Semantic Data Mining based decision support for quality assessment in steel industry

Artificial Intelligence in Research and Applications Seminar

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Motivation

Semantic Data Mining based decision support for quality assessment in steel industry



Integration of machine learning approach with ruled-based quality management systems



Semantic compatibility with current support decision systems



Semantic Data Mining based decision support for quality assessment in steel industry

1. Review of methods related to quality control

2. Description of the Hot Rolling Mill process

3. Ruled-based decision support system in HRM

4. Semantic Data Mining approach





ISO 9001:2015

• The totality of features and characteristics of product or service that bear on its ability to satisfy stated or implied needs revolving around the customer.

British Defence Industries Quality Assurance Panel

• Quality is conformance to specifications.

Degree of preference

• It is the degree to which a particular product is preferred over competing products of similar grade, supported comparative test by customers, normally called as customer's preference.

Manufacturing-based definition

• Quality of a product, means conformance to customer's requirements

Degree of Excellence

• It is a measure of a degree of excellence at a suitable price and control of variability at a suitable cost. this is often a Value-based definition.

Quality Control is a set of activities for ensuring quality starting from raw material to end product.

- devices
- tools
- skills



Decision support system

A decision support system produces detailed information reports by gathering and analyzing data.



A decision support system (DSS) information system that aids a business in decision-making activities that require judgment, determination, and a sequence of actions.

A DSS is either human-powered, automated, or a combination of both.



https://corporatefinanceinstitute.com/resources/knowledge/other/decision-support-s

ISO 9001:2015 norm

International standard that specifies the requirements for companies quality management systems



Work Environment



Lower Limit

-5σ

-4σ

-3σ

-20

-1σ

-6σ



Lean Six Sigma Comprehensive Implementation Model

Well-tested set of instruments and techniques aimed at reducing the variability (tolerance) and defectiveness of a product/process

https://www.researchgate.net/publication/333648011_Quality_a_Key_Value_Driver_in_Value_Based_Management https://lablean.blogspot.com/2015/03/dmaic-applied-to-biopmanufacturing.html

Statistical Process Control

Statistical Process Control is a process of finding and measuring variability in the manufacturing process.



SPC vs Six Sigma



Semantic Data Mining

Data mining is the proces of uncover novel, interesting and understandable patterns related to valuable, useful, and implicit knowledge.

Semantic Data Mining is a knowledge-based analysis approach.

Focused on exploiting the formalized information in order to enhance interpretability of the applied data mining models



Hot Rolling Mill process

Start date - 2019-08-01 00:00:56 End date - 2019-08-31 23:57:18 Furnace Products amount - 9551 coils Parameters amount - 394 Process mesurements amount - 463 401 627 Roughing mill Process nodes: Single pass per product Product - hot slab Walking beam furnace Single value measurements Main parameters - charge/discharge temperatures, heating time ſĻ 5 or 7 passes per product --Finishing mill Product - transfer bar Continuous measurements + single value Roughing mill (RM) Main parameters - temperature, speed, forces, width, thickness ~9000 records for all passes per product Ŷ Single pass per product Product - strip Finishing mill (FM) Continuous measurements + single value Main parameters - temperature, dimensions, forces, rolling mills setups Laminar cooling ~31 200 records per product Û Single pass per product Product - coil Laminar cooling + Coiler Continuous measurements + single value Coiler Main parameter - temperatures, water amount







Roughing mill



Furnace Roughing mill -⊕**©**@⊕ Finishing mill Laminar cooling Coiler

Finishing Mill device

- 100 s of rolling
- Over 10 times thickness reduction
- 3.5 min whole process
- 4 mln tonnes/year production capability











Capability factors

Data cleaning:

- Sensor response time flag
- Sensor default value flag



Distribution after data cleaning

Capability factors

Process capability - Cp: tolerance width divided by the total spread of process (6 Sigma).

Calculation of Process Capability (Cp) :

Cp = <u>Design Tolerance</u> = USL - LSL 6σ 6σ **USL** = Upper Specification Limit **LSL** = Lower Specification Limit

Ср	Defects amount		
1	2700 ppm		
1,33	63 ppm		
1,67	0,57 ppm		

2

0,002 ppm

Process Capability Index - Cpk: indicates shifting of the process, the minimum of Cpk upper and Cpk lower.

Calculation of Process Capability Index (Cpk) :

$$Cpk_{U} = \underline{USL} - \overline{\overline{X}}$$
 and $Cpk_{L} = \overline{\overline{X}} - \underline{LSL}$
 3σ 3σ

https://www.doriane-copar.com/process-capability-index-cpk/

https://techqualitypedia.com/cp-and-cpk/



SPC decision support

3 scopes of information

- Single feature, single product, all measurements (data series)
- Single feature, two statistical factors, many products (single value)
- Many features, many products, single statistical factor

Single coil temperature distribution





SPC decision support



Control chart



SPC decision support



Control chart



SPC decision support - trends control



SPC reporting system on Hot Rolling Mill



Users of quality decision support system



R&D - technology optimisation, Quality department - complaint evaluation Production departments - logistics

Decision support in practise

Goal: find causes of the defect



Semantic Data Mining application



Model input - Feature selection

Single and continuous measured parameters groups

Process parameters data series	Product quality parameters data series	Metadata single data
Speed	Thickness	Product IDs
Gap	Width	Targets and constraints
Left side pressure force	Profile	Products dimensions in all nodes
Right side pressure force	Wedge	Rollers dimensions
Bending	FM exit temp.	Thickness reduction settings
Shifting	Coiling temp.	Chemical composition





Rollers bending





Model design

Metrics	XGBoost	Decision Tree	K–Nearest Neighbor
F1	0,61	0,58	0,5
Accuracy	0,986	0,983	0,981
Precision	0,77	0,61	0,66
Recall	0,51	0,55	0,41

Input dataset - Product quality parameters

ML classifier - XGBoost

Model explanation - SHAP values



Parameter importance with respect to	→ III F1:	~	
Q Search		$\left\{ \begin{array}{c} & & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ & \\ $	$\langle \rangle$
Config parameter	Importance 🛈 🗸	Correlation	
learning_rate			
subsample			
seed			
max_depth			
test_size			

Explainer module - SHAP vs Lime





https://towardsdatascience.com/shap-shapley-additive-explanations-5a2a271ed9c3 https://towardsdatascience.com/lime-explain-machine-learning-predictions-af8f18189bfe https://dl.acm.org/doi/abs/10.1145/2939672.2939778



LIME - Local Interpretable Model-agnostic Explanations

Single prediction results



Predictive maintanance Assesment of oscilating signals like forces or vibrations

Use of machine learning **model to create labels** for subsequent model used for semantic explanations Introduct additional types of machine learning models like LSTM to analysie performance of Finishing Mill device in subsequent stands

New forms of the **results visualization** to show summarized impact of the individual parameter

Related works

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