Quality Classification and Monitoring Using Adaptive Metric Distance and Neural Networks: Application in Pickling Process

S. Bouhouche, M. Lahreche, S. Ziani, and J. Bast

***Abstract*—**Modern manufacturing facilities are large scale, highly complex, and operate with large number of variables under closed loop control. Early and accurate fault detection and diagnosis for these plants can minimise down time, increase the safety of plant operations, and reduce manufacturing costs. Fault detection and isolation is more complex particularly in the case of the faulty analog control systems. Analog control systems are not equipped with monitoring function where the process parameters are continually visualised. In this situation, It is very difficult to find the relationship between the fault importance and its consequences on the product failure. We consider in this paper an approach to fault detection and analysis of its effect on the production quality using an adaptive centring and scaling in the pickling process in cold rolling. The fault appeared on one of the power unit driving a rotary machine, this machine can not track a reference speed given by another machine. The length of metal loop is then in continuous oscillation, this affects the product quality. Using a computerised data acquisition system, the main machine parameters have been monitored. The fault has been detected and isolated on basis of analysis of monitored data. Normal and faulty situation have been obtained by an artificial neural network (ANN) model which is implemented to simulate the normal and faulty status of rotary machine. Correlation between the product quality defined by an index and the residual is used to quality classification.

***Keywords*—**Modeling, fault detection and diagnosis, parameters estimation, neural networks, Fault Detection and Diagnosis (FDD), pickling process.

I. Introduction

FAULT detection and diagnosis is a complex domain particularly in the case of multivariable systems. Generally, system inputs – outputs are highly interconnected. Because there are high interconnections between the system variables, consequence of faults on the production quality in process engineering is very important to predict. We consider in this paper an application of modelling and simulation based on the adaptive scaling and centring analysis [1]-[2]. Adaptive scaling and centring of statistical properties of residuals are used to classify the production quality. Residual is defined as a difference between the optimal process output and the real process output. The process output is modelled by an ANN. The (ANN) was motivated from the study of the human brain, which is made up of millions of interconnected neurons. These interconnections allow humans to implement pattern recognition computations. The ANN was developed in an attempt to mimic the computational structures of the human brain. An ANN is a non linear mapping between input and output which consists of interconnected neurons arranged in layers. The layers are connected such that the signals at the input of the neural net are propagated through the network. The choice of the neuron non linearity, network topology, and the weights of connections between neurons specifies the overall nonlinear behaviour of the neural network [3]-[12]. Fault detection and monitoring is accomplished by comparing performance determined from measurements with some expectation of performance. If the deviation exceeds a threshold, then a fault is indicated. Often this process is divided into two steps as depicted in Fig.1. It is considered fault detection and diagnosis processes. The fault detection process takes measurements from sensors and manipulates them to generate features for diagnosis and classification. On basis of symptom or signature fault is then located and isolated. The fault consequences on the production quality can be used by another model that takes into account of the fault importance and the failure.

Fault detection and diagnosis are obtained from residual analysis which is defined as the difference between the model outputs in normal and faulty situations. Quality evaluation is obtained by the metric distance of the process data distribution and its effect on the production quality level. Optimal operating conditions define an optimal quality production; this correlation is then obtained via another ANN. Fig. 2 gives the principle of fault detection, fault diagnosis and production quality evaluation according to the residual importance.

Manuscript received December 25, 2005. This work was supported in part by the URASM CSC – Welding and Control center, Algerian Ministry of Scientific Research.

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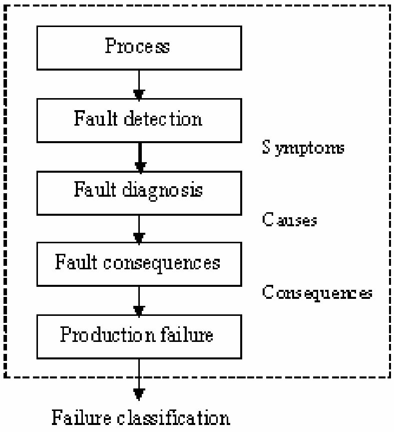

Fig. 1 Principle failure classification using FDD

We consider in this work an approach to predict the production quality according to process data distribution.

- The first step consists to define a class of production quality according to the importance of process output dynamic. High process output stability induces high quality of the production and vise versa.

- The second step is to develop a simulation model. Optimal production quality is given by a minimal metric distance between the centres of the optimal residual and its actual values.

- The third step is to find a complex relationship between the fault importance defined by the residual and its consequence on the production failure.

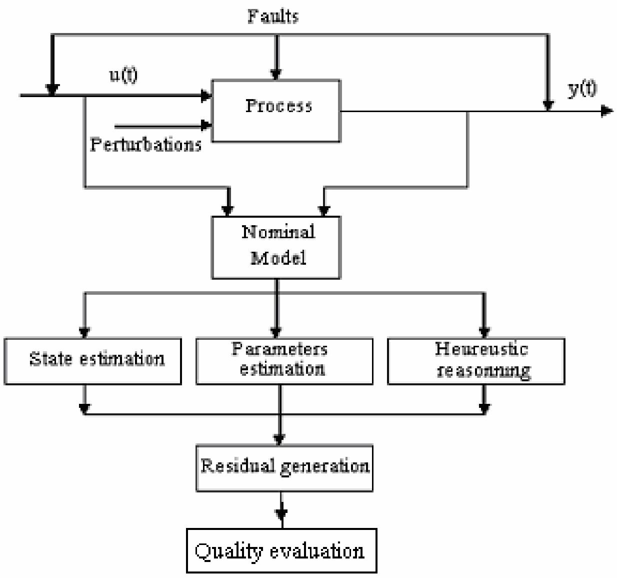

Fig. 2 Principe of quality evaluation using residuals

II. FAILURE DIAGNOSIS

A. Modelling using ANN

We consider a dynamic system which is governed by the following non-linear relationship (NARMA), y(t) is the measured signal and u(t) is a control input

$$y(t) = f(y(t-1),...,y(t-n),u(t-1),.$$
$$...,u(t-m),w(t-1),...,w(t-p)) \quad (1)$$

The identification and modeling principle is shown in Fig. 3. The Back-propagation (BP) algorithm is explained in detail by different works [1-2, 5-6]. We will briefly explain here. The network to be trained consists of L layers of nodes. The k^{th} layer contains N_k nodes, and for L=k, one "bias" node where the activation is always 1. Adjacent layers are exhaustively interconnected by weighted branches. The weight W_{ijk} refers to the branch from node i in layer k to node j in layer k+1. The first layer contains the network input x and the last layer the network output y. z as an exponential function of the weight sums of its inputs in the form.

$$z_{jk} = \frac{1}{1+e^{-u_{jk}}} \quad (2)$$

where

$$u_{jk} = \sum_{i=1}^{N_{k-1}+1} z_{i,k-1} W_{i,j,k-1} \quad (3)$$

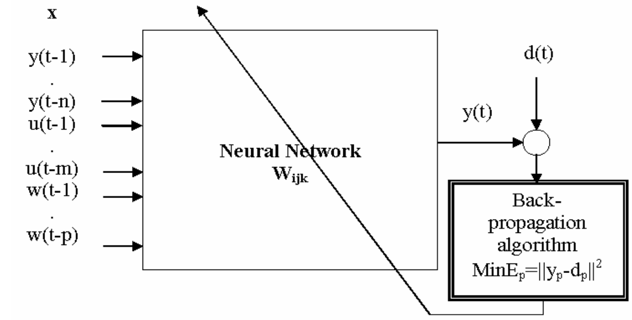

Fig. 3 Principle of (ANN) learning process

The network outputs are the activation of the last column z_L. In the learning mode, a set of training examples consisting of p input/output vector pairs (x_p, d_p) is given. The objective is to select weights that minimize the sum of squared errors between the net predictions y_p and the desired outputs specified by the training examples d_p over all training examples:

$$\min_W J = \sum_{p=1}^{P} E_p \quad (4)$$

Where E_p is the sum of squared errors associated with a single training example and expressed as follows:

$$E_p = \left\| y_p - d_p \right\|^2 \quad (5)$$

For the learning stage, the network is initialized with small random weights on each branch. A training example is selected randomly, and the input vector x_p is propagated through the network to get the predicted output y_p. A gradient in the space of network weights is then calculated using the Generalized Delta Rule (GDR) that gives the steepest descent direction m_p associated with the training example p [1- 2, 4 - 11]. Using the gradient m_p, the weight changes on step q, $\Delta_q W$, are calculated according to the formula:

$$\Delta_q W = \eta m_p + \alpha \Delta_{q-1} W \quad (6)$$

In this expression two constants (α, η) appear, called the learning rates which are equivalent to a step size, and which acts as a momentum term to keep the direction of descent from changing too rapidly from step to step. When the weights are updated, a new training example is selected, and the procedure is repeated until satisfactory reduction of the objective function is achieved.

B. Diagnosis using adaptive metric centering and scaling

Statistical properties of residual are usually used as a tool of diagnosis. Fault consequences on the production quality depend on the dynamic changes of residual. We develop in this part an adaptive scaling and centering of statistical properties which are correlated with the product quality index defined by the process engineering analysis. In order to provide local diagnosis, the centering and scaling parameters are updated using an adaptive method. The mean of each summary statistic are updated with the following filter:

$$\bar{x}_n = \lambda \bar{x}_{n-1} + (1-\lambda)x_n \qquad (7)$$

where $\bar{x}_n$ is the calculated mean after n points, x_n is the new data point, and λ is the filter coefficient that was set 0.5 for this case. The scaling coefficient for each variable summary statistic was updated with the following exact recursive standard deviation formula derived from [3].

$$\sigma_n = \sqrt{(\sigma_{n-1})^2[\frac{n-2}{n-1}] + \frac{1}{n}(x_n - \bar{x}_{n-1})^2} \qquad (8)$$

where σ_n is the calculated standard deviation after n points, $\bar{x}_{n-1}$ is the previous mean value, and n is the umber of points that have gone into the standard deviation thus far. For this filter, value of 10 was used for n during each update.

The relative change in the centering and scaling can be calculated for using as inputs of a neural network to quality index (Q_n) prediction and classification. We search a complex relationship defined as:

$$Q_n(t) = NN[\sigma_n(t), \bar{x}_n(t)] \qquad (9)$$

NN is a neural network model

$\sigma_n(t)$ and $\bar{x}_n(t)$ are respectively the adaptive standard deviation and the mean of the residual in the working windows *n*.

III. Application

A. Process description

Fig. 4 shows a part of pickling process; the main objective is to maintain a stable length of the loop between the roll (1) and (2). The roll (2) is trained by a stable rotary speed defining the production rate. The roll (1) is then trained by the required rotary speed to define a stable length of the loop. Length loop is measured by an optical sensor; this signal is then used to correct the reference rotary speed (1).

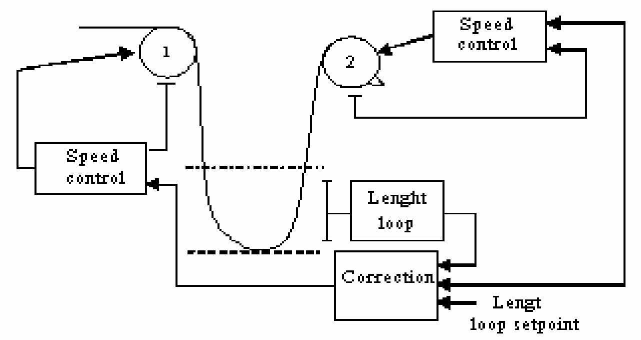

Fig. 4 Principle of pickling process

When a fault appears on the equipment of the rotary control system (1), the reference rotary speed (1) is then disturbed and the length loop also generating a high or a law length loop that causes a shutdown of the production. Dynamic changes of the length loop such as oscillations affect the quality of the product such mechanical deformations.

B. Control scheme

Fig. 5 defines the principle of control length loop by acting the rotary speed V_{s1} according to reference speed V_{s2}. V_{r1} and V_{r2} are the measured rotary speeds, Mlg is the measured length loop. V_{r2} fellows the setpoint V_{s2}.

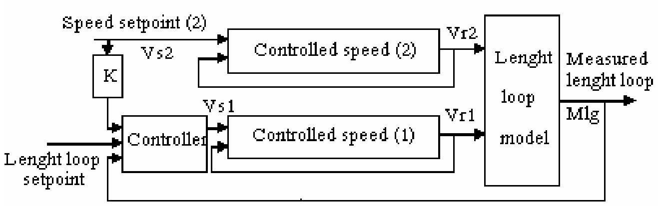

Fig. 5 Principle of length loop control

C. Data acquisition and process modelling

Fig. 6 defines the principle of data acquisition by interfacing the analog control system and the process computer by means of data acquisition package. Data has been stored on the hard disk of process computer in real time.

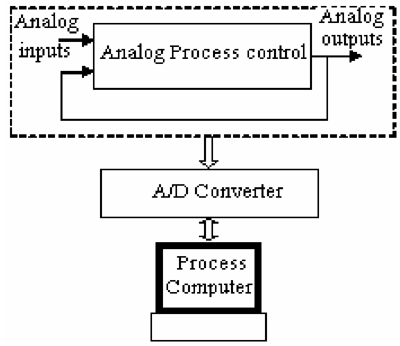

Fig. 6 Principle of data acquisition

Data analysis shows that there is a limited power in the speed (1) it can not track the reference speed given by the control equipment (2). After investigation of different electronic cards, the fault has been located and isolated: There is a problem on the power unit (1). Fault modelling is then obtained using an ANN trained by the acquired data. We are interested to model the dynamic relationship between the measured loop length, the real speeds and setpoints speeds of the rotary mechanism (1) and (2). We consider the following model:

$$M\lg(t) = NN[M\lg(t-1), M\lg(t-2), V_{r1}(t-1), V_{r1}(t-2), V_{r2}(t-1), V_{r2}(t-2), V_{s1}(t), V_{s2}(t)], \quad (10)$$

NN is an ANN structure obtained by learning using the process data in normal operating conditions [11-13].

$$\varepsilon(t) = M\lg(t) - \hat{M}\lg(t) \quad (11)$$

In normal situation $\varepsilon(t) \in D_N$, D_N is an admissible domain that gives an optimal quality of the product, $\varepsilon(t)$ is normally distributed and characterized by its mean $\bar{\varepsilon}$ and its standard deviation σ.

Faulty situation is defined by the variation of $\varepsilon(t)$ in a faulty domain D_F, $\varepsilon(t) \in D_F$. This is caused by the model changes including the structural and parameters variations.

$\Delta NN = NN^F - NN$; NN^F is the faulty model of faulty status

- If $\lim \Delta NN \to 0$ when $t \to 0$: The fault is steady state
- If $\lim \Delta NN \to \Delta NN_0$ when $t \to 0$: The fault is static

Variations of ΔNN induce equivalent variations of the residual that has also an equivalent effect on the quality of the product. The ANN structure and learning process are defined by the following parameters:

Input vector	: 03
Output vector	: 01
Number of the layer	: 02
Number of neurons in the first layer	: 03
Number of neurons in the second layer	: 08
Number of neurons in the output layer	: 01
Momentum	: 0.65
Learning rate	: 0.75

Fig. 7a shows the inputs and outputs data used to train the ANN. Fig. 7b shows the learning convergence. Fig. 7c and Fig. 7d show the dynamic of measured and computed outputs and the dynamic of residual.

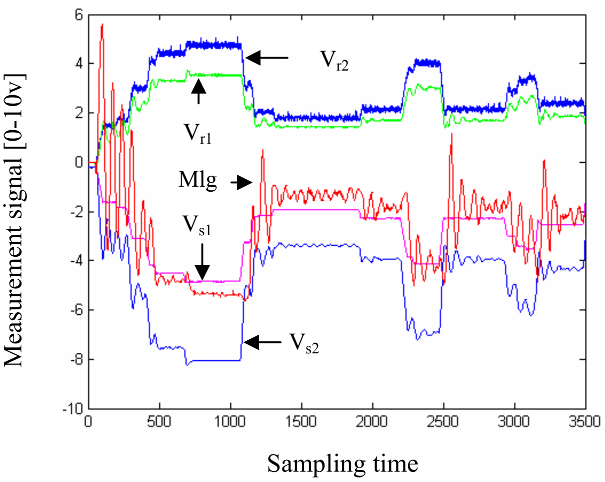

Fig. 7a Inputs – outputs data

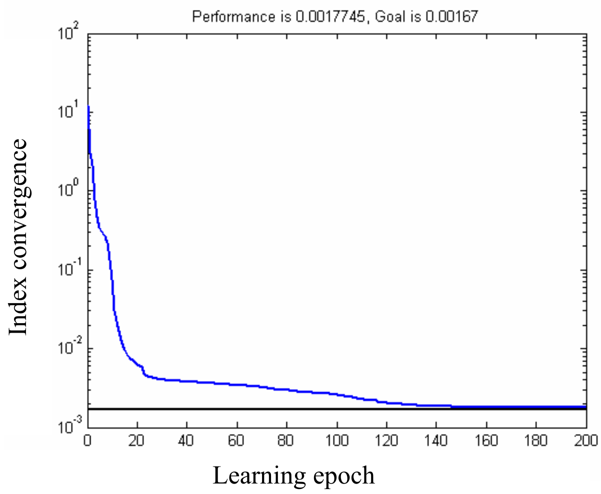

Fig.7b Learning convergence

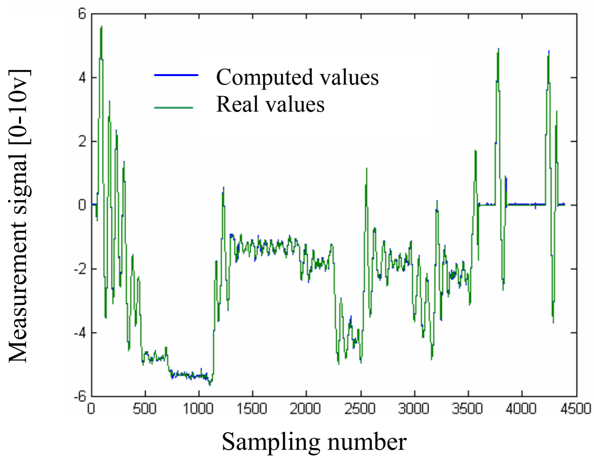

Fig. 7c Computed and real outputs

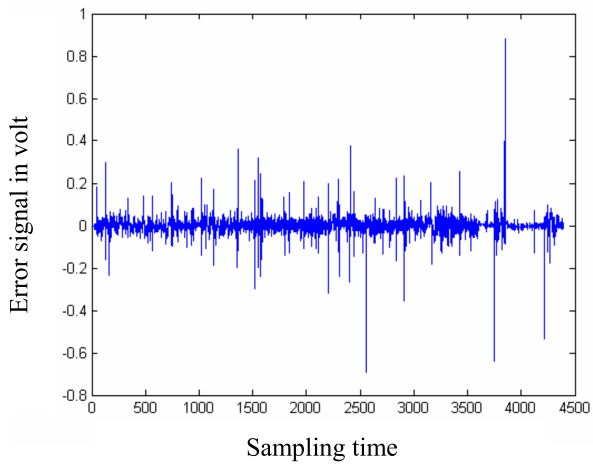

Fig. 7d Residual dynamic (ε_m)

IV. Quality Monitoring

Qualitative feature extraction is the abstraction of trend information. Trend analysis and prediction are important components of process monitoring and supervisory control. Trend modelling can be used to explain the various important events happening in the process, do malfunction diagnosis and predict futures states. Statistical properties of residual $\varepsilon(t)$ are used as a tool to quality evaluation. It is usually applied to several performance indexes characterising the dynamic of the residual. Residual given in Fig.7d is relative to optimal operating conditions. Using the process model obtained by the equation (7) and new inputs data according to different process status, we have obtained the following residuals (Fig. 8).

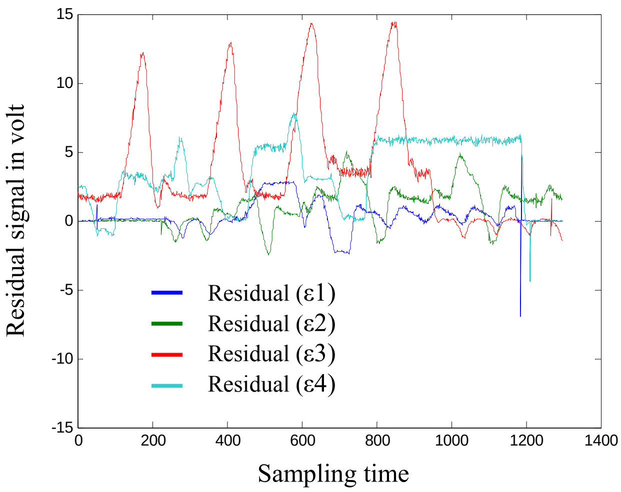

Fig. 8 Residual status

A. Modelling of quality index

The production quality depends on the dynamic of length loop changes, variations of length loop are the deformations of the metal sheet. Oscillations of the metal sheet are equivalent to metal stress solicitations. We define a quality index (Q) as a mixture of the mean and standard deviation of residual.

$$Q = f[\bar{\varepsilon}, std(\varepsilon)] = \alpha.\bar{\varepsilon} + \beta.std(\varepsilon) \quad (12)$$

where,

$$\bar{\varepsilon} = \frac{1}{n}\sum_{i=1}^{n}\varepsilon_i \quad (13)$$

$$sd(\varepsilon) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\varepsilon_i - \bar{\varepsilon})^2} \quad (14)$$

α and β are constant, equation (12) is a simplified form. In order to model the quality index as a function of residual properties defined by the equation (9). An ANN and data given in Fig. 9 have been used.

The used ANN model has the following characteristics:

Input vector	: 02
Output vector	: 01
Number of the layer	: 02
Number of neurons in the first layer	: 04
Number of neurons in the second layer	: 06
Number of neurons in the output layer	: 01
Momentum	: 0.85
Learning rate	: 0.75

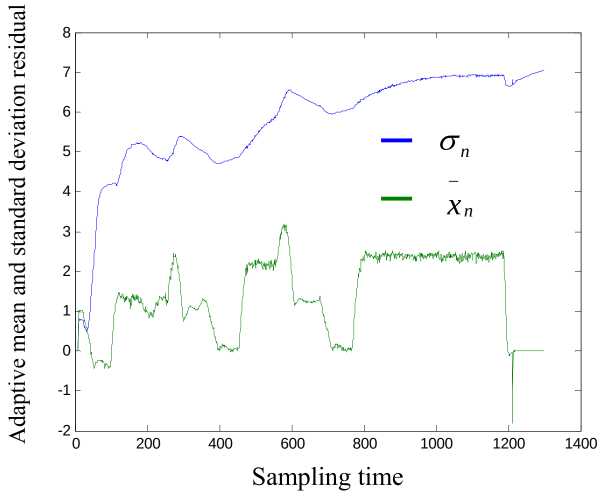

Fig. 9a Adaptive σ_n and $\bar{x}_n$

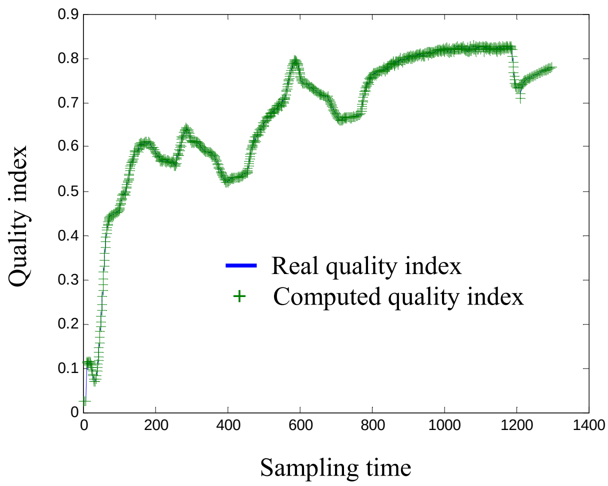

Fig. 9b Computed and real quality index (Q_n)

Fig.9 shows the ANN modelling results. The ANN is trained using data that are representative of the normal conditions.

Statistical properties of the length loop residual i.e, $\bar{x}_n$ and σ_n are correlated with the quality index Q_n. This appears on the dynamic of the learning convergence given in Fig. 9b. The trained ANN is then applied to predict the quality index using new series of data.

B. Quality evaluation and prediction

It is clear in process engineering that the machine defect has direct or indirect consequences on production quality. Generally, the process is formed by a series of machines; the production flow is oriented by several manners in different machine line. The final production quality depends on the operating state of these machines. We suppose that the machine fault or defect of each machine (j) can be defined by the importance of residual $\varepsilon_j(t)$. Consequences on production quality in the process step (j) can be defined by $q_j(t)$. The global production quality $Q(t)$ is a complex relationship of $q_i(t)$. We consider in this work a simple part of pickling process characterized by a simple fault defined by the residual $\varepsilon(t)$ and its quality defect defined by the dynamic of mechanical deformation, i.e., metal stress solicitation. The test and verification of quality evaluation is obtained using new data sets. There are carried out by for (04) examples which are shown in Fig. 10. Quality index increases when the sheet oscillations defined by the statistical properties of the residual such as $\bar{x}_n$ and σ_n are augmented. Quality index (Q_n) is an indicator that qualifies the local quality defect in the working windows n. Consequences of machines and process faults on the product quality have been evaluated using data analysis and modelling. A computerised system for quality monitoring is developed in basis of dynamical data. Relationship between data and quality index is obtained, this permit to evaluate the quality without to use hard operations in quality inspection service. This approach permits us to reduce the quality control cost.

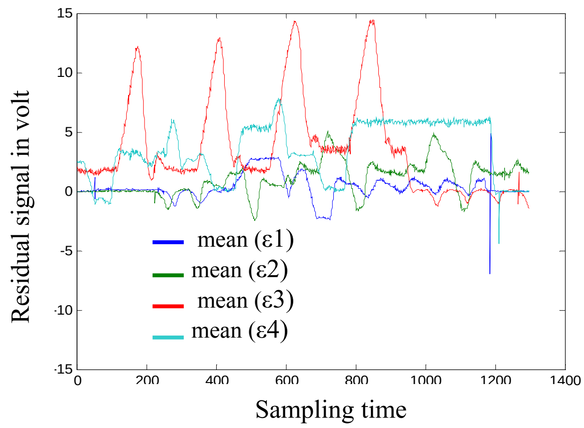

Fig. 10a Adaptive $\bar{x}_n$

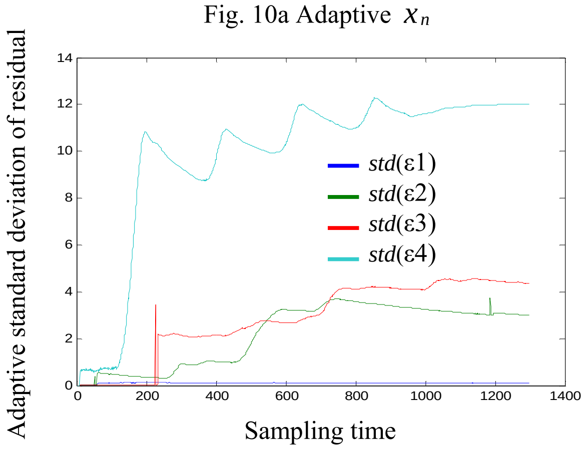

Fig. 10b Adaptive σ_n

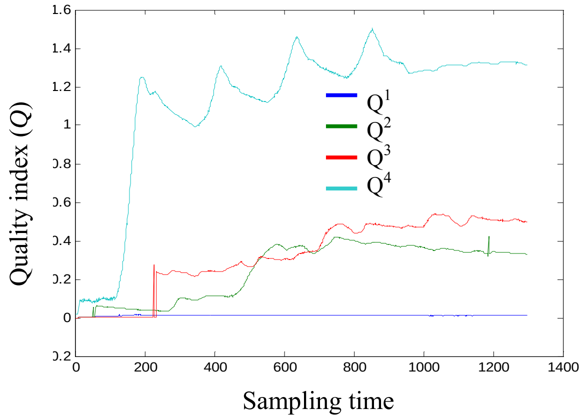

Fig. 10c Computed and real quality index (Q_n)

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