Fast Harmonic Current / Voltage Prediction by using High Speed Time Delay Neural Networks

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Abstract—This paper presents an intelligent approach for fast harmonic current/voltage prediction by using new high speed time delay neural networks. The current/voltage data are collected together in a long vector and then processed as a one input pattern. The proposed fast time delay neural networks (FTDNNs) use cross correlation in the frequency domain between the tested data and the input weights of neural networks. It is proved mathematically and practically that the number of computation steps required for the presented time delay neural networks is less than that needed by classical focused time delay neural networks. Simulation results using MATLAB confirm the theoretical computations.

Keywords— Harmonic Current/Voltage Prediction, Distributed Power System, Harmonic Reduction, Fast Time Delay Neural Networks, Cross Correlation, Frequency Domain.

I. INTRODUCTION

With the increasing use of converters and other thyristor controlled devices, the problem of harmonics is achieving increasing importance. Generally, electrical equipment, when working normally produces only odd harmonics. Even harmonics usually occur during transient conditions, conditions of malfunction or single-phase rectification etc. [1]. Power engineers are interested in harmonics because of the disturbance, distortion and heating effects they cause. In addition, there is always the chance of system resonance causing current and voltage magnification in equipment. More recent problems involve electronic equipment which is very sensitive to pollution of power line. In the presence of harmonics, equipment such as computers, telephone systems, and controllers may respond incorrectly to normal inputs, not respond at all, or give false outputs. The term harmonic component or simply the harmonic is defined as a sinusoidal component of a periodic wave having a frequency that is an integral multiple of the fundamental frequency. Harmonics are generated due to system non-linearities, i.e. the energy conversion from fundamental to harmonic frequencies takes place in non-linear devices connected to the sinusoidal supply. The harmonics thus generated can be regarded as being superposed on the fundamental voltage and current. Because of this superposition and because the three-phase supply can be regarded as linear, the effects of harmonics can be studied and analyzed separately from the fundamental. The growing concern about harmonics comes from:

- Consumers becoming increasingly aware of the distortion caused by harmonics. Motivated by deregulation, they are challenging the energy suppliers improve the quality of the power delivered.
- The proliferation of load equipment with microprocessor-based controls and power electronic devices which are sensitive to harmonics.
- Emphasis on increasing overall process productivity which has led to the installation of high-efficiency equipment, such as adjustable speed drives and power factor correction equipment. This in turn has resulted in an increase in harmonic injected into the power system causing concern about their impact on the system [1].

The main aspects of harmonics are:
1. Modeling and analysis.
2. Instrumentation.
3. Sources.
4. Solutions.
5. Fundamental concepts.
6. Effects.

Any device with nonlinear characteristics which derive their input power from a sinusoidal electrical power system may be responsible for injecting harmonic currents and voltages into the electrical system. The common sources of harmonics in utility or industrial electrical systems are as follows:

- Rectifiers.
- DC motor drives.
- Adjustable frequency AC drives.
- Uninterruptible power supplies (UPS).
- Arc furnaces.
Other sources of harmonics of less importance than those above include pulse burst heating, television sets, personal computers, photocopiers, laser printers, synchronous machines and induction machines [1].

A) Harmonic Source Spectrum:

In harmonic studies, it is convenient to represent harmonic source in the frequency spectrum form in two cases [1] -:

- **Voltage Sources Spectrum**

  The voltage waveform is a clear way to view the bus voltage distortion since each harmonic source spectrum is injected into the system in harmonic spectrum form. It is easy to visualize a spectrum series in a two dimensional array:

  \[
  (v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8, v_9, v_{10}, \ldots, v_h).
  \]

  \[
  (f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8, f_9, f_{10}, \ldots, f_h).
  \]

  Graphically, the series can be displayed in spectrum form. It can also be displayed in time domain by inverse Fourier Transformation.

  \[
  U_t = \sum_{i=1}^{h} |v_i| \sin(i \times \omega_1 \times t + \beta_i) \quad (1)
  \]

  where

  - \(i\) 1, 2, 3, ..., \(h\),
  - \(h\) maximum harmonic order of interest,
  - \(U_t\) instantaneous voltage,
  - \(t\) instantaneous time,
  - \(|v_i|\) magnitude spectrum of harmonic voltage,
  - \(\beta_i\) phase spectrum of harmonic voltage and
  - \(\omega_1\) radian frequency.

- **Current Sources Spectrum**

  The current waveform allows to view the branch current distortion. As with the voltage wave form, the solution for each harmonic source spectrum injected into the system is given in harmonic spectrum form, so that the branch current is also in spectrum format in frequency domain. The sources can be seen as a spectrum series in a two dimensional array:

  \[
  (i_1, i_2, i_3, i_4, i_5, i_6, i_7, i_8, i_9, i_{10}, \ldots, i_h).
  \]

  \[
  (f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8, f_9, f_{10}, \ldots, f_h).
  \]

  Using an inverse Fourier Transformation, The sources can be described mathematically in time domain:

  \[
  I_t = \sum_{i=1}^{h} |i_i| \sin(i \times \omega_1 \times t + \beta_i) \quad (2)
  \]

  where

  - \(i\) 1, 2, 3, ..., \(h\),
  - \(h\) maximum harmonic order,
  - \(I_t\) instantaneous current,
  - \(t\) instantaneous time,
  - \(|I_i|\) magnitude spectrum of harmonic current,
  - \(\beta_i\) phase spectrum of harmonic current and
  - \(\omega_1\) radian frequency.

B) Effects of Harmonics in Distributed Power System

1. Effects on Transformers:

   The primary effect of power system harmonics on transformers is the additional heat generated by the losses caused by the harmonic content of the load current. The additional heating caused by system harmonics requires load capability de-rating to remain within, temperature rating of the transformer [1].

2. Effects on Rotating machines:

   Non-sinusoidal voltage applied to electrical machines may cause overheating, Pulsating torque or noise. Induction motors may either refuse to start or run at high slip. Rotor overheating has been the main problem associated with voltage distortion [1]. An increase in motor operating temperature will cause reduction of the motor operating life.

3. Effects on Protective Relays:

   Waveform distortion does affect the performance of protective relays or may cause relays to operate improperly or not to operate when required. However, distortion may cause a relay to fail to trip under fault conditions, or it may cause tripping when no fault exists [1].

4. Effects on Lighting:

   The incandescent lamp will have a definite loss when operated with distorted voltage. If the operating RMS voltage is above the rated voltage due to harmonics, the elevated filament temperature will reduce lamp life [1]. Continuous operation at 105% rated RMS voltage, lamp life will decrease by 47%.

5. Effects on Circuit Breakers and Fuses:

   There is some evidence that harmonic distortion of the current can affect the interruption capability of circuit...
breakers and fuses. Circuit breakers may fail to interrupt currents due to improper operation or blow out tripping coils. The time-current characteristics of fuses can be altered and the protective relays may experience erratic operation. How harmonic distortion affects the current sensing ability of thermal circuit breakers has been described in [1]. The instantaneous mechanism of some breakers is a solenoid that dissipates additional heat due to losses for frequencies above the fundamental. The additional heat can raise the temperature of thermal devices so that reducing the trip point.

6. Effects on Capacitors:
The use of shunt capacitors to improve the power factor. Voltage also has a significant influence on harmonic levels. If the addition of capacitors tunes the system to resonate near a harmonic frequency present in the load current or system voltage, large over current or voltage at that frequency will be produced. The effect of the harmonic components is to cause additional heating and higher dietetic stress on the capacitor units that may cause blown fuses or capacitor unit failures [1].

7. Effects on Power Cables:
The flow of non-sinusoidal current in a conductor will cause additional heating over and above what would be expected for the RMS value of the waveform. This is due to two phenomena known as "skin effect" and "proximity effect" both of which vary as a function of frequency harmonics is flowing in a cable the equivalent AC resistance of the cable is raised so that amplifying the I^2R losses [1].

8. Effects on Metering:
Metering and instrumentation are affected by harmonic components. Induction Watt-hour meters normally see only fundamental current However. Phase imbalance caused by harmonic distortion can cause erroneous operation of these devices [1].

9. Effects on Neutral Wire:
In the three phase, four wire distribution systems, the odd-numbered triple harmonic line current (3rd, 9th, … etc) are in phase in the neutral conductor. So, the triplen harmonic currents are additive in the neutral and can be as much as 1.7 times of the phase current. Since the neutral conductor is usually sized the same as the phase conductor. The neutral conductor will be over loaded and may be burned in the worst case [1]. The most common is to size the neutral conductor to be at least twice the phase conductor amp city to increase the ability to withstand over heating caused by harmonic contents.

A typical data needed for a distribution harmonic study.

<table>
<thead>
<tr>
<th>Device</th>
<th>Data needed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transformer</td>
<td>Actual turns ratio, connection diagram and short circuit impedance.</td>
</tr>
<tr>
<td>Overhead lines, cables</td>
<td>Phase and neutral conductor size, layout, length, or short circuit impedances; capacitance (when needed).</td>
</tr>
<tr>
<td>Capacitor bank</td>
<td>Voltage rating, var rating and configuration.</td>
</tr>
<tr>
<td>Tuned filter</td>
<td>Tuned frequency, volt , var rating configuration.</td>
</tr>
<tr>
<td>Generator/ large motor</td>
<td>Sub transient impedance, configuration.</td>
</tr>
<tr>
<td>Load (linear)</td>
<td>Watts, power factor, composition, balance.</td>
</tr>
<tr>
<td>Load (nonlinear)</td>
<td>Expected level of harmonic current injection, magnitude and phase angle.</td>
</tr>
</tbody>
</table>

C) Harmonic Measurements
Measurements of current and voltage harmonics are essential for the reliable distribution of electric energy. The following are a few reasons which highlight the importance of measurements:

1. Monitoring existing values of harmonics and checking against recommended or admissible levels.
2. Testing equipment which generates harmonics.
3. Diagnosing and trouble-shooting situations where the equipment performance is unacceptable to the utility or to user.
4. Observing of existing background levels and tracking the trends in time of voltage and current harmonics (daily, monthly, seasonal patterns).
5. Measuring for verification of simulation studies which include harmonic load and flow.
6. Measuring harmonic currents and harmonic voltages with the respective phase angle. Such measurements can be made with and without a part of the nonlinear loads connected, and help determine the harmonic driving point impedance at a given location.

The techniques used for harmonics measurements differ from ordinary power system measurement. The frequency bandwidth of the ordinary measurements of voltage, current and power can be accomplished with attention to a narrow band of frequencies near the distribution frequency. Substantially wider bandwidths (up to 3 KHz) are required in the study of power systems harmonics [1].
D) Basic Equipment Used for the Analysis of Non sinusoidal Voltages and Currents [1].

1. Oscilloscope
The display of the waveform on the oscilloscope gives immediate qualitative information on the degree and type of distortion. Sometimes cases of resonances are identifiable through the visible distortion which is presented in the current and voltage waveforms.

2. Spectrum Analyzers
These instruments display the power distribution of a signal as a function of frequency. A certain range of frequency is scanned and all the components, harmonics and inter harmonics of the analyzed signal are displayed. The display format may be a CRT or a chart recorder.

3. Harmonic Analyzers or Wave Analyzers
These instruments measure the amplitude (and in more complex units, the phase angle) of a periodic function. These instruments provide the line spectrum of an observed signal. The output can be recorded or can be monitored with analog or digital meters.

4. Distortion Analyzers
These instruments indicate Total Harmonic Distortion (THD) directly.

5. Digital Harmonics Measuring Equipment
Digital analysis can be performed in two basic techniques.
   1. By means of digital filter. This method is similar to analog filtering. Dual channel digital signal analyzers include digital filtering. In the setup for a particular measurement, the frequency range to be measured sets up the digital filters for that range. Also, the bandwidth is varied to optimize the capture of smaller harmonics in the presence of a very large fundamental.
   2. The fast Fourier Transform technique. These are real-time, very fast methods of performing spectrum analysis, permitting the evaluation of a large number of functions. Multi-channel analog-digital conversion and micro or mini computers are used for real-time data acquisition.

E) The basic hardware for measuring harmonics
There are four basic elements of the measurement system [1].
1- transducers for voltage and current.
2- Signal conditioners.
3- Spectrum analyzer.
4- Data recorder.
The transducers such as current transformer and voltage transformer is generally accurate up to 5 KHz unless there is something unusual about the burden. The preferred voltage transducer is an unloaded capacitance divider. Permanently-installed dividers with a fixed burden are generally unsatisfactory unless the burden can be safely removed. Potential transformers are usually acceptable up to KHz if they have a sufficiently high impedance burden.

Signal conditioning equipment includes any amplifiers and filters to interconnect the transducers with the recording equipment. Isolating amplifiers are used to control the loading on the transducers and provide adequate signal for recording equipment. Better resolution of the harmonic can be obtained if the fundamental frequency can be filtered out. Spectrum analyzers are devices that specialized in sampling waveforms and determining the harmonic content. These are usually combined with an oscilloscope for displaying the data. Newer models are containing computers that permit the user to perform a myriad of analyses on the data while at the measurement site.

A major concern associated with the proliferation of electronic loads on the distribution system is that all of these loads tend to draw current waveforms that are similar and in phase with each other. This is an inherent characteristic of the diode bridge rectifier with capacitive smoothing. As a result, the lower order harmonics from these loads tend to add on the distribution system with little cancellation. The triplen harmonics can be of particular concern on systems that supply single phase loads line-to-neutral on the transformer primary.

F) Methods for harmonic reduction
Generally, there are two methods for harmonic reduction. Namely, methods not involving harmonic filtering and methods involving harmonic filtering [1].

(i) Methods not involving harmonic filtering
If harmonic currents are above the allowable limits, one or more of the following remedies should be undertaken:

1- Using suitable rectifier connections and increasing rectifier pulses. The maximum practical number of pulses for a rectifier is 12 and use of a half-wave rectification is not recommended because of the direct current component imposed on the network.

2- Relocation of the capacitors to other parts of the circuit may reduce over currents due to partial resonance.

3- Capacitors may be switched off the circuit during periods in which over currents are likely to occur. Automatic control actuated by change in current, change in voltage, change in reactive KVA, or by time switch may be used.

4- Removal of neutral ground, if present. So no path for third, ninth, fifteenth, ... etc. harmonics. This reduces the possibility of interface with communication, system resonant, over voltages, fuse heating on capacitor unit.
5- Isolating the load which is the source of harmonics and feed affected loads from another clean source.
6- Reinforce the system by increasing the short circuit level as the rule of thumb that is the ratio of the system-short circuit to the load current should be at least 100:1 [1].
7- Moving the distorted load to a higher voltage bus to get low % THDv.
8- Not-concerting the distorted loads in a part of the network.
9- Choosing the optimal switching actions which achieve low harmonic distortion and minimum losses.

If these methods fail, it may necessary to resort to the use of reactors of a selected rating. These may be connected in series or shunt with all or parts of the capacitor bank to reduce the harmonic current. The use of reactors requires the determination of the exact harmonic causing excessive current, which may be done with an oscillograph, or harmonic analyzer. Careful consideration must be given to allow for increased voltage or current loading on a capacitor as a result of adding a reactor in series with it.

(ii) Methods Involving Harmonic Filtering:
Generally, harmonic filters are recommended if a problem exists with harmonic distortion before the application of power factor correction, or if the harmonic distortions above the limits. Passive filters have traditionally been used to absorb harmonic currents generated by non-linear loads, because of their low cost and high efficiency. The installation of tuned filters does however have some major, well documented, disadvantages that impair their effectiveness [1].
- The passive filter may cause parallel resonance with the AC sourc. Therefore, amplification of the harmonic currents of the source side at specific frequencies occurs.
- The passive filter can generate a series resonance with the AC source. The problems associated with passive filters has led to the development of the parallel connected active filter. The active filter comprises a reactive energy storage element on the compensator DC side, a high frequency power electronic converter and an output filter that is used for filtering of the converter switching frequency on the output current. The characteristics of the active filters are [1]:
  - The active filters have high losses, compared with the passive filters.
  - The performance obtained with active filters is high compared with that obtained with passive filters.
  - The initial and running costs of the active filters are high compared to that of the passive filters.

G) Nonlinear loads Expansion
Good forecasting leads to good decision. Whatever, in economy, decision making of planning, or in operating power system, etc. Therefore, electrical load forecasting plays a central role in the operation and planning of electric power. The countrywide energy estimation, the planning of new plant, the routine maintaining and scheduling of daily electrical generation are all depended on accurate load forecasting in the future. Large amounts of harmonics are generated by nonlinear industrial loads that make use semi-conductors. Such semi-conductors based loads lead to distorting current and voltage waveforms. So, we are interested in nonlinear-load forecasting.

1. Forecasting system:
Forecasting is the scientific art which depends very much on the experience of the forecaster in conventional and stochastic approaches, none of these methods can provide a consistently good forecast all the time, and thus necessitate constant updating and modification of the models. Forecasting process can normally be broken down according to the forecast period into the following categories:
   1- Current forecasting (up to few minutes)
   2- Short term forecasting (hours/day or several days)
   3- Medium term forecasting (week/several weeks)
   4- Long term forecasting (year/several years)

2. Harmonic Prediction
Harmonics are created by nonlinear loads and devices on the power system. There are a wide variety of devices that generate harmonics and they can be connected to the power system at any voltage level. The power system provides a conceptual system illustrating the interconnection of different harmonic – producing devices on it. There is a divided responsibility between the customer and utility for harmonic voltage levels on the overall power system. The Total Harmonic Distortion of voltage (THDv) should be less than 5% This means that the utility must make sure that system resonance condition do not result in unacceptable voltage distortion levels, even if all customers are within the recommended guidelines for harmonic current generation [1].
The behavior of harmonics is so complicated that the conventional methods do not work so well to predict harmonics. That is due to the following characteristics:
- i) Non-linearity of harmonics,
- ii) Random-like behavior of harmonics for very short term and
- iii) Periodicity of harmonics for a fairly long term.
Adaptive prediction techniques have the following problems [1]:
- i) How to determine the number of input signals and
- ii) How to determine the convergence factor.
A tremendous research effort has been devoted to the development of neural networks over the past ten years. The advantage of neural networks resides in non-algorithmic parallel distributed architecture for information processing. The ANN can be applied to pattern recognition, pattern classification, learning, optimization, load forecasting, etc. [2-7], [9-11], [13-15]. In [18], the authors have proposed a neural network learning technique called the Back Propagation Learning Algorithm (BPLA) with multi-layered perceptions.

II. Power System Harmonics Prediction Using Neural Networks

Today, the idea of considering electricity as a “product” like any other and, defined by a set of technical parameters, is becoming widely accepted in several developed and developing countries. In fact, a common approach to assess the power quality delivered to customers considers three dimensions: i) quality of the electricity product, ii) quality of the technical service associated with the product and iii) quality of the commercial service associated with the product. The key point of the quality of the commercial service is the level of customer satisfaction that usually is assessed through surveys [1]. The quality of the technical service considers all the engineering studies and fieldwork to improve the operation and maintenance of the electrical system. The Harmonic Distortion of the voltage and current waveform and its impact on the electrical system have received much attention in electric utilities [1].

Large amounts of harmonics are generated by nonlinear industrial loads that make use of semi-conductors. Such semi-conductors based loads lead to distorting current and voltage waveforms. Harmonics flow into distribution systems giving rise to troubles in power network operation. Hence it is necessary to analyze and predict the behavior of harmonics so that system operators take an appropriate strategy to decrease harmonics [1].

This paper presents a new method for predicting power system harmonics with ANN. The method is based on the BPLA for feed-forward neural networks. The input is the past harmonics data and the output is one-step ahead prediction of voltage / current or total harmonic distortion. To illustrate the proposed idea, harmonics data of a test system are used to build the model that used in harmonic prediction process. The technique has been successfully applied to adaptive prediction problem.

A) The Prediction Model

The time series analysis, the Auto-Regressive (AR) model is one of linear predictors for stationary process that predicts output with the past output and input of white noise. The input of AR model is the white noise and the output is the present state. This model requires a priori observations of the input and output. The model is constructed to minimize the predicted error [1]. The prediction model is given by as shown in Fig. 1:

\[ X_{t+1} = a_1 X_t + a_2 X_{t-1} + \ldots + a_p X_{t-p} + b_1 u_t + b_2 u_{t-1} + \ldots + b_q u_{t-q} + e_t \]  

(3)

Where

- \( X_{t+1} \): Output at time \( t+1 \),
- \( p, q \): model order,
- \( a_1, a_2, \ldots, a_p \) : model parameters,
- \( b_1, b_2, \ldots, b_q \) : model parameters,
- \( u_t \) is the external variable at time \( t \),
- \( e_t \) : White noise at time \( t \) such that

\[ E[e_t] = 0, \quad \text{Var}[e_t] = \delta_e^2 \]

The prediction of output at time \( t+1 \) with a time series of harmonics \( X_t \) is given by the above equation. The output can be written as:

\[ X_{t+1} = f(X_t, X_{t+1}, X_{t+2}, \ldots, X_{t+p}, u_t, u_{t+1}, \ldots, u_{t-q}) \]

Where \( f(*) \) is ANN Nonlinear function

The problem to be solved is to identify the nonlinear function \( f \) describing the relationship between the input and output. Neural Networks are the best technique for learning nonlinear relationships amongst variables. For harmonic prediction problem we used a feed-forward ANN to learn the relationship between the voltage, current and total harmonic distortion. The ANN is trained using the BPLA.

B) The ANN Learning Technique

The BPLA is essentially an optimization method that uses an iterative gradient descent algorithm. Such algorithm is designed to minimize the mean square error between the actual output of the feed forward network and the desired output [17]. The algorithm is performed in two successive steps: forward propagation and back propagation. In the forward propagation phase, a pattern vector at the input layer together with its desired output pattern at the output layer are simultaneously applied to the network. The error detected at the output layer is then back propagated through the network to update the connection weights according to the Generalized Delta Rule (GDR). The process is repeated until the average system error goes under some pre-specified values where the procedure is terminated. As the network is learnt, it becomes capable for classifying new input pattern vectors. Fig. 2 shows a flow chart of the BPLA.

To predict power system harmonics, it is required to build a database for the harmonic parameters [1]. So, a harmonic data base for the test system is developed to store the hourly recording per phase for fundamental, harmonic voltages, currents, active and reactive powers, total harmonic distortion for voltage (THDv) and current (THDi). The recording data is classified into two groups one for weekend and the other for workday. This Thesis concentrates on the
workday prediction. The measurements are recorded each hour using harmonics analyzers for two weeks. We use the database of the test system for daily prediction for hour 24 of the 5th, 7th and THD of voltage and current. The recorded waveforms of the 5th, 7th harmonic currents and voltages are shown in Figs. (3A-3D) while the recorded waveforms of the THDV and THDI are shown in Figs. (3E and 3F). From Figs we find that the maximum THD for current is 40% and for voltage is 5.2%. The dominant harmonic orders of the test system are 5th, 7th harmonic. The THD of voltage within the IEEE - 519 limit while the THD of current exceeds the limit. This means that the load of the test system produces harmonic current and supply it to the distribution power system. So, it’s required to reduce the harmonic effects on the neighboring distribution system loads. The 5th, 7th harmonic peaks occur at the weekend classes. Also, the THD of voltage and current occur at the same weekend classes. For harmonic prediction we used four ANN structures, two structures for harmonic current and voltage prediction and two structures for prediction of THD of current and voltage.

C) ANN Structure for Harmonic Current / Voltage Prediction

The structure for harmonic current or voltage prediction is described by 4-4-1 (4 input units, 4 hidden units in one layer and one output unit). The structure model is given by:

\[ A(d, i) = f[A(d, i-1), A(d, i-2), A(d-1, i-1), A(d-1, i-2)] \]  (4)

Where:
- \( A(d, i) \): the predicted harmonic voltage / current at day \( d \) and hour \( i \).
- \( A(d-1, i-1) \): the harmonic measured voltage / current for previous day \( d \) and hour \( i \).

The structure for voltage / current harmonic prediction for day \( d \) and hour \( i \) is based on the recording values of last two hours \((i-1, i-2)\) for the same day and the recording of the same hours of previous day \((i=1, i-2)\) of the same day type.

D) ANN Structure for THD prediction

The structure for THD current or voltage prediction is described by 10-10-1 (10 input unit, 10 hidden unit in one layer and one output unit). The structure is given by:

\[ \text{THDA}(d, i) = f[\text{THDA}(d-1, i), \text{THDA}(d-2, i), A_5(d, i), A_5(d, i-1), A_7(d, i), A_7(d, i-1), A_5(d-1, i), A_5(d-1, i-1), A_7(d-1, i), A_7(d-1, i-1)] \]  (5)

Where:
- \( \text{THDA}(d, i) \): prediction of THD of voltage / current for day \( d \) and hour \( i \).
- \( \text{THDA}(d-1, i) \): recorded THD of voltage / current for day \( d-1 \) and hour \( i \).
- \( A_5(d, i) \): the predicted 5th harmonic of voltage / current for day \( d \) and hour \( i \).
- \( A_7(d, i) \): the predicted 7th harmonic of voltage / current for day \( d \) and hour \( i \).
- \( A_5(d-1, i) \): the recorded 5th harmonic voltage / current for day \( d-1 \) and hour \( i-1 \).
- \( A_7(d-1, i) \): the recorded 7th harmonic voltage / current for day \( d-1 \) and hour \( i-1 \).

The structure for prediction THD of voltage / current for day \( d \) and hour \( i \) consists of:

1. THD of previous two days \((d-1, d-2)\) for the same hour \( i \).
2. Predicted values of fifth and seventh harmonic voltage/current of the same day \( d \) and hour \( i \).
3. Recorded values of fifth and seventh harmonic voltage/current of the same day \( d \) and hour \( (i-1) \).
4. Recorded values of fifth and seventh harmonic voltage/current of previous day \((d-1)\) and hour \( i \).
5. Recorded values of fifth and seventh harmonic voltage/current of previous day \((d-1)\) and previous hour \((i-1)\).

The ANN are trained using the harmonic series in the database. Table (1) shows the 5th harmonic current test patterns for hour 24 over one week. By similarity the ANN is trained and tested with 7th harmonic current and voltage. Table (2) shows the prediction errors of 5th harmonic current and voltage for hour 24 over one week using ANN. The percentage error is used as a performance measure for ANN which is equal the difference between ANN output and target (recorded value) divided by target. From Table (2) the Maximum Percentage Error (MPE) is 1.85% for fifth harmonic current prediction and 1.52% for voltage. Table (3) shows the prediction percentage errors for seventh harmonic current and voltage. From results, we find that MPE for seventh harmonic current is 2.6% while for seventh harmonic voltage is 2.12%. Table (4) shows the test patterns of the THD of voltage for hour 24 over one week. From Table (4) the MPE is 1.09% for the THD of voltage.

The comparison between target and output for 5th, 7th harmonic and THD of current and voltage are shown in Figs. (4 and 5). The results illustrate that the range of predicted error ranged from 0.26% to 2.6% and the test results obtained are satisfactory. The performance could have been even better if we use more intelligent tools like Fuzzy and Genetic with neural network.

E) ANN Structure For Harmonic Current / Voltage Prediction

The structure for harmonic current or voltage prediction is described by 4-4-1 (4 input units, 4 hidden units in one layer and one output unit).

The structure model is given by:
A (d, i) = f [A (d, i-1), A (d, i-2), A (d-1, i-1), A (d-1, i-2)].

(6)

Where:
A(d, i): is the predicted harmonic voltage / current at day d and hour i.
A(d-1,i-1): is the harmonic measured voltage / current for previous day and hour.
The structure for voltage / current harmonic prediction for day d and hour i is based on the recording values of last two hours (i-1, i-2) for the same day and the recording of the same hours of previous day (i-1, i-2) of the same day type.

F) ANN Structure for THD prediction
The structure for THD current or voltage prediction is described by 10-10-1 (10 input unit, 10 hidden unit in one layer and one output unit).
The structure is given by:

\[
\text{THD}_A (d, i) = f [\text{THD}_A (d-1, i), \text{THD}_A (d-2, i), A_5(d, i), A_5(d, i-1), A_7(d, i), A_7(d-i-1), A_7(d-1, i), A_7(d-1, i-1), A_7(d-1, i-2), A_7(d-2, i-1)].
\]

(7)

Where:
\(\text{THD}_A (d, i)\): prediction of THD of voltage / current for day d and hour i.
\(\text{THD}_A (d-1, i)\): recorded THD of voltage / current for day d-1 and hour i.
\(A_5(d, i)\): the predicted 5th harmonic of voltage / current for day d and hour i.
\(A_7(d, i-1)\): the recorded 5th harmonic of voltage / current for day d and hour i-1.
\(A_7(d, i)\): the predicted 7th harmonic of voltage / current for day d and hour i.
\(A_7(d, i-1)\): the recorded 7th harmonic voltage / current for day d and hour i-1.

G) The structure for prediction THD of voltage / current for day d and hour i consists of:
1. THD of previous two days (d-1, d-2) for the same hour i.
2. Predicted values of fifth and seventh harmonic voltage/current of the same day (d) and hour (i)
3. Recorded values of fifth and seventh harmonic voltage/current of the same day (d) and previous hour (i-1).
4. Recorded values of fifth and seventh harmonic voltage/current of previous day (d-1) and hour (i).
5. Recorded values of fifth and seventh harmonic voltage/current of previous day (d-1) and previous hour (i-1).

The ANN are trained using the harmonic series in the database. Table (1) shows the 5th harmonic current test patterns for hour 24 over one week. By similarity the ANN is trained and tested with 7th harmonic current and voltage. Table (2) shows the prediction errors of 5th harmonic current and voltage for hour 24 over one week using ANN. The percentage error is used as a performance measure for ANN which is equal the difference between ANN output and target (recorded value) divided by target. From Table (2) the Maximum Percentage Error (MPE) is 1.85% for fifth harmonic current prediction and 1.52% for voltage. Table (3) shows the prediction percentage errors for seventh harmonic current and voltage. From results, we find that MPE for seventh harmonic current is 2.6% while for seventh harmonic voltage is 2.12%. Table (4) shows the test patterns of the THD of voltage for hour 24 over one week. From Table (4) the MPE is 1.09% for the THD of voltage.

The comparison between target and output for 5th, 7th harmonic and THD of current and voltage are shown in Figs. (4 and 5). The results illustrate that the range of predicted error ranged from 0.26% to 2.6% and the test results obtained are satisfactory. The performance could have been even better if we use more intelligent tools Like Fuzzy and Genetic with neural network.

III. Predicting Power System Voltage Harmonics by using Time Delay Neural Network
This paper presents a method for predicting power system voltage harmonics using Time Delay Neural Network (TDNN). The TDNN method is based on the back propagation learning technique for feed forward neural networks. This approach has certain advantages over other conventional schemes, including the potential to track the harmonics in the time-varying power system environment. In order to demonstrate the effectiveness of TDNN, the performance is compared with the conventional methods.

Over the past decade, the electrical environment of power systems has undergone considerable changes. More importantly, our society has increased its dependence upon electronic systems, which now proliferate. This dependence began in the 1980s with the personal computer revolution and it has continued into the 1990s. Energy efficient fluorescent-lighting systems, adjustable-speed motor drive systems, and large uninterruptible power supply systems are all examples of newer technologies which have become integral component's in today's electrical environment because of the numerous benefits they provide to electrical energy consumers [1].

Unfortunately, the impact of these newer technologies has not been entirely positive. The semiconductor switching control used in these nonlinear devices creates harmonic distortion throughout the electric power system. This distortion can potentially cause malfunction in any electric device since they are all designed to operate with an uncorrupted sinusoidal voltage. Ironically, it is often the solid-state switching loads themselves which are most
sensitive to the harmonic distortion. Typical problems associated with these high frequency harmonics include excessive heating in transformers, equipment failure due to resonant over voltages, communication interference, and nuisance tripping of computers or computer-controlled industrial processes [1].

Modeling and predicting the future levels of power system harmonics would allow more control and manageability of their undesirable effects. There are numerous algorithms available for time series prediction [1]. However, field measurements have shown that harmonics encountered in large power systems tend to be nonlinear and non-Gaussian, with varying degrees of stationarity. These factors can often limit the performance of many standard prediction algorithms and techniques [18]. An attractive alternative is to use artificial neural networks for prediction of the harmonics. A multilayer perception (MLP) with a single hidden layer (with back-propagation learning) was used in [1] for one-step ahead prediction of a harmonic voltage [1].

A) The Focused Time Delay Neural Network (TDNN)

The focused TDNN topology has been successfully used in nonlinear system identification, time series prediction, and temporal recognition [1]. A focused TDNN with one hidden layer and a tap delay line with k+1 taps is shown in Fig. 6. If we replace the input PEs of an MLP with a tap delay line give a new topology, this topology is called the focused Time Delay network (TDNN) and it is called focused because the memory is only at the input layers [1].

The delay line of the focused TDNN stores the past samples of the input. The combination of the tap delay line and the weights that connect the taps to the PEs of the first hidden layer are simply linear combiners followed by a static nonlinearity. The first layer of the focused TDNN is a filtering layer, with many adaptive filters PEs in the first hidden layer. The outputs of the linear combiners are passed through a nonlinearity (of the hidden-layer PE) and are then further processed by the subsequent layers to achieve one of the following tasks:

1. In classification the goal is to find weights that separate the signal trajectories, which correspond to different time patterns.
2. In system identification the goal is to find the weights that produce a network output that best matches the present output of the system by combining the information of the present and a predefined number of past samples (given by the size of the tap delay line).
3. In prediction the goal is to approximate the next samples as a nonlinear combination of past input samples (given, once again, by the size of the tap delay line).

B) Training the Focused TDNN

One of the appeals of the focused TDNN is that it can still be trained with static back propagation, provided that a desired signal is available at each time step. The reason is that the tap delay line at the input does not have any free parameters, so the simply use the back propagation algorithm without any modifications. We have already successfully used static back propagation to train the network weights.

To predict the power system harmonics with the proposed model, it is required to build database for harmonics. The test system is a 11 K.V residential feeder in Alexandria. The database for the test system is developed to store hourly harmonic records. The recording data for 2 weeks are used to build the model. The recording data was shown for 2 weeks in Fig. 7. The network was trained using 75% of the data and the remaining 25% of data was used for the testing and validation.

The time series uses a linear prediction to predict the next value in a signal, given the last values of that signal. A comparison is made by the input to the network by the last values of the signal ranged from (1-5) cases to get a high accuracy. A comparison is made between the five cases. The last five values of the signal case(5)( v(t-1),v(t-2), v(t-3) , v(t-4) , v(t-5)) is more accurate case for the prediction model as shown in table (5).

The harmonics prediction was evaluated using stochastic method and TDNN. In order to demonstrate the effectiveness, the performance of TDNN and stochastic method are compared for the prediction accuracy as shown in table (6). It is clear from compassion between conventional method and TDNN that the RMSE is very less by using TDNN. It is observed that TDNN is better for predicting power system harmonics.

IV. FAST HARMONIC CURRENT/VOLTAGE PREDICTION BY USING HIGH SPEED TIME DELAY NEURAL NETWORKS

Computing the resulted output; for a certain pattern of information; in the incoming serial data, is a prediction problem. First neural networks are trained to predict the current/voltage harmonic and this is done in time domain. In pattern detection phase, each position in the incoming matrix is processed to predict the current/voltage harmonic by using neural networks. At each position in the input one dimensional matrix, each sub-matrix is multiplied by a window of weights, which has the same size as the sub-matrix. The outputs of neurons in the hidden layer are multiplied by the weights of the output layer. Thus, we may conclude that the whole problem is a cross correlation between the incoming serial data and the weights of neurons in the hidden layer [2-7], [9-11],[13-15].
The convolution theorem in mathematical analysis says that a convolution of \( f \) with \( h \) is identical to the result of the following steps: let \( F \) and \( H \) be the results of the Fourier Transformation of \( f \) and \( h \) in the frequency domain. Multiply \( F \) and \( H^* \) in the frequency domain point by point and then transform this product into the spatial domain via the inverse Fourier Transform. As a result, these cross correlations can be represented by a product in the frequency domain. Thus, by using cross correlation in the frequency domain, speed up in an order of magnitude can be achieved during the detection process [2-7], [9-11], [13-15]. Assume that the size of the virus code in 1xn. In virus detection phase, a sub matrix I of size 1xn (sliding window) is extracted from the tested matrix, which has a size 1xN. Such sub matrix, which may be a virus code, is fed to the neural network. Let \( W_i \) be the matrix of weights between the input sub-matrix and the hidden layer. This vector has a size of 1xn and can be represented as 1xn matrix. The output of hidden neurons \( h(i) \) can be calculated as follows:

\[
 h_i = g\left( \sum_{k=1}^{n} W_i(k)I(k) + b_i \right)  \tag{8}
\]

where \( g \) is the activation function and \( b(i) \) is the bias of each hidden neuron \( i \). Equation 8 represents the output of each hidden neuron for a particular sub-matrix \( I \). It can be obtained to the whole input matrix \( Z \) as follows [2-4]:

\[
 h_i(u)=g\left( \sum_{k=-n/2}^{n/2} W_i(k) Z(u+k) + b_i \right)  \tag{9}
\]

Eq.9 represents a cross correlation operation. Given any two functions \( f \) and \( d \), their cross correlation can be obtained by [17]:

\[
 d(x)\otimes f(x)=\left\{ \sum_{n=-\infty}^{\infty} f(x+n)d(n) \right\}  \tag{10}
\]

Therefore, Eq. 9 may be written as follows [2-4]:

\[
 h_i = g(W_i \otimes Z + b_i)  \tag{11}
\]

where \( h_i \) is the output of the hidden neuron \( i \) and \( h_i(u) \) is the activity of the hidden unit \( i \) when the sliding window is located at position \( u \) and \( (u) \in [N-n+1] \).

Now, the above cross correlation can be expressed in terms of one dimensional Fast Fourier Transform as follows [2-4]:

\[
 W_i \otimes Z = F^{-1}(F(Z)\cdot F^*(W_i))  \tag{12}
\]

Hence, by evaluating this cross correlation, a speed up ratio can be obtained comparable to focused neural networks. Also, the final output of the neural network can be evaluated as follows:

\[
 O(u) = g\left( \sum_{i=1}^{q} W_0(i) h_i(u) + b_0 \right)  \tag{13}
\]

where \( q \) is the number of neurons in the hidden layer. \( O(u) \) is the output of the neural network when the sliding window located at the position \( u \) in the input matrix \( Z. W_0 \) is the weight matrix between hidden and output layer.

The complexity of cross correlation in the frequency domain can be analyzed as follows:

1- For a tested matrix of 1xN elements, the 1D-FFT requires a number equal to \( N \log_2 N \) complex computation steps [16]. Also, the same number of complex computation steps is required for computing the 1D-FFT of the weight matrix at each neuron in the hidden layer.

2- At each neuron in the hidden layer, the inverse 1D-FFT is computed. Therefore, \( q \) backward and \((1+q)\) forward transforms have to be computed. Therefore, for a given matrix under test, the total number of operations required to compute the 1D-FFT is \((2q+1)N\log_2 N\).

3- The number of computation steps required by FNNs is complex and must be converted into a real version. It is known that, the one dimensional Fast Fourier Transform requires \((N/2)\log_2 N\) complex multiplications and \( N \log_2 N \) complex additions [16]. Every complex multiplication is realized by six real floating point operations and every complex addition is implemented by two real floating point operations. Therefore, the total number of computation steps required to obtain the 1D-FFT of a 1xN matrix is:

\[
 \rho=6((N/2)\log_2 N) + 2(N \log_2 N) \tag{14}
\]

which may be simplified to:

\[
 \rho=5N\log_2 N \tag{15}
\]

4- Both the input and the weight matrices should be dot multiplied in the frequency domain. Thus, a number of complex computation steps equal to \( qN \) should be considered. This means \( 6qN \) real operations will be added to the number of computation steps required by FNNs.

5- In order to perform cross correlation in the frequency domain, the weight matrix must be extended to have the same size as the input matrix. So, a number of zeros = \( (N-n) \) must be added to the weight matrix. This requires a total real number of computation steps = \( q(N-n) \) for all neurons. Moreover, after computing the FFT for the weight matrix, the conjugate of this matrix must be obtained. As a result, a real number of computation steps = \( qN \) should be added in order to obtain the conjugate of the weight matrix for all neurons. Also, a number of real computation steps equal to \( N \) is required to create butterflies complex numbers \( e^{j2\pi k/n} \), where \( 0<k<L \). These \( (N/2) \) complex numbers are multiplied by the elements of the input matrix or by previous complex numbers during the computation of FFT. To create a complex number requires two real floating point operations. Thus, the total number of computation steps required for FNNs becomes:

\[
 \sigma=(2q+1)(5N\log_2 N) + 6qN + q(N-n) + qN + N \tag{16}
\]
which can be reformulated as:
\[ \sigma = (2q+1)(5N\log_2 N) + q(8N-n) + N \] (17)

6- Using sliding window of size 1xn for the same matrix of 1xN pixels, \(q(2n-1)(N-n+1)\) computation steps are required when using Focused TDNNs for certain virus detection or processing (n) input data. The theoretical speed up factor \(\eta\) can be evaluated as follows:
\[ \eta = \frac{q(2n-1)(N-n+1)}{(2q+1)(5N\log_2 N) + q(8N-n) + N} \] (18)

FTDNNs are shown in Fig. 8.

V. EXPERIMENTAL RESULTS OF TIME DELAY NEURAL NETWORKS FOR FAST HARMONIC CURRENT/VOLTAGE PREDICTION

First neural networks are trained to classify virus from non virus examples and this is done in time domain. In the virus detection phase, each sub-matrix (1xn) in the incoming data (probe matrix 1xN) is tested for the presence or absence of the virus. At each position in the incoming input matrix, each sub-matrix is multiplied by a window of weights which has the same size as the sub-matrix. This multiplication is done in the time domain. The outputs of neurons in the hidden layer are multiplied by the weights of the output layer. When the final output is high this means that the sub-matrix under test contains a virus and vice versa. Thus, we may conclude that this searching problem is cross correlation in the time domain between the incoming data and the input weights of neural networks [9-11].

Time delay neural networks accept serial input data with fixed size (n). Therefore, the number of input neurons equals to (n). Instead of treating (n) inputs, the proposed new approach is to collect all the incoming data together in a long vector (for example 100xn). Then the input data is tested by time delay neural networks as a single pattern with length L (L=100xn). Such a test is performed in the frequency domain as described in section IV. The virus inserted in the incoming data may have real or complex values in a form of one or two dimensional array. Complex-valued neural networks have many applications in fields dealing with complex numbers such as telecommunications, speech recognition and image processing with the Fourier Transform [8,12]. Complex-valued neural networks mean that the inputs, weights, thresholds and the activation function have complex values. In this section, formulas for the speed up ratio with different types of inputs (real /complex) will be presented. Also, the speed up ratio in the case of a one and two dimensional incoming input matrix will be concluded. The operation of FNNs depends on computing the Fast Fourier Transform for both the input and weight matrices and obtaining the resulting two matrices. After performing dot multiplication for the resulting two matrices in the frequency domain, the Inverse Fast Fourier Transform is calculated for the final matrix. Here, there is an excellent advantage with FNNs that should be mentioned. The Fast Fourier Transform is already dealing with complex numbers, so there is no change in the number of computation steps required for FNNs. Therefore, the speed up ratio in the case of complex-valued time delay neural networks can be evaluated as follows:

1) In case of real inputs

A) For a one dimensional input matrix

Multiplication of (n) complex-valued weights by (n) real inputs requires (2n) real operations. This produces (n) real numbers and (n) imaginary numbers. The addition of these numbers requires (2n-2) real operations. The multiplication and addition operations are repeated (N-n+1) for all possible sub matrices in the incoming input matrix. In addition, all of these procedures are repeated at each neuron in the hidden layer. Therefore, the number of computation steps required by focused neural networks can be calculated as:
\[ \theta = 2q(2n-1)(N-n+1) \] (19)

The speed up ratio in this case can be computed as follows:
\[ \eta = \frac{2q(2n-1)(N-n+1)}{(2q+1)(5N\log_2 N) + q(8N-n) + N} \] (20)

The theoretical speed up ratio for searching short successive (n) data in a long input vector (L) using complex-valued time delay neural networks is shown in Figures 9, 10, and 11. Also, the practical speed up ratio for manipulating matrices of different sizes (L) and different sized weight matrices (n) using a 2.7 GHz processor and MATLAB is shown in Figure 12.

B) For a two dimensional input matrix

Multiplication of \((n^2)\) complex-valued weights by \((n^2)\) real inputs requires \(2(n^2)\) real operations. This produces \((n^2)\) real numbers and \((n^2)\) imaginary numbers. The addition of these numbers requires \((2n^2-2)\) real operations. The multiplication and addition operations are repeated \((N-n+1)^2\) for all possible sub matrices in the incoming input matrix. In addition, all of these procedures are repeated at each neuron in the hidden layer. Therefore, the number of computation steps required by focused neural networks can be calculated as:
\[ \theta = 2q(2n^2-1)(N-n+1)^2 \] (21)

The speed up ratio in this case can be computed as follows:
\[ \eta = \frac{2q(2n^2-1)(N-n+1)^2}{(2q+1)(5N^2\log_2 N^2) + q(8N^2-n^2) + N} \] (22)

The theoretical speed up ratio for detecting \((nn)\) real valued submatrix in a large real valued matrix \((NN)\) using complex-valued time delay neural networks is shown in Figures 13, 14, 15. Also, the practical speed up ratio for
manipulating matrices of different sizes (NxN) and different sized weight matrices (n) using a 2.7 GHz processor and MATLAB is shown in Figure 16.

2) In case of complex inputs

A) For a one dimensional input matrix

Multiplication of (n) complex-valued weights by (n) complex inputs requires (6n) real operations. This produces (n) real numbers and (n) imaginary numbers. The addition of these numbers requires (2n-2) real operations. Therefore, the number of computation steps required by focused neural networks can be calculated as:

\[ \theta = 2q(4n-1)(N-n+1) \]  

The speed up ratio in this case can be computed as follows:

\[ \eta = \frac{2q(4n-1)(N-n+1)}{(2q+1)(5N\log_2 N + q(8N-n)+N) } \]  

The theoretical speed up ratio for searching short complex successive (n) data in a long complex-valued input vector (L) using complex-valued time delay neural networks is shown in Figures 17, 18, and 19. Also, the practical speed up ratio for manipulating matrices of different sizes (L) and different sized weight matrices (n) using a 2.7 GHz processor and MATLAB is shown in Figure 20.

B) For a two dimensional input matrix

Multiplication of \((n^2)\) complex-valued weights by \((n^2)\) real inputs requires \((6n^2)\) real operations. This produces \((n^2)\) real numbers and \((n^2)\) imaginary numbers. The addition of these numbers requires \((2n^2-2)\) real operations. Therefore, the number of computation steps required by focused neural networks can be calculated as:

\[ \theta = 2q(4n^2-1)(N-n+1)^2 \]  

The speed up ratio in this case can be computed as follows:

\[ \eta = \frac{2q(4n^2-1)(N-n+1)^2}{(2q+1)(5n^2\log_2 n + q(8n^2-n^2)+N) } \]  

The theoretical speed up ratio for detecting \((nxn)\) complex-valued submatrix in a large complex-valued matrix \((NxN)\) using complex-valued neural networks is shown in Figures 21, 22, and 23. Also, the practical speed up ratio for manipulating matrices of different sizes \((NxN)\) and different sized weight matrices \((n)\) using a 2.7 GHz processor and MATLAB is shown in Figure 24.

For a one dimensional matrix, from Figs. 9,10,11,12,17,18,19 and 20, we can conclude that the response time for vectors with short lengths are faster than those which have longer lengths. For example, the speed up ratio for the vector of length 10000 is faster than that of length 1000000. The number of computation steps required for a vector of length 10000 is much less than that required for a vector of length 40000. So, if the vector of length 40000 is divided into 4 shorter vectors of length 10000, the number of computation steps will be less than that required for the vector of length 40000. Therefore, for each application, it is useful at the first to calculate the optimum length of the input vector. The same conclusion can be drawn in case of processing the two dimensional input matrix as shown in Figs. 13,14,15,16,21,22,23, and 24. From these tables, it is clear that the maximum speed up ratio is achieved at matrix size \((N=200)\) when \(n=20\), then at image size \((N=300)\) when \(n=25\), and at matrix size \((N=400)\) when \(n=30\). Another interesting point is that the memory capacity is reduced when using FTDNN. This because the number of variables compared to Focused TDNN is reduced.

VI. Conclusion

FTDNNs for prediction of harmonic current/voltage in real-time have been presented. Theoretical computations have shown that FTDNNs require fewer computation steps than focused ones. This has been achieved by applying cross correlation in the frequency domain between the input data and the input weights of time delay neural networks. Simulation results have confirmed this proof by using MATLAB. Furthermore, the memory complexity has been reduced when using the fast neural algorithm. In addition, this algorithm can be combined with any other protection programs. Moreover, it can be applied successfully for any application that uses time delay neural networks.

References


Fig. 1. The prediction model.
Harmonics Data

Form prediction model

Identify the hour of prediction

Identify the ANN parameters, no. of input, output, hidden nodes, η, α, and no. of iterations

Form database from the training and test sets

Train the neural network using the back propagation algorithm

Using the trained ANN for prediction of harmonics

Calculate the absolute percentage error

Is APE < Limit

Y

Print the result

Go to step 2

Y

Predict another hour

N

Update the historical database with recorded values

Stop

Go to step 3

Train the neural network with other parameters

N

Fig. 2. Flow Chart of Prediction Technique using BPLA
Fig. (3A). Fifth Harmonic Current Waveform.

Fig. (3B). Seventh Harmonic Current Waveform.

Fig. (3C). Fifth Harmonic Voltage Waveform.
Fig. (3D). Seventh Harmonic Voltage Waveform

Fig. (3E). Total Harmonic Distortion of Current Waveform.

Fig. (3F). Total Harmonic Distortion of Voltage Waveform.
Fig. 4. Comparison between Target and output of 5th and 7th harmonic current and their total harmonic distortion for hour 24.

Fig. 5. Comparison between Target and output of 5th and 7th harmonic voltage and their total harmonic distortion for hour 24.
Fig. 6. A focused TDNN with one hidden layer and a tap delay line with \( k+1 \) taps.

Fig. 7. Recording Harmonics Voltage For Two Weeks Of The Test System.
Fig. 8. Fast time delay neural networks.

Fig. 9. A comparison between the number of computation steps required by FTDNNs and focused TDNNs in case of real-valued one dimensional input matrix and complex-valued weight matrix (n=400).
Fig. 10. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of real-valued one dimensional input matrix and complex-valued weight matrix (n=625).

Fig. 11. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of real-valued one dimensional input matrix and complex-valued weight matrix (n=900).
Fig. 12. Practical speed up ratio for time delay neural networks in case of one dimensional real-valued input matrix and complex-valued weights.

Fig. 13. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of real-valued two dimensional input matrix and complex-valued weight matrix (n=20).
Fig. 14. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of real-valued two dimensional input matrix and complex-valued weight matrix (n=25).

Fig. 15. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of real-valued two dimensional input matrix and complex-valued weight matrix (n=30).
Fig. 16. Practical speed up ratio for time delay time neural networks in case of two dimensional real-valued input matrix and complex-valued weights.

Fig. 17. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of complex-valued one dimensional input matrix and complex-valued weight matrix (n=400).
Fig. 18. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of complex-valued one dimensional input matrix and complex-valued weight matrix (n=625).

Fig. 19. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of complex-valued one dimensional input matrix and complex-valued weight matrix (n=900).
Fig. 20. Practical speed up ratio for time delay neural networks in case of one dimensional complex-valued input matrix and complex-valued weights.

Fig. 21. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of complex-valued two dimensional input matrix and complex-valued weight matrix \((n=20)\).
Fig. 22. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of complex-valued two dimensional input matrix and complex-valued weight matrix (n=25).

Fig. 23. A comparison between the number of computation steps required by FTDNNs and Focused TDNNs in the case of complex-valued two dimensional input matrix and complex-valued weight matrix (n=30).
Fig. 24. Practical speed up ratio for time delay neural networks in case of two dimensional complex-valued input matrix in and complex-valued weights.

Table (1): The 5th Harmonic Current Patterns for Hour 24.

<table>
<thead>
<tr>
<th>Days</th>
<th>Input</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(d) (d) (d-1) (d-1) (I_{5h1}) (I_{5h2}) (I_{5h1}) (I_{5h2})</td>
<td>(I_{5h1})</td>
</tr>
<tr>
<td>Saturday</td>
<td>23.0 25.30 5.0 20.0 23.0</td>
<td>23.0</td>
</tr>
<tr>
<td>Sunday</td>
<td>4.0 28.0 23.0 25.0 4.0</td>
<td>4.0</td>
</tr>
<tr>
<td>Monday</td>
<td>5.0 13.0 4.0 25.0 5.0</td>
<td>5.0</td>
</tr>
<tr>
<td>Tuesday</td>
<td>7.0 10.0 5.0 13.0 7.0</td>
<td>7.0</td>
</tr>
<tr>
<td>Wednesday</td>
<td>5.0 20.0 7.0 10.0 5.0</td>
<td>5.0</td>
</tr>
</tbody>
</table>

Table (2): The Prediction Error of 5th Harmonic Current and Voltage for hour 24 using ANN.

<table>
<thead>
<tr>
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<th>Current</th>
<th>Voltage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Target</td>
<td>Output</td>
</tr>
<tr>
<td>Saturday</td>
<td>23.0</td>
<td>22.7</td>
</tr>
<tr>
<td>Sunday</td>
<td>4.0</td>
<td>4.015</td>
</tr>
<tr>
<td>Monday</td>
<td>5.0</td>
<td>5.02</td>
</tr>
<tr>
<td>Tuesday</td>
<td>7.0</td>
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<tr>
<td>Wednesday</td>
<td>5.0</td>
<td>5.02</td>
</tr>
<tr>
<td>Thursday</td>
<td>5.0</td>
<td>5.02</td>
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</table>
Table (3): The Prediction Error of 7th Harmonic Current and Voltage for hour 24 using ANN.

<table>
<thead>
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<th>Days</th>
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<th>Voltage</th>
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<td>Output</td>
<td>Error%</td>
<td>Target</td>
<td>Output</td>
<td>Error%</td>
</tr>
<tr>
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<td>4.5</td>
<td>4.42</td>
<td>1.77</td>
<td>2.1</td>
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<tr>
<td>Sunday</td>
<td>0.5</td>
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<td>2.7</td>
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<td>0.925</td>
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<td>2.6*</td>
<td>1.3</td>
<td>1.325</td>
<td>-1.923</td>
</tr>
<tr>
<td>Tuesday</td>
<td>1.0</td>
<td>0.9911</td>
<td>0.89</td>
<td>0.9</td>
<td>0.8937</td>
<td>0.7</td>
</tr>
<tr>
<td>Wednesday</td>
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<td>3.042</td>
<td>-1.4</td>
<td>0.9</td>
<td>0.8809</td>
<td>2.12*</td>
</tr>
<tr>
<td>Thursday</td>
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<td>1.976</td>
<td>2.4</td>
<td>0.9</td>
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Table (4): The Patterns and Percentage Error of THD of Voltage.

<table>
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<tr>
<th>Days</th>
<th>(THD_V)</th>
<th>(THD_V)</th>
<th>(V_3)</th>
<th>(V_3)</th>
<th>(V_5)</th>
<th>(V_5)</th>
<th>(V_7)</th>
<th>(V_7)</th>
<th>(THD_V)</th>
<th>(THD_V)</th>
<th>(THD_V)</th>
<th>(THD_V)</th>
<th>(THD_V)</th>
<th>(THD_V)</th>
<th>(THD_V)</th>
<th>(THD_V)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>d-1</td>
<td>d-1</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
<td>d</td>
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<tr>
<td>Saturday</td>
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<td>2.7</td>
<td>0.9</td>
<td>0.8</td>
<td>2.7</td>
<td>2.1</td>
<td>0.6</td>
<td>1.0</td>
<td>0.9</td>
<td>2.2</td>
<td>2.176</td>
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<tr>
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<td>1.5</td>
<td>3</td>
<td>0.8</td>
<td>0.7</td>
<td>3.2</td>
<td>2.7</td>
<td>0.9</td>
<td>2.7</td>
<td>2.1</td>
<td>1.5</td>
<td>1.504</td>
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<td>0.5</td>
<td>0.6</td>
<td>1.7</td>
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<td>0.8</td>
<td>3.2</td>
<td>2.7</td>
<td>1.5</td>
<td>1.504</td>
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<tr>
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<td>2</td>
<td>0.4</td>
<td>0.2</td>
<td>1.0</td>
<td>0.9</td>
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<td>1.1</td>
<td>0.6</td>
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<td>0.6</td>
<td>0.4</td>
<td>1.0</td>
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<td>0.6</td>
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<td>0.9</td>
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</table>

Table (5) A comparison between the input patterns RMSE of the prediction model

<table>
<thead>
<tr>
<th>Case</th>
<th>Input Patterns</th>
<th>Training time</th>
<th>Test Error (RMSE)</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>v(t-1)</td>
<td>0.431</td>
<td>0.00017</td>
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<tr>
<td>2</td>
<td>v(t-1) v(t-2)</td>
<td>0.1</td>
<td>0.0001414</td>
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<tr>
<td>3</td>
<td>v(t-1) v(t-2) v(t-3)</td>
<td>0.12</td>
<td>0.0001385</td>
</tr>
<tr>
<td>4</td>
<td>v(t-1) v(t-2) v(t-3) v(t-4)</td>
<td>0.1</td>
<td>0.0001322</td>
</tr>
<tr>
<td>5</td>
<td>v(t-1) v(t-2) v(t-3) v(t-4) v(t-5)</td>
<td>0.09</td>
<td>0.00013</td>
</tr>
</tbody>
</table>

Table (6) Comparison between RMSE of Stochastic Method and Time Delay Neural Network (TDNN).

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
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</thead>
<tbody>
<tr>
<td>LR</td>
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<tr>
<td>TDNN</td>
<td>0.01</td>
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<tr>
<td>MA</td>
<td>0.10</td>
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<tr>
<td>AR</td>
<td>0.04</td>
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</tbody>
</table>