Cooling Bed of Rebar Process Evaluation using Temperature Monitoring and Soft Sensing Methods

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Abstract

In recent years the sensitivity of infrared cameras has been improved considerably. This increase in sensitivity has led to new investigations to determine their usefulness in a variety of testing and diagnostic applications. A method for process quality evaluation and temperature monitoring of Rebar is considered, this method extracts residual as a difference between the measured temperature and a reference values. Temperature field measured by an infrared camera is affected by several factors. Fault detection and its allied methods such as the combined use of residual analysis and fuzzy reasoning are used for a global evaluation of the monitored area of the rolling bar. This approach is applied in Rebar process for building a complementary condition monitoring system which permits an online quality and process evaluation. Simulation results based on the measured surface temperature and the analysis of generated residuals show that the new approach is easily implementable. While giving online good results

Key words
Rebar process, Rolling process, Infrared temperature measurement, Residual generation, intelligent modeling, Fuzzy quality evaluation.

1. Introduction
In metalworking, rolling is a metal forming process in which metal stock is passed through a pair of rolls. Rolling is classified according to the temperature of the metal rolled. If the temperature of the metal is above its recrystallization temperature, then the process is termed as hot rolling. If the temperature of the metal is below its recrystallization temperature, the process is termed as cold rolling. Hot rolling is a metalworking process that occurs above the recrystallization temperature of the material. After the grains deform during processing, they recrystallize, which maintains an equiaxed microstructure and prevents the metal from work hardening. The starting material is usually large pieces of metal, like semi-finished casting products, such as slabs, blooms, and billets. The raw material billet is the primary raw in the rebar process, billet size of 135x135x6,000mm. Reheating Furnace a pusher type reheating furnace (Peel Bar) is recommended to heat the billets to the rolling temperature of about 1150 -1200°C, depending on steel grade. Charging of the furnace is performed laterally through by Hydraulic pusher. Billets are pushed inside and discharge by Billet Ejector. The furnace uses natural gaz as its fuel. Rolling process theoretically, this is a Constant volume process. The billet is heated up to 1180 - 1200 C and passes to sequence of rolls with profile grooves until reaches the desired product size. This continuous rolling mill has a constant pass line and comprises in total 16 stands for using a billet size of 135 mm square. Six stands are provided in the roughing mill, 4 stands in the intermediate mill and six stands in the finishing mill.

Quenching process for manufacturing superior quality of reinforcing bars with improved yield strength and weldability. The Quenching process produces a composite microstructure with strong tempered rim and ductile core, through low air cooling temperature that results a thin and compact mill scale on the rebar surface. The rebar product size varies from 12mm to 40 mm diameter in bundles with product length of 12m. The aim of the present paper is to develop a soft sensing approach to evaluate the process capability using temperature measurement and soft sensing method; this is carried out by an analysis of the rebar surface temperature measured by an infrared camera. The

evaluation method is based on the residual generation and analysis, residuals is obtained as a difference between an optimal temperature profile and a real temperature measured by an infrared camera. Fig.1 shows the principle of the temperature monitoring and process evaluation system in rolling process, the calamine and other perturbations are considered as a noise that disturbs the measurement, in this work it is develop a method to evaluate the process using intelligent approach and measurement repeatability. There are many developed general works in the field of quality control and evaluation, the most commonly cited are:

- The evaluation - based computer vision and signal processing methods, which allow non destructive on-line real-time processing [1-7] The input of the system in this case is an information of one or two dimensions signal (image). The used algorithms are based on simple or complex analysis such as the comparative thresholds or other complex techniques.
- Intelligent methods including fuzzy methods and expert systems have also been considered in several works [8-10]. The system uses fuzzy rules and membership functions of linguistic variables, conducts inference and defuzzification, and gives a global quality evaluation of welding.

Fault detection and isolation (FDI) methods based on Multivariate statistical process control (MSPC) techniques, including the residual generation, have been widely considered as a promising approach for mining monitoring and control - relevant information from process history data, its successful applications have been reported in numerous process industries [11-13] Traditionally, the FDI method as a part of the MSPC technique takes an important place in monitoring methods, some works are extended to process and quality evaluation [14]. Quality evaluation of calamine in continuous casting using FDI based residual analysis remains relatively new, it will be developed in this paper. In this work, an extension of FDI methods using the combined approach based on the fuzzy reasoning of generated residual is considered. This approach combines the following two steps:

- The first step is a modeling and residual generation part: residual is generated by the difference between the real thermal distribution (y^t) measured by an infrared camera and an optimal thermal distribution (y_r^t) .
- The second step is a fuzzy evaluation of the generated residual for condition monitoring and process capability evaluation rolling bar.

This approach gives a global evaluation of the process according to the residual evolutions, the main motivations to use such approach based on residual generation and fuzzy reasoning are:

- The nature of the process application, characterized by a contactless temperature measurement using infrared camera;
- The evaluation technique requires a soft sensing approach;
- Usually, a combined approach between residual generation and evaluation is strongly recommended for an automatic evaluation. Generally, the residual is used in fault detection and diagnosis without an analysis of its impacts on the product quality [15-17].
- The quality evaluation of continuous and batch processes is naturally a fuzzy form: it uses a comparison
- of the quality level between different repeated steps.

This paper is organized as follows: In section 2, a brief description of the bar rolling scheme characterized by the heat transfer in cooling zones and its impact on the calamine appearance. Section 3 gives the principle of thermographic measurements of surface bar. In Section 4, the condition monitoring of rolling bar temperature based on residual generation and fuzzy reasoning is developed, and a computing scheme is proposed. It is given results analysis and evaluation of the quality on the basis of the residual importance. The fuzzy system is tested; a good agreement between the quality evaluated by expert and the measured surface temperature in the considered area are obtained.

2. Surface temperature monitoring in rebar process

It is considered in this part the dynamic behaviour of rolling bar surface temperature as a noised system. On the measurement point, we suppose that the measured surface temperature is affected by a random noise characterized by its statistical and distribution properties. The principle of surface quality evaluation is given by the following Figure1.

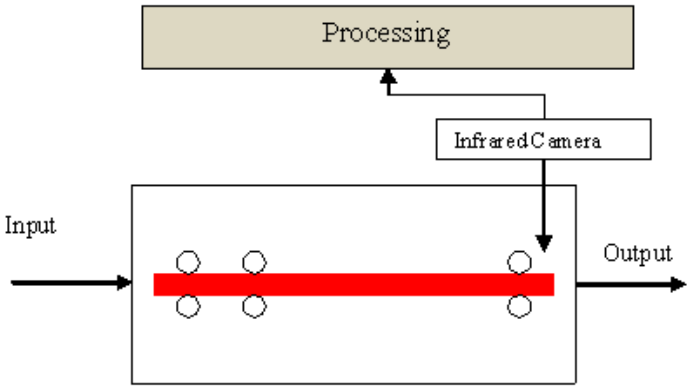

Fig.1: Principle of rebar surface temperature monitoring

As shown in Figure 2, the surface temperature is controlled by the process variable such as the air flow rate; the presence of the calamine is modeled by a random noise. Extracting this noise permit an evaluation of the cooling bed quality according to the temperature repeatability.

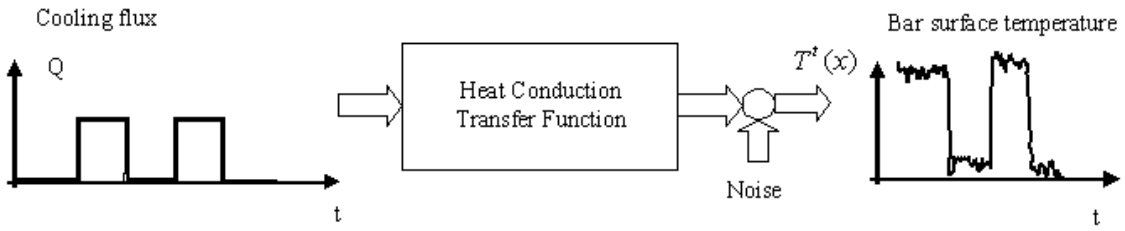

Fig.2: Principle of Measurement Model

3. Thermographic measurements at the surface of rebar

Surface rolling bar temperature measurement is affected by different disturbances; the commonly known is the calamine. Calamine is a result of the surface billet oxidation; its intensity depends of the steel grade, cooling conditions and other process parameters. In the past decade, some works in this field have been developed and the majority is based on the use of the infrared pyrometer equipped by a mechanical system to clean the surface measured point. In this paper, it is developed a soft sensing approach for quality evaluation. The vision system elaborated within the framework of the research described in the paper has been assigned to such processes. The system has included hardware and software parts. The hardware part has consisted of a camera and a portable PC to make recordings in real time. The main task of this part was to observe the process by means of IR camera. The device used was a FLIR ThermaCAM A40Fw imaging system. It has a 240×320 pixels focal-plane-array uncooled microbolometer detector, with a sensitive range of 7.5-13 mm. Imaging and storage was made at a frequency rate of 50.

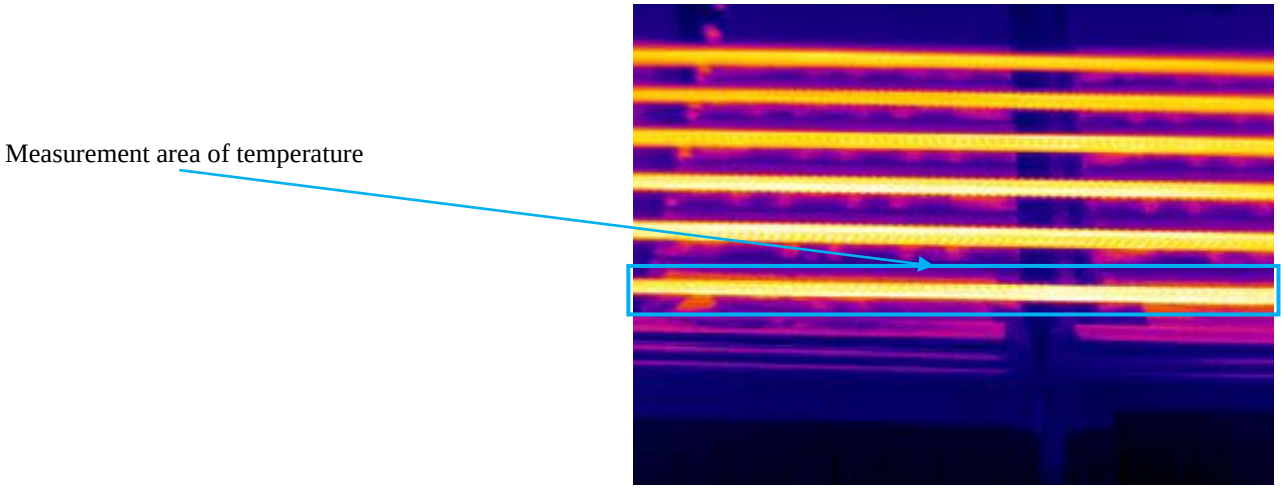

Fig. 3: Thermograhic image of rebar in cooling bed

4. Condition monitoring and evaluation

In the last decade, quality control methods have proved to be a powerful tool in the area of product and process engineering for solving low cost quality control and inspection using classification and evaluation methods. However, their online application needs data acquisition, training, validation and testing using new algorithms, which are time-consuming in the case of large data sets. In rebar process, generally, an optimal thermal profile of the strand machine guaranteed an optimal quality of the cooled product (rebar), the set point temperature at each point of the strand is generally constant. Any deviation between the optimal thermal distribution (y_r^t) and the real thermal distribution (y^t) is considered as a source of a possible defect in process repeatability. In recent years, many works based on conventional and advanced methods have been considered; however, FDI theory and methods are not yet fully tested and applied.

The quality evaluation and monitoring scheme proposed in this paper uses the FDI principle which is divided into two parts: the first part is a residual generator and the second is a fuzzy reasoning approach. Evaluation is naturally a fuzzy expert-system because it generally uses rules and word evaluation such as “good”, “poor”, “medium” etc.

4. 1. Residual generation

The proposed scheme for calamine intensity evaluation is based on the residual fuzzy sets analysis and it is illustrated in Fig.4. It first considers a residual $e(t)$ obtained as the difference between the optimal and real thermal distributions (y^t) and (y_r^t) respectively, then fuzzy rules for $e(t)$ and $\Delta e(t)$ are used to evaluate changes.

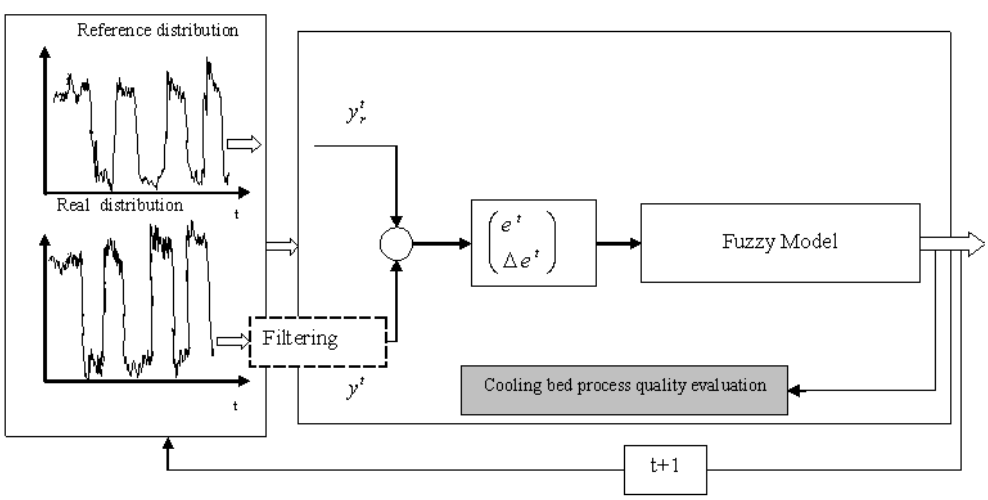

Fig. 4: Principle of welding quality evaluation by residual fuzzy reasoning

We can now describe the scheme in details:

Let the optimal thermal profile (y_r^t) and the real measured thermal profile (y^t), the optimal thermal profile is defined as the quadratic form of the considered area. It is computed by the following formula:

$$y_r^t = \|T_r(i, j)\| \tag{1}$$

The value of the real thermal profile is defined by:

$$y^t = \|T(i, j)\| \tag{2}$$

This temperature is filtered via a low frequency filter defined by

$$y_f^t = (1-\alpha) y_f^{t-1} + \alpha y^t \tag{3}$$

The residual is defined as:

$$e(t) = y_f^t - y_r^t \tag{4}$$

The residual change can be computed as:

$$\Delta e(t) = e(t) - e(t-1) \tag{5}$$

Figure 5 shows a typical thermal distribution, using such reference profile, residuals have been generated and plotted in different graphs of Figure 6.

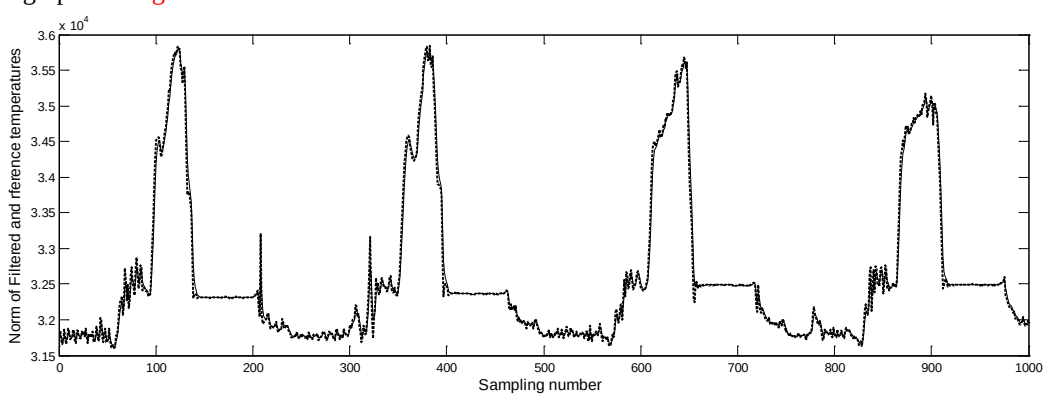

Fig.5. Typical real and filtered thermal profile

4. 2 Evaluation using fuzzy sets

Fuzzy rule-based systems have been successfully applied to various applications in different areas such as control and classification [18-19]. While the main objective in the design of fuzzy rule-based systems has been to maximize performance, their comprehensibility has also been taken into account in some recent studies. The comprehensibility of fuzzy rule-based systems is related to various factors:

- Comprehensibility of fuzzy partitions (e.g., linguistic interpretability of each fuzzy set, separation of neighboring fuzzy sets, the number of fuzzy sets for each variable).
- Simplicity of fuzzy rule-based systems (e.g., the number of input variables, the number of fuzzy if-then rules).
- Simplicity of fuzzy if-then rules (e.g., type of fuzzy if-then rules, the number of antecedent conditions in each fuzzy if-then rule).
- Simplicity of fuzzy reasoning (e.g., selection of a single winner rule, voting by multiple rules).

This paper shows how a small number of simple fuzzy if-then rules based on the residual and its variations can be selected for designing a comprehensible fuzzy rule-based system for condition monitoring and evaluation. As shown in Fig. 6, fuzzy reasoning operates on the residual.

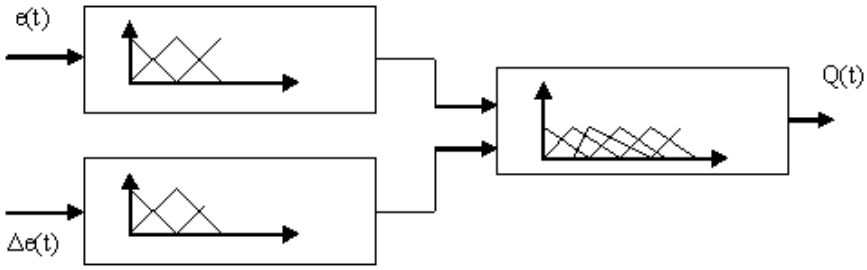

Fig. 6: Principle of Fuzzy evaluation of quality index

To evaluate the welding quality, we use in this scheme the residual value Q_i and its variation ΔQ_i. Theoretically, it is possible to extend the residual variations to a higher derivative form such as $\Delta^2 Q_i$, $\Delta^3 Q_i, \ldots, \Delta^n Q_i$. This extension is useful for systems that have high dynamic variations, but generally a Jacobean or/and Hessian form of dynamic residual $e(t)$ is sufficient.

Using if-then rules of the following form of n-dimensional pattern classification problem is defined as:
Rule R_q: If x_1 is A_{q1} and….and x_n is A_{qn} then Class C_q with CF_q
where R_q is the label of the qth -fuzzy if-then rule, $x = (x_1, \ldots. x_n)$ is an n-dimensional pattern vector, A_{qi} is a fuzzy set, C_q is a consequent class, and CF_q is a weight rule or membership value in the unit interval [0, 1].
The precision of correlated relation between the different HAZ distribution is given by the residual. The quality of welding from a pass to another is evaluated according to the importance of the residual Q_i and its change ΔQ_i, its fuzzy reasoning based rules are used as a tool for qualifying the quality of welding on the basis of the quality evaluation connected to the residual importance. It uses linear memberships functions as shown in Fig.7.
The following fuzzy rules associated to the linear membership functions are applied:

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

According the above rules, the quality index can be written as:

$$quality = fuzzy[Q_i, \Delta Q_i] \tag{6}$$

Evaluation system is given by a fuzzy system defined by its membership functions of inputs (Fig.7a and Fig.7b), the membership function of output is given by Fig.7c. Fig.8 shows the residual and its variations. Final quality evaluation illustrated by Fig.9 is obtained using the above membership function and fuzzy rules. It is considered a fuzzification and rules based on the Q_i and its changes ΔQ_i, this permits to take into account of the dynamic behavior of the residual. Output of the fuzzy system is an evaluation of the quality using an index in the range of [0-1] (Fig.9).

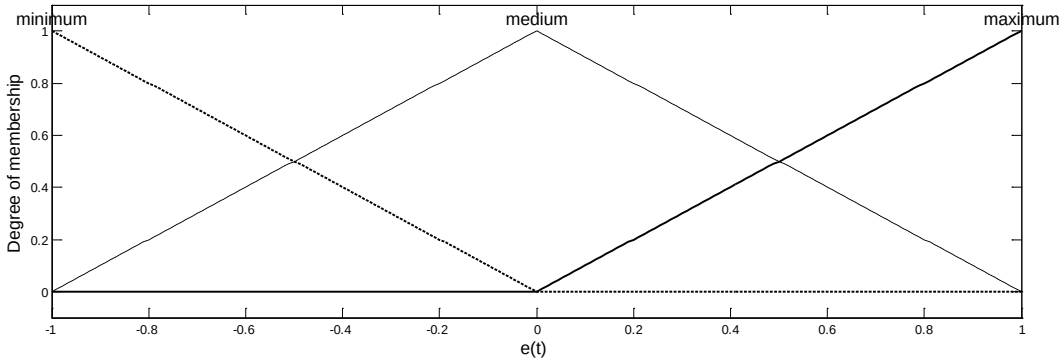

Fig. 7a: Membership function of *e(t)*

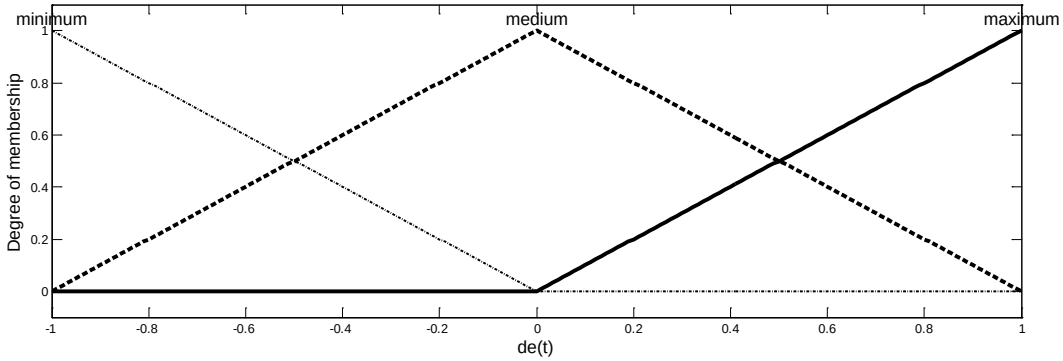

Fig. 7b: Membership function of Δ*e(t)*

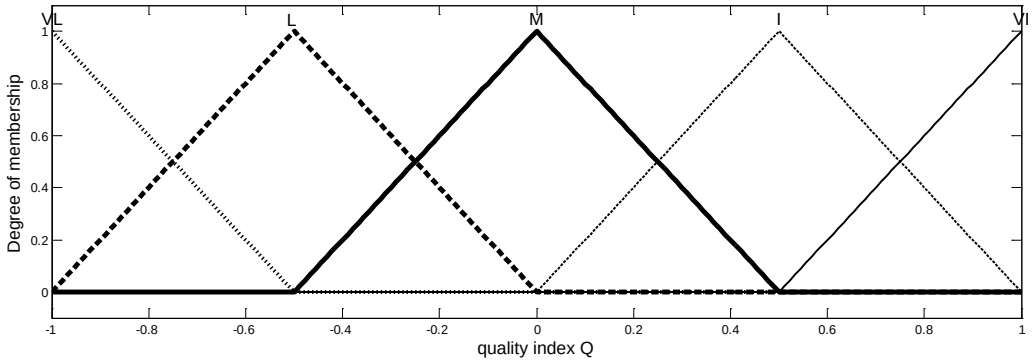

Fig.7c: Membership function of output Q (quality index)

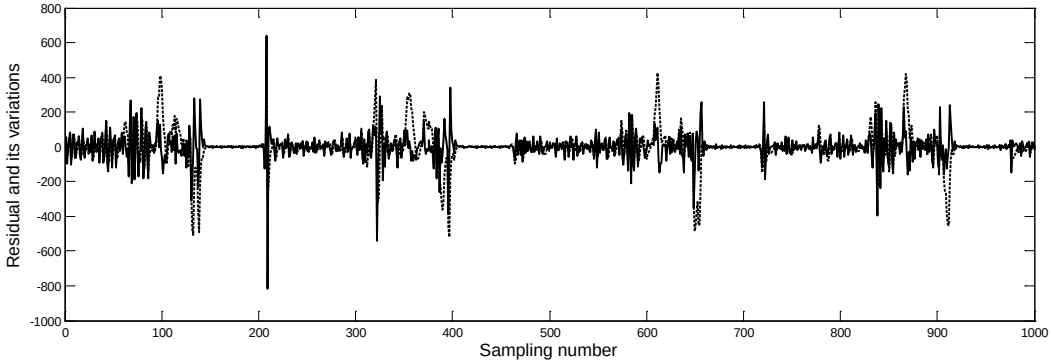

Fig.8: Evolution of residual [e(t) and Δe(t)]

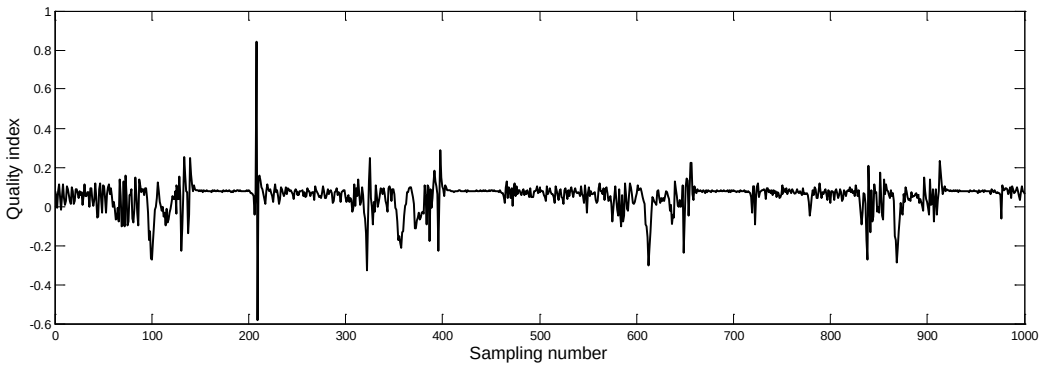

Fig.9: Evolution of quality index (Q)

5. Conclusion

On line quality evaluation is carried out by residual processing, fuzzy system based membership functions and fuzzy rules is applied and a global quality evaluation is done according to the temperature changes from their habitual values, this temperature is measured using IR camera. The application of such method is made using typical and real temperature distribution in rolling bar process. The proposed approach improves the rebar process monitoring and gives a global quality evaluation and reduces the quality control cost. For maintaining consistently high product quality and procurement of fine quality raw material, thermal techniques are used for rebar quality

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