Quality Evaluation Based Fuzzy Residual Modelling. Application in Hot Rolling

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Abstract: - On line quality evaluation is an important domain particularly in the complex processes where the characteristic of the product quality is difficult to measure directly. Evaluation based modelling techniques can be considered as an alternative to solve such complex problem. We consider in this work a contribution for product quality evaluation in hot rolling using fuzzy models. Residual changes are used to obtain an evaluation of product quality. Fuzzy rules are implemented in basis of the residual and first derivative changes. Application in hot rolling shows that this approach can be recommended as part of a tool of on line quality evaluation and classification.

Key-Words: - Fuzzy reasoning, On-line Quality Control, Quality Classification, Hot Rolling Process

1 Introduction

Generally modern manufacturing environment is a combination of individual cells, designated to complex assembly and material processing tasks. The success of such a system is greatly depended on fault-free and stable operation of every unit. Deviations from normal situation decrease productivity. Continuous monitoring is therefore required to maintain the functionality and quality of the production.Connected with continuous monitoring, estimating the evolution of the failures becomes possible and predictive maintenance policy can be achieved. Product quality analysis is also complicated due to uncertainties in time delay necessary to achieve correct results particularly in complex systems. Quality control of manufacturing processes has traditionally based on limit value checking of analysis results. Moreover, thresholds that define the normal conditions are often dependent on the operating point of the system. Detection and isolation of small, simultaneous faults is therefore difficult with signal-based limitsModel based fault detection methods have been used in production industry to overcome difficulties that arise with limit checking. These methods have many advantages, for example a higher performance - smaller faults can be detected and different faults can be isolated. Disadvantages are that an accurate model of the process is necessary for efficient operation [1]. In recent years, many soft computing methods have been introduced for fault detection. Neural networks and fuzzy logic are typical examples of artificial intelligence methods, generally model-based reasoning [2]. Fuzzy set theory, for example, is an effective tool when dealing with uncertainty in systems [3]. Fuzzy rules are easy to interpret and causal relations of the system can be presented in the form of natural language. Neural networks are data-driven methods with the ability to generalise on the basis of collected information [4]. In addition, linguistic equations framework has been introduced and applied for several process control and monitoring tasks [5], [6], [7], [8], [9]. In this work, various different modelling and monitoring strategies are combined in order to achieve a general quality monitoring framework. A possibility of on line quality monitoring is investigated. To reach the targets, intelligent hybrid methods are considered and applied together with traditional data mining and analysis approaches, including expert knowledge. In the proposed framework, data are explored via systematic analysis technique. Models for normal and abnormal situations are then constructed on the basis of analysis results, and information collected from real process. Finally, outputs of the models are interpreted in order to identify the production quality. Functioning of the method in different process environments is ensured using selected analysis techniques. Principle of the developed quality monitoring system is demonstrated with simulated data. Quality monitoring is a continuous on line task of determining the conditions in a physical system. It consists of recording information, recognising changes, detection of abnormalities in the systems behaviour and classification [10]. Fault is a deviation of at least one characteristic property or parameter from an acceptable condition. It is a state, which may lead to a malfunction or failure of the system [11]. Detection of faults is based on symptoms that are changes of observable quantities from their normal behaviour. Symptoms can be generated from analytic and heuristic information. Analytic symptoms consist of characteristic values of the system. Measurement data processing has to be performed in order to construct these values. Various methods are used, namely [11]: Limit value checking of directly measured signals. The characteristics values are exceeded signal tolerances, Signal analysis of measurements with signal models like spectral analysis or frequencies, variances, amplitudes and model parameters, Process analysis using mathematical process models, parameter estimation, state estimation and parity equation methods. In this case characteristic values are model parameters, state variables and residuals of the models. The resulting changes in characteristic values can be considered as analytic symptoms. Heuristic symptoms, on the other hand, are based on qualitative information obtained from human operators. Further sources for producing heuristic symptoms are process history, maintenance reports, statistical data, lifetime and load measures [11]. Fault detection includes recognition of an unacceptable behaviour in a system. Abnormal conditions can be detected with analysing existing symptoms that are observable notifications of fault situation. Fault isolation, that is the determination of the type and location of the fault, is performed after detection. Strategies for monitoring process abnormalities are called Fault Detection and Isolation (FDI) methods [11]. Quality monitoring of production systems includes observation of the product quality, process quality and functioning of machines. Also the reporting can be considered as a monitoring method. Information about process conditions and quality data enables the analysis and implementation of process and quality control mechanisms [10]. In the following steps a combined use of process model and fuzzy residual is applied to quality index monitoring in hot rolling process.

2. Proposed on line quality Evaluation Method

The development of models based fuzzy reasoning for quality control according to the importance of the process changes is a challenge. This permits a reduction of quality cost management in different branches of industry. Sometimes, it is very difficult or impossible to measure a certain quality parameters in real time. Modelling based residual analysis connected to real fuzzy rules is a tool that we develop in this work.

2.1 Modelling and Residual Processing

Fig1 shows the principle of modeling and residual generation. Model is obtained using optimal operating conditions data and the required learning algorithm [11], residual *e(t)* is defined as the difference between the actual process output y(t) and the model output $y_M(t)$. Decisions are carried out by a whole of fuzzy reasoning based on the dynamic behavior of the residual such as *e(t)* and $\Delta e(t)$.Let a process characterised by its input process variables X and its output defined by a quality index Q. The objective is to find a complex relationship between X and Q. Operating conditions are defined as normal (N), fault 1 (F_1), fault 2 (F_2),….fault n (F_n) according to residual changes of *e(t)* and $\Delta e(t)$. Consequences of such faults are generally a degradation of quality index Q.

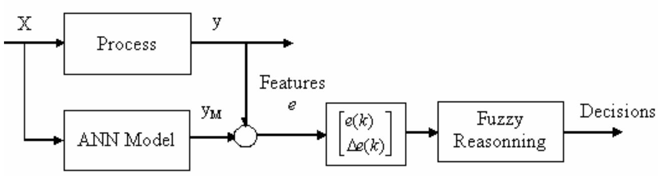


Fig.1: Principle of quality monitoring using modeling and fuzzy classification

Feed forward neural networks are composed of neurons in which the input layer of neurons is connected to the output layer through one or more layers of intermediate neurons. The training process of neural networks involves adjusting the weights till a desired input/output relationship is obtained. The mathematical characterisation of a multilayer feed forward network is that of a composite application of functions. Each of these functions represents a particular layer, e.g. all the units in the layer are required to have same activation function. The overall mapping is theses characterised by a composite function relating feed forward network inputs to output.

2.2 Classification Using Fuzzy Sets

Many fuzzy modelling methods have been proposed in the literature [12], [13]. Most are based on collections of fuzzy IF-THEN rules of the following form:

IF x_1 is B^1 and….and x_n is B^n THEN y is C (1)

Where $x = [x_1,....x_n]$ and y are the input and output linguistic variables respectively, and B^i and C are the linguistic values characterising the membership functions. It is considered that this fuzzy rules representation provide a convenient framework to incorporate human expert's knowledge. Systems consisting of many rules are more conveniently expressed using relational arrays. However, the use of relational models in engineering application has a number of limitations. Firstly, their use is normally limited to systems with a small number of variables in view of their large size and computing requirements. Another problem posed by relational fuzzy models is that there is no simple approach for deriving numerical optimisation search techniques.

An alternative method of expressing fuzzy rules proposed by Takagi and Sugeno has fuzzy set only in the premise part and a regression model as the conclusion:

IF x_1 is B^1 and….and x_n is B^n THEN

$$y = C_0 + C_1 x_1 + ... + C_n x_n \qquad (2)$$

Where, x, y and B^i are defined in above, and C_i are real – valued parameters. Since this form of rule representation contains more information, the number of rules required will typically be much less than relational fuzzy models (a complex high dimensional non linear model valid within certain operating regimes defined by fuzzy boundaries). Fuzzy inference is then used to interpolate the outputs of the local models in a smooth fashion to get a global model. This modelling approach provides better modelling accuracy than relational fuzzy models and it is free of the problem arising from model incompleteness which limits the usefulness of relational fuzzy models [12], [13].

The principle of quality classification given in Fig.1 is summarised by a computing procedure.

As shown in the flowshart of Fig.2, starting by data acquisition as an input this method gives a computed quality index Q as an output.

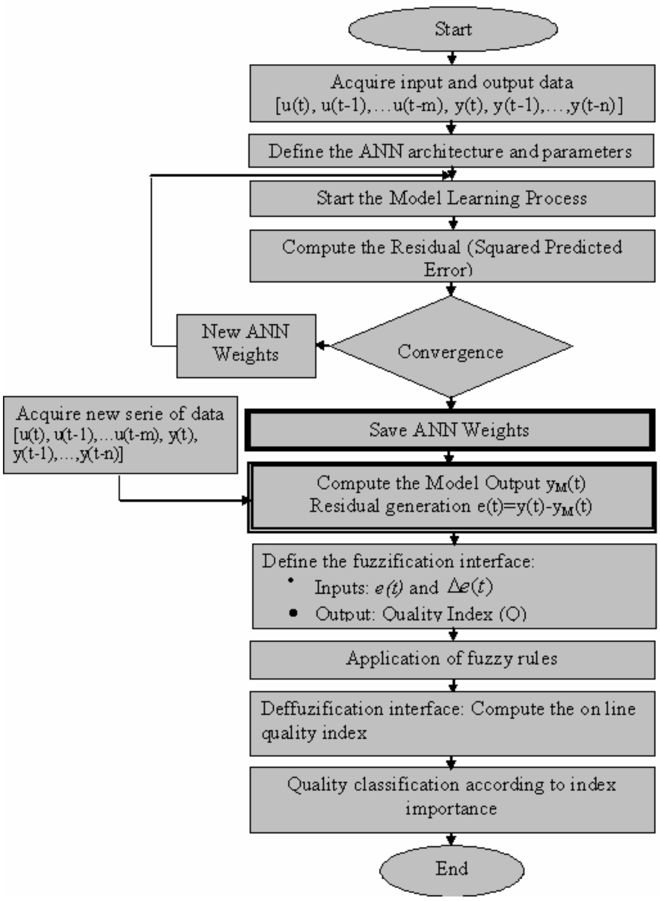


Fig. 2: Principle of quality index computing procedure

The ANN learning Process is carried out by the required data and algorithm. After the convergence, the ANN model is used to generate residual $e(t)$ $\Delta e(t)$ and $e(t)$ are used as inputs to fuzzy system. This system is defined by the fuzzification interface, the fuzzy rules and the deffuzification interface. Fuzzy rules give relational fuzzy model between the input and the output. Output is the quality index.

3. APPLICATIONS IN HOT ROLLING PROCESS

3.1 Process Description

In the finishing mill of hot rolling, the strip thickness is reduced while the strip passes through each of the 6 strands by controlling the rotary speed**.** Each strand has its rotary speed v_i, i=1:n. In this case of study, there is 06 strands (n=06).

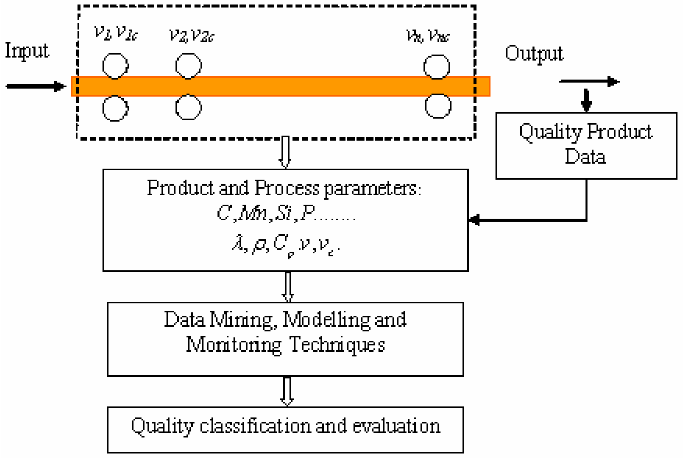


Fig.3: Principle of Quality monitoring in Hot Rolling

Optimal operating conditions are essentially defined by a constant relationship between different rotary speed v_i. In real cases, this relation is submitted to different changes in the process and physical properties of the material that are directly connected with the final product quality. Physical properties are generally defined by the chemical composition C, Mn, Si and physical characteristics λ, ρ, C_p. Residual and its variations is a part of the quality monitoring and evaluation system. Residuals are obtained from a hot rolling using real and model data.

3.2 Quality Evaluation Based Fuzzy Residual

Using residuals, quality index has been obtained by a fuzzy reasoning of residual. Fig.4 shows the principle of quality index prediction. This principle uses 02 inputs defined by e(t) and Δe(t), 01 output defining the quality index (Q) and a model defined by fuzzy logic reasoning. Fig.6a, Fig.6b and Fig.6c show the membership functions of inputs and output respectively. All data are defined in a normalized range of -1 to 1.

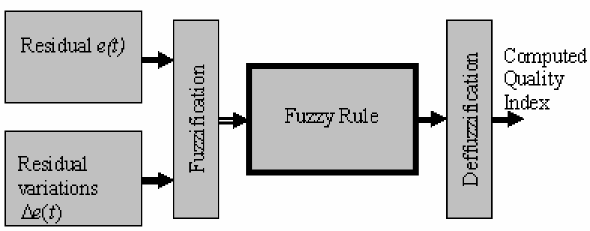


Fig. 4: Principle of prediction of quality index

The fuzzy rules are defined as follows:

1. If Δe(t) is Minimum AND e(t) is Minimum THEN the quality is Very Good (VG)
2. If Δe(t) is Minimum AND e(t) is Medium THEN the quality is Good (G)
3. If Δe(t) is Minimum AND e(t) is Maximum THEN the quality is Medium (M)
4. If Δe(t) is Medium AND e(t) is Minimum THEN the quality is Good (G)
5. If Δe(t) is Medium AND e(t) is Medium THEN the quality is Medium (M)
6. If Δe(t) is Medium AND e(t) is Maximum THEN the quality is Poor (P)
7. If Δe(t) is Maximum AND e(t) is Minimum THEN the quality is Poor (P)
8. If Δe(t) is Maximum AND e(t) is Medium THEN the quality is Poor (P)
9. If Δe(t) is Maximum AND e(t) is Maximum THEN the quality is Very Poor (VP)

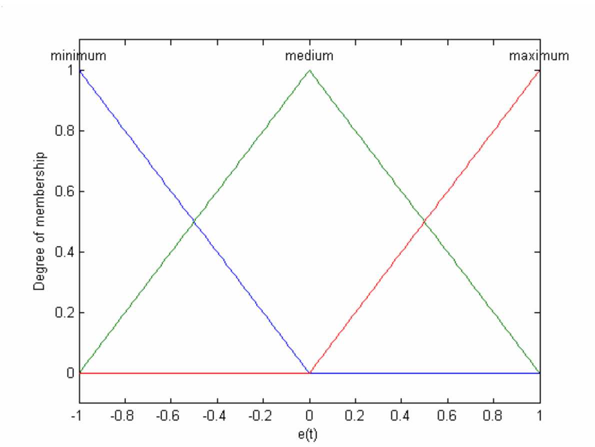


Fig.5a: Membership function of *e(t)*

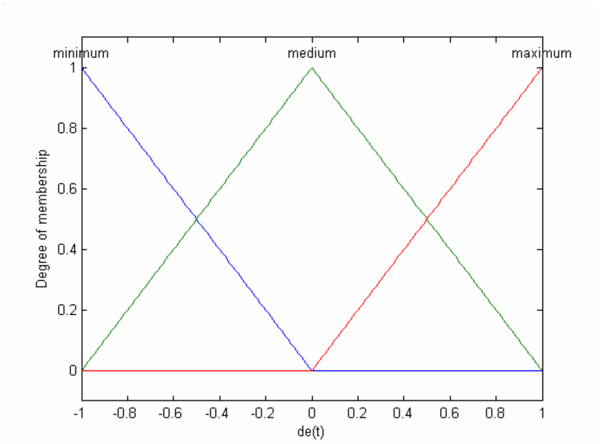


Fig.5b: Membership function of Δ*e(t)*

Simulation based real world measurements is carried out by 04 cycles of rolling. Fig.5a, Fig.5b and Fig.5c show the membership function of the inputs and the output respectively. Fig.6a and Fig.6b give the corresponding computed residual e(t) and its variation Δe(t) respectively. Using the fuzzy rules based membership functions and residual changes given in Fig.6a and Fig.6b, a corresponding quality index is computed (Fig.6c).

The obtained results confirm the logical dependence between inputs (e(t) and Δe(t)) and output Q (quality index). It is clear that according to changes importance of process variables, quality index changes are equivalent. To qualify each rolling cycle, statistical properties of quality index can be used.

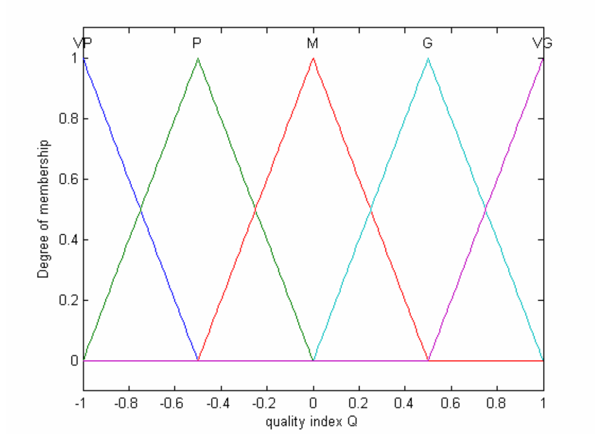
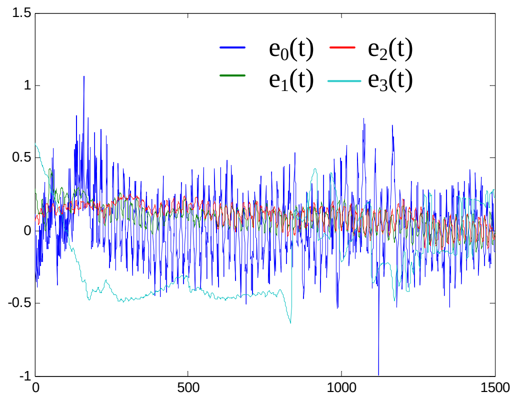


Fig.5c: Membership function of output Q (quality index)



Sampling number (k)

Fig.6a: Evolution of residuals *e(t)*

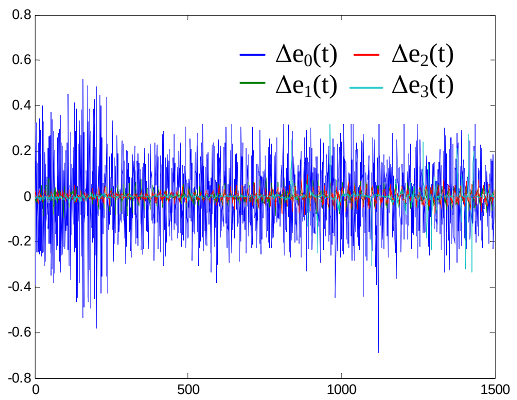


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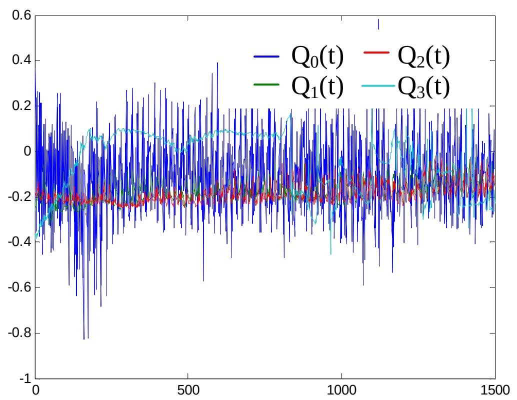
Fig.6b: Evolution of residuals variations Δ*e(t)*



Sampling number

Fig.6f: Computed Quality Index

Table1. Values of global Quality Index

$Qu_i = Q_i * Q_i^T$	Value
Qu_0	215.3508
Qu_1	77.8195
Qu_2	79.2805
Qu_3	85.4921

4 Conclusion

A new approach of on line quality monitoring using modeling and fuzzy reasoning is developed. Application in finishing mill of hot rolling is carried out by real data and modeling techniques. Residual analysis coupled to a fuzzy reasoning are applied and a on line quality evaluation is obtained. Global quality evaluation Qu_i is given by the quadratic quality index Q_i defined in the table1. This work can be easily integrated in the complex monitoring system without a hard investment. This can be obtained by some soft modifications in the sftware package.

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