with the data from the beta hosting mill.

The next step is to develop the graphical user interface that allows the user to build a mill model. Once the model is complete, the team expects that the product quality data can be used together with the mill process data through this inferencing model.

In terms of the product quality data, the beta testing was successful. Figure 19 shows the fused data collected from both the eddy current device and the imaging device.

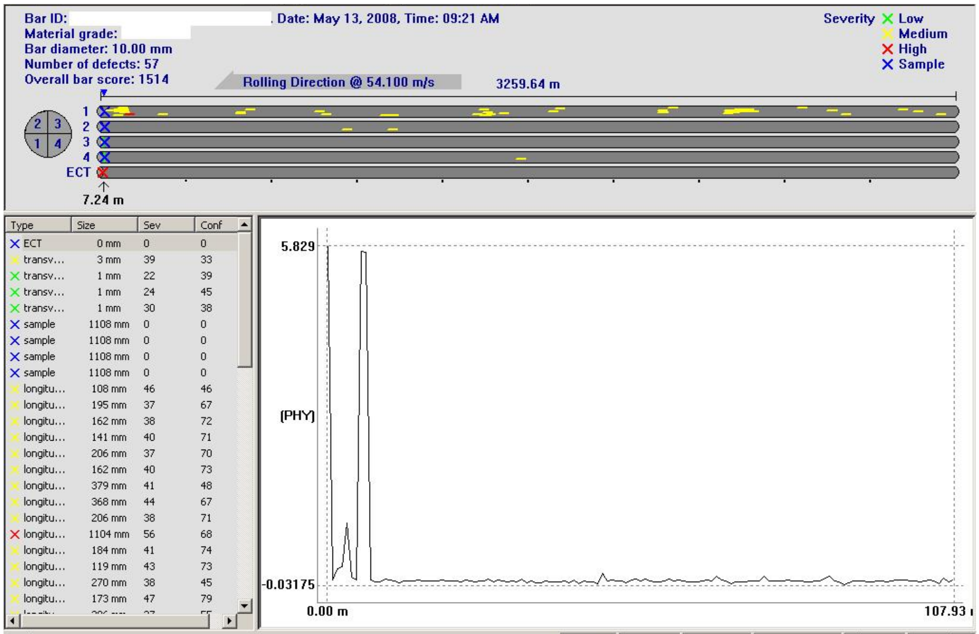


Fig. 19. ECT data shown in the HotEye® data file.

It is worth noting that the B count signal of ECT is matched with a HotEye® detection, and an image of the defective site is available (Figure 20, the zoom-in corner from Figure 19).

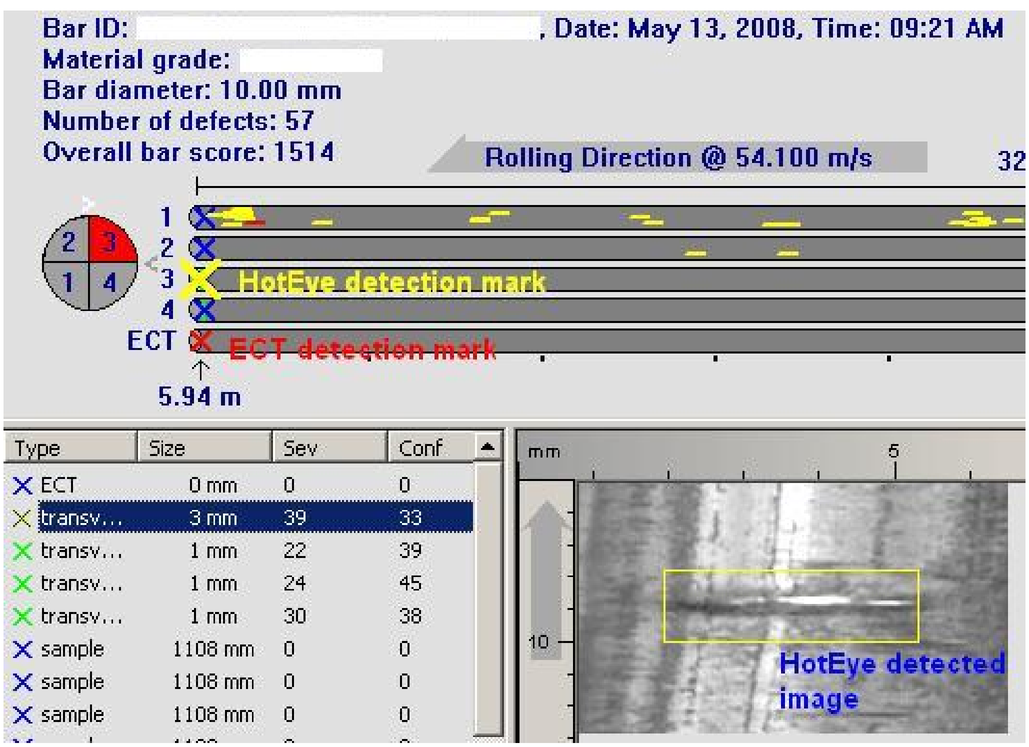


Fig. 20. Image of the dual detections.

G. Mill Trial Examples

Several of the technologies developed are commercialized and in use in steel mills. The benefits of the technologies have multiple perspectives and are mill dependent. Two examples are discussed in this section to illustrate the benefits. Both mills have been operating with the technologies for over 18 months.

Example #1

Mill #1 is a wire rod mill with an annual production volume of 600,000 tons. The products are manufactured into springs, gears, fasteners, and so forth. The developed technologies, along with the effort from the mill operation, achieved a reduction in its internal rejection rate with a saving over 4,000 tons (12 months operation with the technologies vs. 12 months operation prior to adopting the technologies). During the same period, the number of its customer complaints was also substantially reduced. The material savings of 4,000 tons equates to annual savings of 64,000 MMBTU[3] and reduction of 6,000 tons of CO_2 emission[4].

Prior to adopting the SQA technologies, Mill #1 was suffering from mill setup issues, particularly those associated with rolling parting lines, and cracks. The in-line inspection technologies helped in providing immediate feedback, and thus controls to address the setup issues. The advanced data analysis and process control approach delivered a solution to ease the issue of cracks.

Example #2

Mill #2 is a bar mill with an annual production volume of 350,000 tons. 90% of the products of this mill is for automotive applications such as coiled springs, anti-rolling bars, gears, and axles. The developed technologies, along with the effort from the mill operation, achieved less billet grinding, less internal rejects, less quality control inspection and less customer complaints.

Prior to adopting the SQA technologies, this mill had double-digit customer complaints. Billet inspection and grinding is a very typical way to handle quality issues in an SBQ (special bar quality) mill. Mill #2 back then was practicing double inspection and double grinding, as well as double quality control inspection, in hope to cope with the associated surface defect issues reported by its customers. That was costly in both labor and production yield. With the adoption of the SQA technologies, Mill #2 was able to discover the root cause of their issues. With the solution, Mill #1 stopped practicing double grinding. In fact, it reduced its billet inspection to less than 15% with minimal grinding, resulting in a yield improvement of over 0.5%, or 1,750 tons per year, in addition to the savings in processing cost. At the same time, its products carrying surface defects were reduced from over 60% plus to less than 15%, significantly reduced the need of rework and peeling, resulting a yield improvement of over 1.5%, or 5,250 tons per year. Its internal reject rate was cut in half, resulting in an annualized saving of over 1,200 tons. As of the end of 2008, the number of its customer complaints dropped down to 1 over an 18-month span. The associated benefits include annual energy savings 131,200 MMBTU and CO2 reduction of 12,300 tons.

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[3] 16 MMBTU per ton of steel.

[4] 1.5 tons of CO_2 per ton of steel.

ACCOMPLISHMENTS

Papers and Presentations

- Huang, H., Gutchess, D. and Chang, T., "Imaging-based in-line surface defect inspection for bar rolling," International Roll Design Conference (Richmond, VA, May 5, 2005).
- Chang, T., "Updates on imaging-based surface inspection systems for steel bars and rods," International Roll Design Conference (Boston, MA, October 2, 2008).
- Chang, T., "Deployment of imaging-based surface inspection systems for steel bars and rods," International Surface Inspection Summit 2008 (Amsterdan RAI, The Netherlands, February 26-27, 2008).
- Li, J., Shi, J. and Chang, T.S., 2007, "On-line Seam Detection in the Rolling Processes using Discrete Wavelet Transform", *Journal of Manufacturing Science and Engineering*, Vol. 129, pp. 926-933.
- Jin, N., Zhou, S., Chang, T.S. and Huang, H., 2008, "Identification of Influential Functional Process Variables for Surface Quality Control in Hot Rolling Processes," *IEEE transactions on Automation Science and Engineering*, Vol. 5, pp. 557-562.
- Chen, N., Zhou, S., Chang, T.S. and Huang, H., 2008, "Attribute Control Charts Using Generalized Zero-inflated Poisson Distribution," accepted by *Quality and Reliability Engineering International*.
- Huang, H., Lin, C., Jia, H., Chang, T., and Lupini, R., "Imaging based in-line surface inspection for continuously cast billets," AISTech 2008 (Pittsburgh, PA, May 2008).

Products

OGT has offered the HotEye® RSB systems to the steel bar and rod mills. In this product line, modules developed in this project are all integrated into the system for sale. These modules bring new capabilities, such as better detection capability and accuracy; enhanced system calibration/configuration; data rendering, analysis and process control capability; and integration with other mill instruments, to the HotEye® RSB product line.

The HotEye® RSB products have been sold to 6 countries over 4 continents, as documented on OGT's webpage (www.ogtechnologies.com). OGT has also set up sales channels in North America, China, Japan and South Korea. It is actively interviewing candidates for the sales services in Europe. To date, the cumulative HotEye® related sales revenue has exceeded $10 million. In 2008, the HotEye® RSB sales revenue was over $4 million.

Patent

The patent US Pat. No. 7,275,404 "A method and apparatus to control the lateral motion of a long metal bar being formed by a mechanical process such as rolling or drawing" was issued by the US Patent and Trademark Office.

Awards

During this project period, OGT received two major awards: the 2006 R&D 100 Award (for OGT's HotEye® RSB products) and the 2007 Michigan 50 Award. The two awards documented OGT's technological and business achievements, respectively.

CONCLUSION

The project has been successfully executed with many technologies developed, commercialized and in use worldwide. The SQA team accomplished many technological breakthroughs, evidenced by the technical journal papers. The breakthroughs would not only benefit the commercialization aspect of this program, but also have the potential to trigger additional R&D activities and/or be used in other complex manufacturing processes.

The commercialization strategy adopted by the SQA team has proven to be effective for the target market. The public funding leveraged the private investments, resulting in a new hi-tech product for the steel industry. The "commercialization on the fly" approach has also proven to be effective. OGT was able to sell its products with incremental improvements. Such an approach was adopted because OGT is a small business and could not wait until the completion of the entire project with its limited resources.

However, it is worth noting that technology development associated with an energy intensive industry, such as the steel industry, is full of obstacles. First, the process is typically very complex and dangerous. The mills would not risk involving external R&D workforce unless there are well developed plans and compelling reasons. Second, given the scale of the process, there is no chance but to conduct the R&D in a manufacturing environment. Yet, there is a dilemma. When the business is slow, the mills are lack of the adequate resources to support any R&D, even if it is only the in-kind contribution. When the business is good, there is little room to fit the R&D activities into the manufacturing schedule. With this in mind, public funding has been a very positive incentive for the mills to open their doors to the SQA team.

RECOMMENDATIONS

OGT will continue its commercialization path and extend the success of this project to other energy-intensive processes such as continuous casting, steel rail and seamless tube manufacturing. Additional R&D and demonstration may be required due to the process differences. However, the successful experiences from the rolling mills will form a good foundation for future adventure.

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