Electric Arc Furnaces (EAFs), widely used for steel production industries, are highly nonlinear time-variant disturbing loads because of the random change of the electric arc length results in arc voltage and furnace/supply current fluctuations. Consequently, Power Quality (PQ) problems such as undesirable variations of reactive power, poor power factor, harmonics, and voltage flickers may appear. The main objective of this paper is to provide the wavelet transform method for EAF to perform particular studies for Voltage Flicker Recognition. For this purpose, the mathematical equations and the dynamic model of the EAF voltage flicker are developed. Both Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT) are employed to detect flicker fluctuations, estimate its duration, magnitude to eliminate the expected fluctuations. Despite nonlinearities and harmonics often encountered in EAFs, a comprehensive comparison between DWT and CWT approaches are exhibited towards enhancing PQ problems. Simulations results, via MATLAB™/Simulink, reveal that the proposed Daubechie’s DWT can be successfully used for ensuring significant decision for flicker compared to the Daubechie’s CWT approach. It is evident to mention that, the results of this study open the way to explore a new standard based on Wavelet Transform (WT) for voltage flicker recognition.

Keywords: Continuous and Discrete Wavelet Transform, Electrical Arc Furnace, Power Quality, Voltage Flicker.

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1. Introduction

Electric power production must be of an acceptable quality to guarantee the correct behavior of the equipments within power distribution systems. Power Quality (PQ) is the deviation of voltage and/or current from the ideal permissible values, but whether or not the deviation is critical depends on the purpose of the installation and the design of the equipment. Besides power interruptions, PQ issues encompass a wide range of phenomena including harmonics, voltage fluctuations, voltage dips, power frequency variations and voltage imbalance. Voltage flicker, as a PQ problem, occurs when heavy loads are periodically turned on/off in a weak distribution system. If the distribution system’s short circuit capacity is not high enough, voltage fluctuations will occur. Electric Arc Furnaces (EAFs), widely used for steel production industries, are highly nonlinear time-variant disturbing loads because of random change of the electric arc length results in fluctuations in the arc voltage and the furnace/supply currents [1-3]. The real spectrum of the generated harmonic voltage from the AC EAF causes either characteristic or non-characteristic harmonics besides the probable voltage unbalance [4–7]. Flicker severity mainly depends on the voltage fluctuation amplitude and its repetition rate. Two major flicker meters are currently used worldwide. Both IEC 61000-4-15 and IEEE standard 1453 flicker meters are conveniently and officially used for flicker measurements worldwide [8,9]. Melting and refining processes are the main arc furnaces processes. Voltage fluctuation is influenced by the arc characteristics mostly dependent on melting or refining materials; the melting stage;
the electrode position; the system stiffness; the short-circuit capacity; the furnace ratings; the supply system voltage and its impedance, and its X/R ratio [4,5,10]. During the melting process, the large consumed power causes significant and undesirable PQ problems such as strong variations of reactive power, poor power factor, harmonics, and voltage flickers of voltage magnitude variation in the range of ±10% of nominal voltage and with frequencies between 0.2 to 30 Hz. Mitigation of the voltage flicker is realized by using either Voltage Source Converter (VSC) or thyristor-based mitigation devices [11,12]. Obviously, EAFs require a large amount of current, which causes a decrease in voltage. This voltage depression may cause a visible flicker on lighting circuits connected to the same power system. Voltage flickers are extremely harmful to both sensitive electronic and computerized equipments which efficiently operate at fixed stable voltage. According to IEEE practice documentations, the voltage flickers limits are highlighted in IEEE 519-1992 [13] and IEEE 141-1993 [14]. Although the slight differences between these IEEE standards, both display the recommended practice on an x, y graph including two borderlines. The first is concerned with visibility and the other is for the irritation curve (related to the continuity, the amplitude, and the frequency aspects of the voltage fluctuations). Indeed, the detection or prediction of the arc flicker is important. After its detection, the arc should be classified as normal or faulted one. EAF can be detected using traditional methods based on arc light, arc sound and temperature which are inconvenient for power supply and distribution line because of position limitations [15-18]. Also, some studies prove that the real harmonic spectrum of the arc furnaces contains some subharmonics and interharmonics as well [19,20].

In the literature, different techniques for EAF’s level evaluation have been proposed such as: the Fast Fourier Transform (FFT) in which the stationary time-invariant signals are considered [21-26]. The Indirect Demodulation Method (IDDM), the most popular application of FFT, is undesirably sensitive to harmonic disturbances of harmonics and power frequency shifting [23,27,28]. For tracking nonstationary voltage flicker, the Least Absolute Value State Estimation (LAVSE) and the Extended Kalman Filter (EKF) have been applied [29]. Genetic Algorithm (GA) and Practical Swarm Optimization (PSO), as metaheuristic techniques, have been proposed for measuring both the flicker and the power system voltage magnitudes [30,31]. However, the large mathematical burden and the lack of accuracy of these optimization techniques’ parameters are still their negative drawbacks.

There are many wavelet analysis that deals with the PQ problems especially harmonic calculation in time varying waveforms [32-38]. The authors usually treat the events with only one kind of disturbance, contained in a certain theoretical signal. Candido et al. (2008) have presented a technique for the detection, classification, and correction of signals with multiple disturbances, typical in the EAF operation [32]. In [39], Chang et al. (2006) have studied a steel-making power system where the AC EAF is dominant nonlinear load. Harmonic analysis of steel plants with an AC EAF load has been addressed using Matlab/Simulink for actual measuring data. Then, Candido et al. (2008) have proposed the WT conveniently applied to non-stationary signals of an industrial plant with three EAF for signals of single/multiple disturbance(s) [32]. Prieto et al. (2008) have examined the application of Wavelet Packet Transform (WPT) for AC EAF voltage/current waveform harmonic identification [36]. Moreover, Prieto et al. (2008) have studied three identification of the AC EAF current and voltage waveforms’ frequency components and the effects of the interharmonics components on the application of the FFT. Golkar et al. (2008) have reviewed different EAF models with different level of complexity, for flicker study. Then, a new developed time domain model for EAF has been developed using MATLAB™ (Simulink) [40]. Plata et al. (2006) have described methods used for analysing problems associated with EAFs and their influence on the power system. WT for harmonic, flicker and unbalance detection has been proposed [41]. Abd El-Gawad has suggested two routines
to diagnosis the flicker by using discrete wavelet analysis. The routines aim to classify the flicker voltage limits of the signals whether acceptable or not according to the standard limits. The first routine depends on the values of details and approximations due to the wavelet analysis. The second is related to separating the residuals (the amount of deformation on the signals due to flicker) by wavelet analysis. Then, the residuals’ stored energy have been determined by applying FFT transform to evaluate it. The suggested two routines can be implemented for different types of loads such as amps, arc furnace and induction motors. Comparisons between the two routines have been reported with the complete investigations. Using MATLAB™, the simulation results have been verified with many demonstrations [43].

Recently, Duan et al. (2014) have proposed a new approach for EAF detection using a wavelet transform based on multi-resolution analysis [15]. Mallat algorithm has been considered for the decomposition of load current samplings to low/high frequency signals. The EAF fault diagnosis criteria mainly depend on the mean and its difference of the reconstructed wavelet high frequency coefficients. Significantly, such approach has a reduced computational burden; high diagnostic reliability and accurate capability distinguish between fault arcs and others. In [1], Olay et al. (2014) have used the insulated-gate bipolar transistors for mitigating flicker generated by the AC EAFs. The evaluation of the fast tap-changer topologies’ abilities is studied according to technical and economic criteria [1]. Chang et al. (2014) have modelled the dynamic voltage-current (v–i) characteristics of the AC EAF using a combination of the DWT and the Radial Basis Function Neural Network (RBFNN)-based methods [11]. Hsu et al. (2014) have presented comparative statistical analyses of EAF measurements based on present Pst and DV10 standards of flicker planning level design. The different synchronous flicker severity indices in 10-min intervals have been compared in addition to the analysis of the daily flicker statistical reference values measured at the Point of Common Coupling (PCC) of both AC and DC EAF facilities [8]. In [21], Eghtedarpour et al. (2014) have calculated the voltage flicker characteristics by using the voltage waveform envelope which captures the main flicker characteristics. The voltage rms values have been instantaneously estimated using a moving window approach. Then, voltage flicker components have been extracted via S-transform (ST) for each frequency. In [42], Hooshyar et al. (2013) have proposed a modified IEC flicker meter to overcome the expected inaccurate measurements because of high-frequency interharmonics. The enhanced measurements of the modified IEC flicker meter compared to the original one has been verified by PSCAD/EMTDC. In [4], Elnady et al. (2011) have introduced the adaptive notch filters for flicker disturbance extraction and mitigation. The frequencies of flicker disturbances have been tracked and instantaneously extracted.

To the best knowledge of the authors, the voltage flicker classification using the DWT has been rarely discussed particularly when accounting for the possible nonlinearities and harmonics. The wavelet transforms application schemes in the literature are of continuous. Thus, the main contribution of this paper is to compare between the DWT and the CWT approaches to identify which of both could be properly used for the flicker monitor system in PQ dilemma.

2. Wavelet Transform

a. Wavelet Transform Principles

Wavelet transforms have recently become well known as a useful tool for various signal-processing applications [44]. Given a time-varying signal f(t), wavelet transform can be seen as the computation of coefficients that are inner products of the signal and family of wavelet basis functions. Then, by defining the wavelet function as a scaled (stretched or
compressed) and shifted version of this prototype, the continuous wavelet transform was originally derived as:

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \Psi^*\left(\frac{t-b}{a}\right) dt$$

(1)

where, a and b are the scaling (dilation) and translation (time shift) constants, respectively. The term $\Psi(t)$ is the wavelet function 'mother wavelet' and its dilation and translation are simply 'wavelets'. Wavelet transform of sampled waveforms can be obtained by implementing the discrete wavelet transform using:

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_k f(k) \Psi^*\left(\frac{n - ka_0^m}{a_0^m}\right) dt$$

(2)

where, the parameters a and b in Equation 1 are replaced by $a_0^m$ and $ka_0^m$. k and m are integer variables. In a standard discrete wavelet transform, the coefficients are sampled from the continuous WT on a dyadic grid, $a_0 = 2$ and $b_0 = 1$, yielding $a_0^0 = 1$, $a_0^{-1} = 1/2$, $b = (k \times 2^i)$, where i is being an integer variable. Actual implementation of the DWT involves successive pairs of high-pass and low-pass filters at each scaling stage of the WT. As a kind of successive approximations of the same function, each approximation providing the incremental information related to a particular scale (frequency range), the first scale covering a broad frequency range at the high frequency end of the spectrum, and the higher scales covering the lower end of the frequency spectrum even with progressively shorter bandwidths. Conversely, the first scale will have the highest time resolution as higher scales will cover longer time intervals. For many signals, the low-frequency content is the most important part as it gives the signal its identity. The high-frequency content, on the other hand, imparts flavour or nuance. In wavelet analysis, approximations and details are considered. The approximations are related to the high-scale, low-frequency components of the signal. The details are concerned with the low-scale, high-frequency components.

The filtering process, at its most basic level, can be shown in Fig. 1. The original signal, S, passes through two complementary filters as two output signals, A and D represent the approximation and the details respectively. These signals A and D are interesting due to the existence of subtle way to perform the decomposition using discrete wavelets. Breaking down a signal into many lower resolution components or coefficients depending on the desired level 'N' called (decomposition process). The wavelet coefficients may be divided...
into smoothed version (approximation) ‘$a_j$’ and detailed versions ‘$d_j$’; where ‘j’ takes successively the values from ‘1’ to ‘N’ to create the wavelet decomposition tree. In Fig. 2, the decomposition tree of level 5 is illustrated the analysis of the signal (S), are attained corresponding to its 5th approximation coefficient ($a_5$) and detail coefficients ($d_5$, $d_4$, $d_3$, $d_2$ and $d_1$) are depicted respectively.

Fig. 2. DWT : Wavelet Trees.

B. Wavelet Transform Hypothesis

Wavelets can be smooth, compactly or wavelets, wavelets with simple mathematical expressions and wavelets with simple associated filters. Depending on $\psi(t)$ many families of WTs can be named like Haar, Daubechies, Symlets, Coiflets, Gaussian and Mexican hat wavelets. For Daubechies, it is established that N is the order and db is the surname. These families are suitable for the applications either CWT or DWT. The transform by Daubechies wavelets is more convenient in analyzing various frequency components of a signal. The used Daubechies WT results in high flexibility in monitoring any frequency of interest in a waveform. For voltage flickers study, after many revises and investigations, Daubechies WT ($db5$) is selected to be implemented with decomposition of level 5.

Fourier Transforms (FT), a well-known signal analysis, breaks down a signal into constituent sinusoids of different frequencies. Fourier analysis is as a mathematical technique for transforming the signal from time-based to frequency-based. Although Fourier analysis is extremely useful because the signal’s frequency content is of great importance, its main drawback is the lost of time information during the transformation into frequency domain. The FT outputs are frequency components (spectral components) of the signal. If the signal properties are time invariant, the signal is therefore stationary. It is important to study signals that contain numerous nonstationary or transitory characteristics such as drift, trends, abrupt changes besides the beginnings and ends of events. Although these characteristics are often important parts of the signal, Fourier analysis cannot detect them. If the time localization of the spectral components is requested, another transform approach for attaining the time-frequency representation becomes necessary. Therefore, Short-Time Fourier Transform (STFT) that have the ability to map the signal into a two-dimensional function of time and frequency, is convenient for such condition and has a minor difference with FT. In STFT, the signal is divided into segments small enough, that can be assumed to be stationary. For this purpose, a window function "w" is chosen. The width of this window must be equal to the signal segment where its stationarity is valid. If a window of infinite length is used, FT that gives perfect frequency resolution, but no time information, is applied to obtain the stationarity. Windows should be small enough to get stationary signals. The narrower the window, the better the time resolution and the
stationarity assumption. However, the frequency resolution becomes poorer. The WT can therefore solve the dilemma of resolution to a certain extent. Wavelet analysis with a windowing technique of variable-sized regions will be the next step. Wavelet analysis allows the use of long time intervals of more precise low-frequency information and shorter regions for high-frequency. Wavelet analysis does not use a time-frequency region, but a time-scale region as shown in Fig. 3 [44].

![Fig. 3. Methods for signal analysis.]

3. Estimation of Arc Furnace Voltage Flicker

The furnace is an unbalanced, nonlinear and time varying load can cause power system quality problems such as harmonics, inter-harmonics and voltage flicker. The factors that affect the arc furnace operation are the melting or refining materials, the electrode position, the electrode arm control scheme, and supply system voltage and impedance. Thus, the description of an arc furnace load depends on the arc voltage, the arc current and arc length (which is determined by the position of electrode) [5].

Flicker is a visible change in brightness of a lamp due to rapid fluctuations in the power supply voltage. The voltage drop is generated over the source impedance of the grid by changing the load current of an equipment or facility. The effects can range from disturbance to epileptic attacks of photosensitive persons. Flicker may also affect sensitive electronic equipment such as television receivers and/or industrial processes relying on constant electrical power. Flicker can be observed for repetitive voltage fluctuations up to a specified frequency where it is impossible for the eye to detect the fusion of images. This frequency limit is approximately from 0 - 30 Hz for voltage changes less than 10%.

IEEE Standard 1453 – IEEE recommended practice for measurement and limits of voltage fluctuations and associated light flicker on AC power systems is the key standard with regard to flicker. \( P_{lt} \) is the measure of long-term perception of flicker obtained for a two-hour period. This value is made up of 12 consecutive \( P_{st} \) values. \( P_{st} \) is the measure of short-term perception of flicker obtained for a ten-minute interval. \( P_{st} \) and \( P_{lt} \) should not exceed the planning levels given in Table 1 with a minimum assessment period of one week, where LV, MV, HV-EHV refer to Low Voltage, High Voltage, High Voltage-Extra High Voltage respectively.
Table 1: $P_{st}$ and $P_{lt}$ limits

<table>
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<tr>
<th></th>
<th>LV</th>
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<th>HV-EHV</th>
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<tbody>
<tr>
<td>$P_{st}$</td>
<td>1.0</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>$P_{lt}$</td>
<td>0.8</td>
<td>0.7</td>
<td>0.6</td>
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To evaluate flicker limitations, several criteria have been proposed. In most Asian countries, such as Japan and China, the voltage 10-Hz equivalent value $\Delta V_{10}$ is served as a measure to evaluate the severity of flicker. Fig. 4 plots the relationships between the sensitivity coefficient $A_n$ and the flicker frequency $f_n$. From the biological viewpoints, the human visibility is sensitive to the illumination flicker within the range of 0.2 to 30 Hz. In Fig. 4, when the frequency is equal to 10 Hz, the value of $A_n$ becomes 1. This mapping reveals that the most sensitive frequency of human eyes is 10 Hz. Once $\Delta V_{10}$ is known, the seriousness of the voltage flickers can be evaluated such as [28]:

$$\Delta V_{10} = \sqrt{\sum_{n} (A_n \Delta V_n)^2}$$

(3)

where $A_n$ indicates the flicker sensitivity factor, and $\Delta V_n$ is twice the flicker amplitude.

![Flicker sensitivity coefficient curve.](image)

EAF is a network load problem particularly because of meltdown and refining processes that last respectively, (70-90 minutes, 0.5-2 hours. Almost melting technique depends on the short-circuit between two phases (two electrodes) and the third phase is with no current. The rapid change in current is mainly during the meltdown process cases. In such conditions, voltage flicker that is defined as a Short–Circuit Depression Value (SCDV); depends on $MW_p$, the furnace rating in MW and $MVA_{SC}$ besides the three phase fault level at the point of coupling; and can be calculated as [45]:

$$SCDV = \frac{2 \times MW_p}{MVA_{SC}}$$

(4)

$$SCDV \begin{cases} < 1.9 \% & , \text{lamps at 230 V} \\ \approx 1.9 \% & , \text{lamps at 230 V} \end{cases}$$

(5)

Usually compensating element like static VAR compensator is utilized to eliminate flicker.

From the literate survey, different suggestions have been presented to diagnose and to estimate the flicker. Most of them contain some difficult measurements and complex calculations. In this paper, particular studies concentrated on voltage flicker due to EAF for voltage flicker to design a simple flicker monitoring system based on WT are introduced. The static arc models are formed by using mathematical equation for generating voltage using MATLAB™. Then, the dynamic model for an arc furnace is presented. Both DWT and CWT are considered to perform the required investigations about the flicker voltage for the resulting signals.
A. Mathematical Equation

A voltage signal containing flicker due to arc furnace can be expressed as [46]:

\[ V(t) = \sqrt{2} V_{\text{rms}} [1 + 0.5 \sum_n \Delta V_n \cos(2\pi f_n t + \phi_n)] \cos(2\pi f t) \]  

(6)

where:
- \( f_n \): modulation frequency \( n \) Hz of flicker.
- \( \phi_n \): modulation phase angle of flicker.
- \( \Delta V_n \): voltage fluctuation of frequency \( n \) Hz.
- \( V_{\text{rms}} \): voltage effective value of 60 Hz.

The required signals are generated through this equation by using MATLAB\textsuperscript{TM}.

B. Dynamic Model

To simulate the arc furnace behavior using one of MATLAB toolboxes (simulink), it is suggested to use an uncomplicated arc furnace system as shown in Fig. 5. \( Z_s \) and \( Z_t \) represent the system and arc transformer impedance respectively. By choosing suitable values for them and also for \( V(t) \), the simulation model can be built as shown in Fig. 6.

![Fig. 5. Arc furnace system.](image)

The mathematical relationships for building the model have been comprehensively explained in [47].

![Fig. 6. MATLAB model of the arc furnace.](image)

4. Simulation Results

The results for mathematical equation and dynamic model using DWT and CWT are reported for the different cases listed in the Appendix, as follows:

A. Results for Mathematical Equation

Fig. 7 contains the parameters required for both generating the normal voltage signal creating the flicker for signals under study. Fig. 7 also, contains a plot of the 1\textsuperscript{st} detail...
coefficients $d_i$ intended for each case, $d_i$ depicts the flicker level condition resulting from applying DWT with function db5 with decomposition of level 5 as described in Fig. 2 [8].

Fig. 7: Studied cases for voltage flicker using mathematical equations.

In this paper, the authors have compared between the CWT and the DWT methods used for conveniently monitoring the voltage flicker according to the change of parameters ($f_n$) and ($\Delta V_n$) ignoring $\phi_n$ for simplicity as shown in Equation 7.

Fig. 8. DWT analysis for normal case 1.
In Fig. 9, the signal envelope has the shape of scaled modulated signal and of a periodic period length between 0-50, with $f_n=30$. The scaled modulated period length decreases when the modulated frequency increases as shown in Fig. 11, with max $f_n=200$. The $d_1$ values are the most obvious items that clarify the difference. It is found that their values are very small, nearly $\approx$ zero, for normal case as shown in Fig. 8. For Case 2 the value of $d_1$ is relatively higher with range between 200 : -200, as shown in Fig.9. In this case, the max $\Delta V= 0.5$ and $\Delta V/V \approx 0.227\%$. Cases 3 and 4 are approximately similar to Case 2. On the other hand, for Cases 6 and 7, values of $d_1$ are evidently high nearly (-1000:1000). At Case 7, the max $\Delta V= 7.5$ and therefore $\Delta V/V \approx 3.4\%$ as shown in Fig. 9. Also, $d_1$ picks up the high frequency component of the signal. It is clear that the signal shape at Case 7 is more distorted than Case 2 and Case 5. Therefore, clear discrimination between the different cases of flicker can be performed according to the fluctuation amplitude and the modulated frequency.

The detail $D_1$ show the kind of variation and has, roughly speaking, the local period irregularities caused by flickers.

(a) Case 2: ($f_n=5, 10, 30$ and $\Delta V_n=0.125, 0.5, 0.375$)

(b) Case 5: ($f_n=8, 15, 30$ and $\Delta V_n=0.5, 1, 1.5$)

(c) Case 7: ($f_n=100, 150, 200$ and $\Delta V_n=2.5, 5, 7.5$)

Fig. 9: DWT analysis

Fig. 10, illustrates CWT coefficients plotted in Case 2 by using (db5) wavelet, zoomed view. Scale and position are on the vertical and horizontal axis, respectively. Horizontal $b$-axis contains 300 samples. The vertical axis contains the $a$-values from 1- 64. The coefficients, between min and max values, are plotted by using 64 levels of pink. It includes the coefficient line plot corresponding to a certain scale ’a’=32 that corresponds to frequency=0.021.

Fig. 10 show the plots for Cases 2, 5 and 7 respectively. From the different plot coefficients, it is simple to detect the period of flicker for all cases. Although Case 7 is more distorted than the other two cases especially below scale 32 (higher frequencies), it is still hard to distinguish between the different cases situation of flicker due to the fluctuation amplitude and the modulated frequency by simple way. Artificial Intelligence (AI) based
methods such as Artificial Neural Networks (ANN) can be considered to overcome this problem. However, calculating CWT coefficient at possible scales is relatively complex and generates lot of data. As choosing the implemented function is very important, it is not recommended to do these analyses using CWT. Generally, the function db5 is more suitable for analysis with DWT than CWT. Therefore, another function like Gaussian wavelet function, categorized as a kind of CWT, can be used to get better results.

Fig. 10. CWT analysis.
B. Results for Dynamic Model

Simulated arc furnace system using MATLAB™, is implemented by connecting the suggested arc furnace model through sinusoidal source of 220 volts – 60Hz. To distinguish between normal voltage signal and distorted signal with flicker, investigations can be done for each signal by using DWT (db5). The $d_1$ values are very small for normal case ($\approx$ zero), as shown in Fig. 11 (the starting and ending periods). With changing the gains value at the model represented in Fig. 11, many signals can be generated polluted by flicker voltage. In Fig. 11, one generated flicker case is established. The value of $d_1$ is significantly high (-200:200). The scaled modulated period length will decrease if the modulated frequency increased. The scaled modulated period length is also relatively small. The max modulated frequency $f_n$, is more than 30 Hz, as depicted Fig. 11. By using such analysis, the normal and upnormal cases can be distinguished. Moreover, the shape of $d_1$ at flicker period is clearly more distorted than other normal periods as illustrated in Fig. 11.

Fig. 11. DWT analysis for voltage flicker.

Fig. 12 illustrates CWT coefficients plot in flicker period by using (db5) wavelet. From the coefficients plot, it is found that the period of flicker can be detected especially below scale 1 (for most higher frequencies). However, it is still recommended to use DWT rather than CWT analysis.

To illustrate the effectiveness of the proposed model we have presented illustrative case study. The model has been implemented and solved with the commercial optimization package MOSEK Solver Engine – Premium Solver Platform, version 6.0, Frontline System, Inc., on 3.0 GHz PC with 1 GB of RAM.

5. Conclusions and Perspectives

Wavelet Transform approaches will continue to provide solutions to challenging issues associated with the EAF flicker and power quality problems. In view of the highly nonlinear time-variant voltage flicker fluctuation and harmonics, the mathematical equations and the dynamic model of the voltage flicker of the EAF have been developed. Then, the continuous and the discrete WT methods, CWT and DWT respectively, have been applied to detect and estimate the duration of flicker. Moreover, their applications are extended to depict the magnitude of the flicker fluctuations and perform the necessary calculations to eliminate them. The results obtained from the dynamic model cope with those of mathematical equations. According to the study, a new standard analysis based on WT can be proposed compatible with the standards to provide less calculations and measurements options.

The better performance of DWT for studying the flicker problems compared to CWT pave the way to the authors to validate the proposed DWT approach using PSCAD/EMTDC considering faults at EAF system (with more detailed model) in the forthcoming work. In addition, ANN, FL and neuro-fuzzy can be employed to check offline flicker monitoring system based on the DWT coefficient results.

6. Appendix

Frequency for the AC network: \( f = 60 \text{ Hz}, \ V = 220 \text{ V} \)
The different Cases of study for the EAF recognition:
Case 1: \( f = 60 \text{ Hz}, \ V = 220 \text{ V} \) (Normal Condition)
Case 2: \( f_n = 5, 10, 30 \) and \( \Delta V_n = 0.125, 0.5, 0.375 \)
Case 3: \( f_n = 5, 10, 30 \) and \( \Delta V_n = 0.5, 1, 1.5 \)
Case 4: \( f_n = 3, 5, 10 \) and \( \Delta V_n = 0.5, 1, 1.5 \)
Case 5: \( f_n = 8, 15, 30 \) and \( \Delta V_n = 0.5, 1, 1.5 \)
Case 6: \( f_n = 35, 45, 55 \) and \( \Delta V_n = 2.5, 5, 7.5 \)
Case 7: \( f_n = 100, 150, 200 \) and \( \Delta V_n = 2.5, 5, 7.5 \)
References


