Arc Voltage Signals-Based Flicker Effect Analysis Using SampEn Multi-scale Entropy Algorithm

Salim AOUABDI[1]
[1]Research Center in Industrial Technologies CRTI,
P.O.Box 64, Cheraga-Algiers-ALGERIA.
s.aouabdi@crti.dz

Nadir BOUTASSETA[2] and Hocine BENDJAMA[3]
[2,3]Research Center in Industrial Technologies CRTI,
P.O.Box 64, Cheraga-Algiers-ALGERIA.
{n.boutasseta and h.bendjama}@crti.dz

Abstract — Real-time monitoring in the steel and metallurgical production sector is of great importance. To ensure competitiveness, the industrial process will have to innovate and evolve towards better quality. Therefore, the monitoring of the voltage signal in Electric Arc Furnace (EAF) has a vital role in keeping a nominal operation of electrical components in order to achieve high performance. A new monitoring method based on multi-scale Sample Entropy (SampEn) (MSE) algorithm for EAF voltage flicker is proposed. In the proposed method, different percentages of flicker effect analysis are presented. The current voltage characteristic of the EAF in conjunction with MSE and comparison of observed values with those predicted from a Cassie and Mayr model built using nominally healthy data are analysed. In order to achieve the classification procedure, five extracted features are used to adapt the subtractive clustering network for each state of the flicker effect and the performance of the classifier during the training is given with success.

Keywords — Electric Arc Furnace (EAF), power quality, Voltage flicker, Voltage unbalance, SampEn Multi-scale entropy algorithm, subtractive clustering.

I. INTRODUCTION

Electrical network quality analysis is an important technical step to keep a nominal operation of an electrical installation [1]. In order to analyze the network, we use a new algorithm based on measurement acquisitions that allow a complete diagnosis of the state of health of the arc furnace. The system to be modeled is the AC arc furnace [2]; this work focuses on monitoring the arc furnace operating in both modes. An anomaly detection tool based on the combined approach, current voltage characteristic vectors of the electric arc and multi-scale entropy (MSE) [3] is presented. The studied flaw in the present work are the flicker effect and the voltage imbalance [4, 5]. The arc furnace behaves like a nonlinear load and creates energy quality problems such as unbalanced voltages and voltage flickers that were the subject of many research works [6-8]. Several arc furnace models have been developed to analyze the flicker effect caused by EAF according to needs and their application [9, 10]. The Mayr model is an appropriate representation of an arc for weak currents, while the Cassie model gives good results for high current arcs [11]. Under normal operating conditions, the power grid is subject to electrical stress [12]. The emphasis is increased during transients, such as load variations, which may lead to electrical failure and degradation of arc furnace operation [13]. Many of the advanced Flicker effect analysis techniques have been used; these techniques have their respective advantages and disadvantages [14, 15]. This study focuses on a robust method for the early analysis of flickers effect, where an anomaly is defined as a deviation from the expected behavior of the process dynamics. Signal processing techniques are used for flicker detection. The methodology is mainly guided by the data. The idea is first to understand the mechanisms of the flicker effect [16], then apply the data processing techniques to extract the information that gives the indication of the state of operation of studied system. The analysis of flicker signatures as well as the information on the different variations of the flicker percentage studied is not easily discernible directly from arc voltages, especially for the small percentage of flicker [17]. The multi-scale entropy strategy has been adopted to identify flicker signatures. Indeed, to improve the optimal operation of the arc furnace it is necessary to know at every moment the state of operation of this system and to be able to discriminate normal and abnormal states. The control of the arc furnace is determined by two parameters, the quality and quantity of the load introduced in addition to the wear and heating of the material [18]. The load is related to the scrap products, and the arc connected to the priming with or without liquid metal load. To achieve a minimum merge, it is necessary to place in the load the optimal power by making a compromise between the following criteria [19]:

- Monitoring the energy consumed according to the energy allocated by the distributor.
- Heating connections and in particular electrodes.
- Overload of the furnace transformer.

The following flow diagram shows the evolution of the system and possibility of successive failures with the taking into account the improvement of the driving of the system. The proposed diagnosis strategy shows the progress of different approaches:

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- Fault modeling,
- Generation of the database of arc currents and voltages,
- Diagnostic techniques,
- Extraction and selection of indicators,
- Classification method and statistical tests.

In order to achieve the best performance of the monitoring, a diagnostic strategy for analyzing flicker is desirable.
The ability of MSE to analyze the flicker caused by EAF depends on the optimization of the calculated parameters of the SampEn measure, by analyzing the voltage waveforms from obtained model of EAF [2, 8].

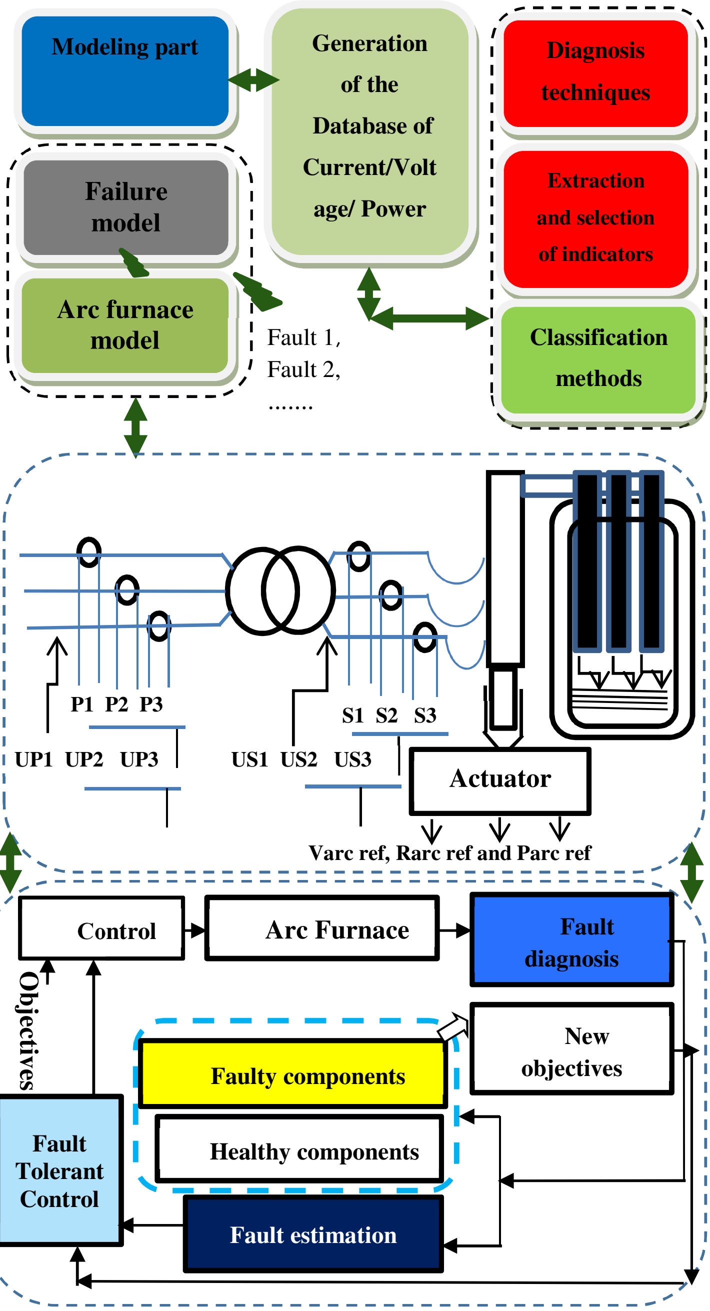

Fig. 1. Flow diagram of the proposed strategies and future work.

II. EAF VOLTAGE FLICKER DETECTION VIA SAMPEN MULTI-SCALE ENTROPY ALGORITHM

The signal data acquisition issued from the EAF voltage in different cases is processed and then passed to inspect the presence of abrupt variation in the signal. We used the data provided by [2].

The use of the Multi-scale entropy (MSE) strategy for the monitoring and diagnosis of EAF voltage flicker effect is an advantage because this strategy makes possible the improvement of EAF voltage and take into account not only the dynamic non-linearity, but also the effects of interaction and coupling between the system components [3].

Via MSE analysis, a coarse time series is first constructed from the original time series $\{V_1, \ldots, V_v, \ldots, V_N\}$. Coarse consecutive time series $\{y^{(\tau)}\}$ are constructed with the scaling factor $\tau\ \{\tau = 1.2, \ldots N\}$ according to equation:

$$y_j^{(\tau)} = 1/\tau \sum_{v=(j-1)\tau+1}^{j\tau} V_v \tag{1}$$

Where τ represents the scale factor, and we have: $1 \leq j \leq N/\tau$.
In order to adjust the values of the parameters for the arc voltage signal, we have simulated the SampEn algorithm for the optimal values of: $m = 2$ and $r = 0.15$.

The time series of N points is given by: $\{V(1), \ldots, V(v), \ldots, V(N)\}$, and the SampEn algorithm is defined as follows [20-26]:
Train m length vectors $V'_m(v)$

$$V'_m(v) = \{V(v), V(v+1), \ldots, V(v+m-1)\} \quad 1 \leq v \leq N-m+1 \tag{2}$$

The distance between two vectors is defined as follows:

$$d[V'_m(v), V'_m(j)] = \max_{k\in[1,m-1]}(|V(v+k) - V(j+k)|) \tag{3}$$

For each $V'_m(v)$ and the fixed tolerance r, leave A_v the number of vectors satisfying $d[V'_m(v), V'_m(j)] \leq r$, then $B_v^m(r)$ as follows:

$$B_v^m(r) = \frac{A_v}{N-m+1} \quad 1 \leq v \leq N-m \tag{4}$$

The average $B_v^m(r)$ is designed as:

$$B^m(r) = \frac{1}{N-m} \sum_{v=1}^{N-m} B_v^m(r) \tag{5}$$

By increasing the dimension of $m+1$ and repeating the previous steps to find $B^{m+1}(r)$, the SampEn is defined as follows:

$$\mathrm{SampEn}(m,r) = \sum_{N\to\infty} -\ln \frac{B^{m+1}(r)}{B^m(r)} \tag{6}$$

For a finite number of data points N we have:

$$\mathrm{SampEn}(m,r,N) = -\ln \frac{B^{m+1}(r)}{B^m(r)} \tag{7}$$

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In order to reduce the number of the input signal and in the same time to achieve the classification performance, we use five statistics indicators over MSE of the EAF voltage signal (phase A). Five indicators are extracted from the SampEn algorithm and the results are given in the next section.

III. ANALYSIS OF FLICKER SIGNATURES

Through the use of both approaches : current voltage characteristic of the EAF in conjunction with MSE and comparison of observed values with those predicted from a Cassie and Mayr model built using nominally healthy data, we can describe EAF voltage flicker phenomena. A suitable 2-D representation is based on the current voltage characteristic. The complete Arc model is given by [2]:

$$g_1 = g_{min} + \left((1 - e^{-\left(\frac{i_f}{i_0}\right)^2}\right)\left(\frac{i_f}{E_1}\right)^2 \frac{1}{g_1} + e^{-\left(\frac{i_f}{i_0}\right)^2} \frac{i_f^2}{P_0} - \theta_a \frac{dg_1}{dt} \tag{8}$$

With

$$\theta_a = \theta_0 + \theta_1 e^{-\alpha|i_f|} \tag{9}$$

Where $\alpha > 0$ and $\theta_1 \gg \theta_0$ and we can see that θ_a function of arc current from (9).

$$g_1 = g_{min} + \left((1 - e^{-\left(\frac{i_f}{i_0}\right)^2}\right)\left(\frac{i_f}{E_1}\right)^2 \frac{1}{g_1} + e^{-\left(\frac{i_f}{i_0}\right)^2} \frac{i_f^2}{P_0} - \left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)\frac{dg_1}{dt}$$

$$= g_{min} + \left(\frac{i_f}{E_1}\right)^2 \frac{1}{g_1} - \left(\frac{i_f}{E_1}\right)^2 e^{-\left(\frac{i_f}{i_0}\right)^2} \frac{1}{g_1} + e^{-\left(\frac{i_f}{i_0}\right)^2} \frac{i_f^2}{P_0} - \theta_0 \frac{dg_1}{dt} - \theta_1 e^{-\alpha|i_f|} \frac{dg_1}{dt}$$

$$= g_{min} + i_f^2 \left[\frac{1}{g_1 E_1^2} - \frac{1}{g_1 E_1^2} e^{-\left(\frac{i_f}{i_0}\right)^2} + \frac{1}{P_0} e^{-\left(\frac{i_f}{i_0}\right)^2}\right] - \theta_0 \frac{dg_1}{dt} - \theta_1 e^{-\alpha|i_f|} \frac{dg_1}{dt}$$

$$= g_{min} + i_f^2 \left[\frac{1}{g_1 E_1^2} - \frac{1}{g_1 E_1^2} e^{-\left(\frac{i_f}{i_0}\right)^2} + \frac{1}{P_0} e^{-\left(\frac{i_f}{i_0}\right)^2}\right] - \theta_0 \frac{dg_1}{dt} - \theta_1 e^{-\alpha|i_f|} \frac{dg_1}{dt}$$

$$g_1 + \left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)\frac{dg_1}{dt} = g_{min} + i_f^2 \left[\frac{1}{g_1 E_1^2} - \left(\frac{1}{g_1 E_1^2} - \frac{1}{P_0}\right) e^{-\left(\frac{i_f}{i_0}\right)^2}\right]$$

$$\frac{dg_1}{dt} = -\frac{g_1}{\left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)} + \frac{g_{min}}{\left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)} + i_f^2 / \left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)\left[\frac{1}{g_1 E_1^2} - \left(\frac{1}{g_1 E_1^2} - \frac{1}{P_0}\right) e^{-\left(\frac{i_f}{i_0}\right)^2}\right] \tag{10}$$

We have

$$v = \frac{i}{g} \tag{11}$$

So

$$\frac{dg_1}{dt} = -\frac{g_1}{\left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)} + \frac{g_{min}}{\left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)} + i_f / \left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)\left[\frac{v}{E_1^2} - \left(\frac{v}{E_1^2} - \frac{i_f}{P_0}\right) e^{-\left(\frac{i_f}{i_0}\right)^2}\right]$$

$$\frac{dg_1}{dt} = -\frac{1}{\left(\theta_0 + \theta_1 e^{-\alpha|i_f|}\right)}\left[g_1 - g_{min} - i_f\left(\frac{v}{E_1^2} - \frac{i_f}{P_0}\right) e^{-\left(\frac{i_f}{i_0}\right)^2}\right] \tag{12}$$

Equation (12) indicate the dynamic specification of EAF is affected by conditions of the furnace.
The sinusoidal variation can be expressed mathematically as:

$$E_1(t) = E_{01}\left(1 + m \sin(\omega_f t)\right) \tag{13}$$

Where m and ω_f are modulation index and flicker frequency respectively.

IV. RESULTS AND DISCUSSION

Reporting and analysis of waveforms in healthy case is presented by the figures (Fig 2-4), and the waveform report and analysis in faulty case is presented in the figures (Fig 5-7).

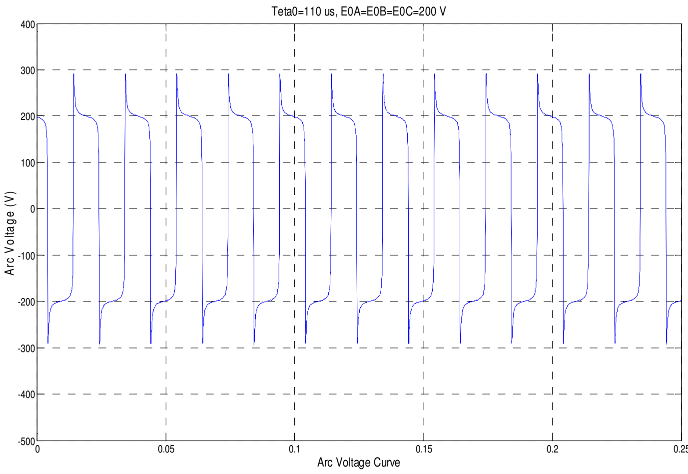

Fig.2. Arc voltage curve in healthy case.

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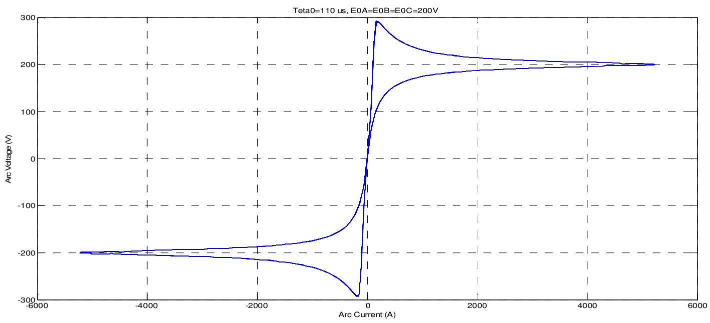

Fig.3. Arc Voltage Current voltage characteristic of the EAF.

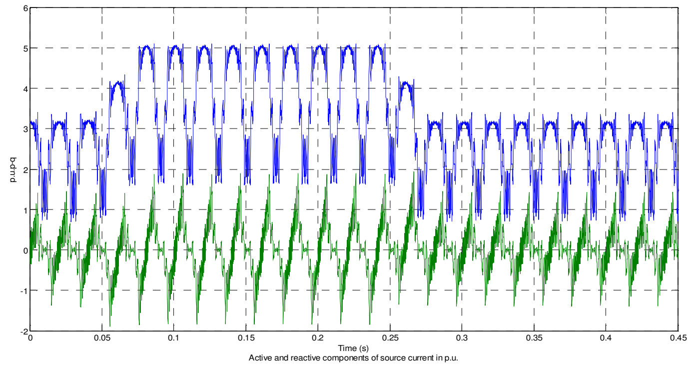

Fig.4. Active and reactive power in healthy case.

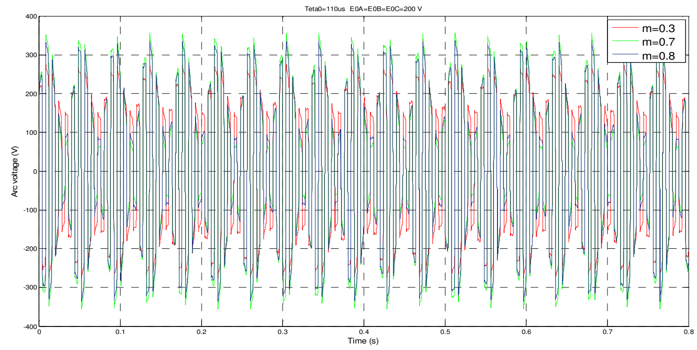

Fig.5. Arc Voltage with unflagging flicker percentage variation without unbalance conditions.

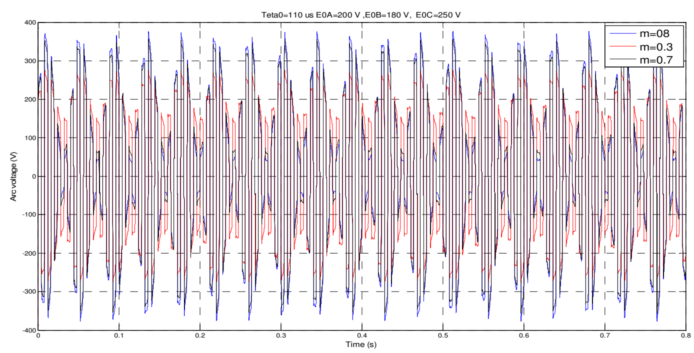

Fig.6. Arc Voltage with unflagging flicker percentage variation with unbalance conditions.

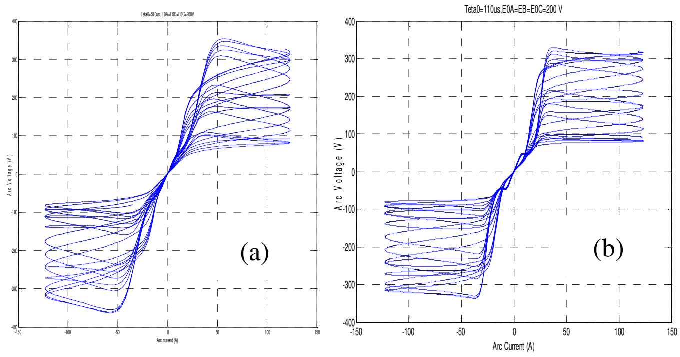

Fig.7. Current voltage characteristic of EAF (a) Teta=510 us (b): Teta =110 us.

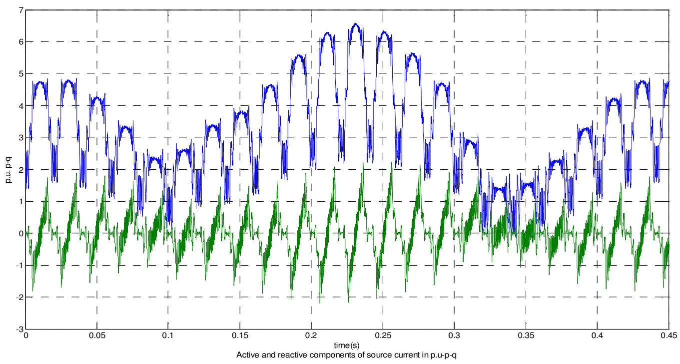

Fig.8. Active and reactive power in faulty case.

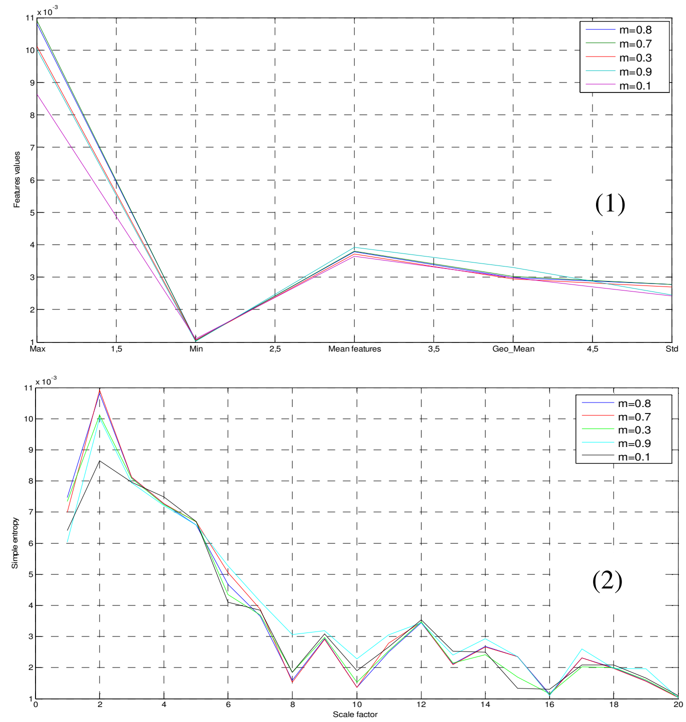

Fig. 9. Waveforms of flicker percentage variations in the case without unbalance conditions. (1): Teta=110us : Five statistics during MSE. (2) : MSE over 20 scales.

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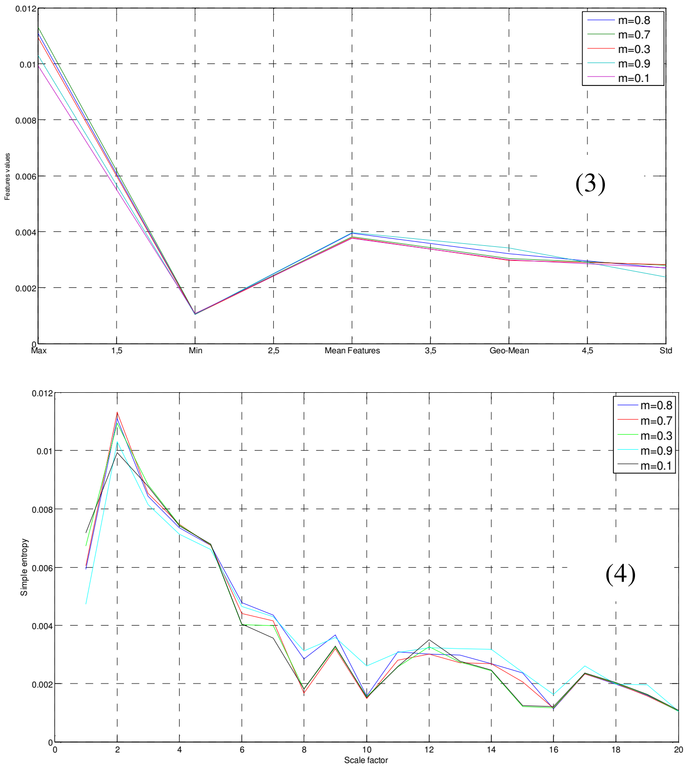

Fig. 10. Waveforms of flicker percentage variations in the case without unbalance conditions. (3): Teta=510 us : Five statistics during MSE. (4): MSE over 20 scales.

The dynamic I-V characteristic of the obtained electric Arc has been shown in Fig.3 and Fig.7 (a) and Fig. 7(b). The dynamic voltage variation, obtained by the simulation, is graphically shown in Fig. 2 and Fig. (5-6). In order to analyze the flicker effect caused by the electrical Arc, the simulation results obtained by using the different variation of the flicker percentage and the comparison of the data measured in both cased with Teta =110 us and with Teta =510 us as shown in Fig. 5 and Fig. 6. The dynamic characteristic of the electrical arc by flicker effect is observed as shown in Fig. 7 (a) and Fig. 7 (b). Multi-scale entropy is used to inspect the different variation of voltage flicker, MSE across 20 scales are computed from a set of features containing information about the state indicating evolution of different variations present in the Arc voltage Fig. 9 (b) and Fig. 10 (b). Five statistics are extracted from the set of original characteristics Fig. 9 (a) and Fig. 10 (a). The reduced feature vectors in the case of different percentage of flickers with Teta =110 us compose the database of the expert system for fault diagnosis (Figs .13-16). The global database is divided into a training data set (500 samples) and the local database is divided into training data set (100 samples) and the global testing data set (375 samples) and local testing data set (75 samples). The training data set is used to train the classifier model, in order to predict the expected outputs.

The figure 11 and 12 shows the performance of the classifier during the training procedure.

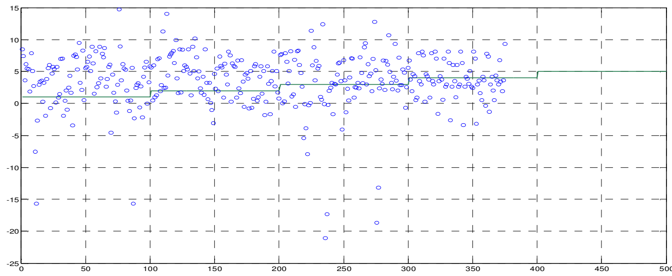

Fig. 11. The simulation of the model output against checking data.

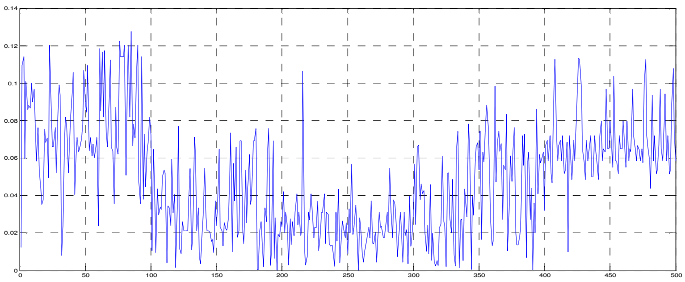

Fig.12. The root mean square error generated by the training data.

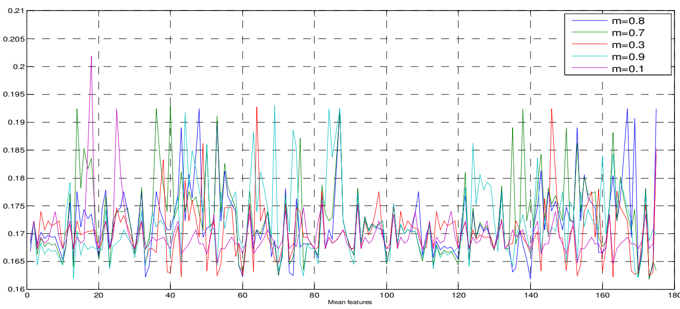

Fig. 13. Mean features of the expert system in the case of the teta=110 us.

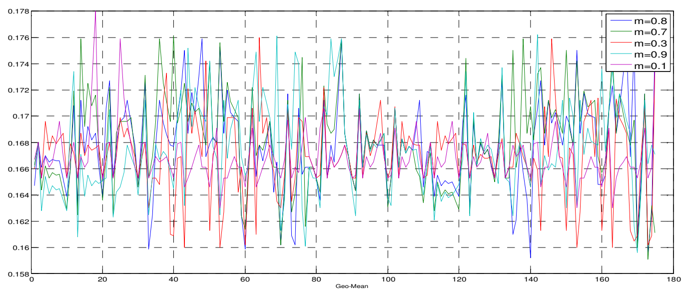

Fig. 14. Geometric-Mean of the expert system in the case of the teta=110 us.

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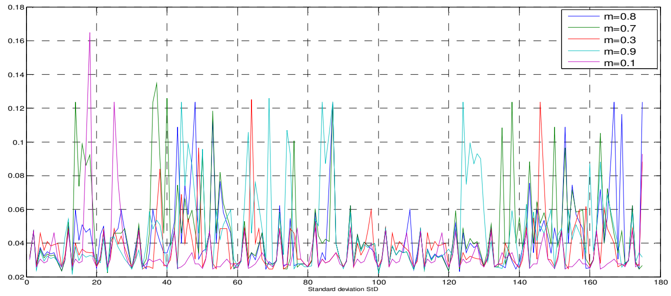

Fig. 15. Standard deviation of the expert system in the case of the teta=110 us.

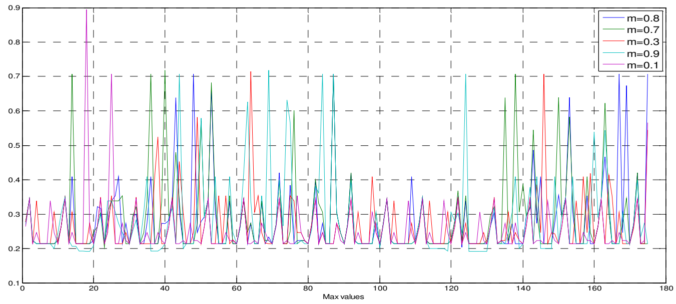

Fig. 16. Maximum values of the expert system in the case of the teta=110 us.

V. CONCLUSION

A new approach for monitoring AC Arc furnace has been presented. A theoretical analysis was presented. This inspection was made for both conditions (healthy and faulty case). MSE across 20 scales is extracted to take into account for dynamic nonlinearity as well as coupling and interaction effects between process elements. In order to reduce the number of entries approaching training process, five statistics are used through MSE. The classification procedure is then executed to determine the state at which the system is operating using the features extracted from the arc voltage signal. The used approaches can be also effective for assessing the level of the abrupt change of Flicker.

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