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Compendium of Computational Tools for Power Systems Harmonic Analysis

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Abstract

Harmonic analysis comes into limelight at this contemporary world as a result of pro-
liferation of non-linear loads producing waveform distortions in power systems. It has
apparently outshined other important phrases such as power outage, power factor and
so on which are known for their devastating impacts. The emergence of distorted wave-
form has adverse effects which could be slow or rapid damage of key apparatus and
equipment, namely power transformers, electric motors and other sensitive computer
as well as communication facilities. In fact, it is very easy to assess the menace of power
outage or power factor since both the utility and consumers keep watchdog on their bill-
ings/operating costs in case of power factor or the economic losses when there is outage.
Unfortunately, the detection of harmonics could only be analysed using high-tech power
systems harmonic analysers and there is a need to provide stakeholders in the industry
compendium of computational tools for fast harmonic analysis. Thus, the harmonic data
acquired were used to train an artificial neural network (ANN) implemented on MATrix
LABoratory (MATLAB 8) software platform to facilitate accurate prediction of harmonic
distortions.

Keywords: artificial neural network, harmonic emulator

1. Introduction

In the present era of utility deregulation and competition, the impact of harmonics as well
as interharmonics on equipment and system operations has been raising serious concerns.
Nowadays, it is well known that harmonics have adverse effects on the whole power systems

such as misoperation of important control and protective equipment, overheating of trans-formers and overloading of other power apparatus [1–4]. On the other hand, interharmonics cause lighting flickers, erroneous firing of thyristor apparatus and display or monitor image fluctuation [5–7].

Power quality (PQ) problems are primarily due to voltage distortion in form of flat-topping. Harmonic currents create voltage distortion as they pass through the impedance of a power system. A high impedance system can create very high voltage distortion. However, when the voltage distortion becomes very severe, it can cause problems with connected equipment such as premature failure, reduced ride-through capability and other power quality problems. Harmonic distortion of voltages and currents can be generated either external or internal to an industrial or commercial facility, while at times, it can be exported to the utility network in an interconnected system. Power utility's consumers feel their effects and the end results of harmonics, therefore, are distorted waveforms in power outlets that supply very sensitive computer-based equipment. These devices have their useful lives reduced besides being unable to function correctly [8]. More so, power utility consumers cannot be exonerated. They are equally contributing negatively to the present menace of power waveform distortions due to use of non-linear loads, which inherently produce harmonics. By drawing currents in pulses rather than in pure sinusoidal forms, these devices, such as computer equipment, generate harmonic currents and the harmonic currents produced can then create overheating and power quality problems if left uncontrolled.

Generally, harmonics may be initiated in a power system from the following sources:

1. power electronic devices;

2. transformers, reactors, AC arc furnaces and fluorescent lamps; and

3. synchronous and induction motors.

Harmonic power distortion phenomenon was recognized by Utilities in the early 1920s and 1930s when distorted voltage and current waveforms were observed in transmission lines [9, 10]. Harmonics are high-frequency steady-state power involving multiple frequencies of 50/60 Hz flowing along with the fundamental frequency on a power network which may adversely affect the system performance. Over the past two decades in modern power systems, significant effort and advancement have been made to standardize the power system harmonic analysis, component models and simulation procedure for harmonic studies. The procedure for analyzing the harmonic problem could be classified into frequency domain [11, 12] and time-domain [13, 14], which are followed up with flexible control strategy adopted in recent time [12, 15]. Indeed, power system components such as overhead lines and underground cables, transformers, rotating machines and other non-linear loads on the system must be accurately modeled ever more than before, to determine their vulnerability to harmonic power flow. In harmonic power flow analysis, parameters of the system are specified in phasor domains and solutions are invoked by iterative methods. Time-domain methods, on the other hand, utilize time representation for the system components and other harmonic-producing devices to arrive at steady-state solutions.

Power system harmonic analysis is a tool for assessing the impact of harmonic producing loads on a power system. Harmonic analysis has been widely used for system planning, system performance and evaluation, equipment design, troubleshooting and verification of standard compliance [16]. A rigid power system, comprising linear system impedance and harmonic source with constant and characteristics harmonic currents may be solved efficiently using the iterative harmonic power flow method. However, the presence of non-linear and time-varying elements in the system can significantly change the manner by which harmonic currents and voltages propagate through the network. As a consequence, the simplest system model using harmonic power flow by way of superposition of harmonic sources within the system may be invalidated thereby yielding inaccurate results. Therefore, researchers are now adopting new techniques to overcome the dynamic phenomena by invoking time-domain modeling and simulation or probabilistic modeling and simulation.

A general purpose time-domain simulation tool such as Electromagnetic Transient Programme (EMTP) and Simulation Program with Integrated Circuit Emphasis (SPICE) could be used to obtain steady-state solution of non-linear circuits by letting the simulation to run while starting from some initial conditions. This method is applicable to small-scale network but some practical cases of systems with low damping factor or widely far apart time constant (i.e. a stiff system) could prolong the simulation time or may even make the simulation not to converge at all [17]. Therefore, the time-domain method is still at its developmental stage and accordingly, the approach is only limited to simulation of simple networks.

In order to further reinforce the modeling techniques, harmonic distortion indices need to be accurately measured and detected early enough so as to proffer appropriate mitigation measures against its adverse effects. Also, any variation in the monitored waveforms that might be due to unpredictable activities within the substation network outlay should be recorded over long period of time. In Ref. [18], it was suggested that monitoring periods should be carried out at least 2 days or more. Thus, for adequate measurement of harmonics at distribution reticulations, it is prudent to monitor and record voltage and current harmonics at the customer's metering point using portable spectrum analysers that have facilities to acquire harmonic voltages and currents for the recommended periods. The data could be collected to help in the correlation of the load cycle patterns of non-linear loads with distortion indices such as THD_V, THD_I, the 3rd, 5th and 7th harmonic magnitudes. In this context, therefore, the chapter presents the measurement procedure for harmonic studies in distribution infrastructures.

Figure 1 summarizes the framework that could be adopted. It comprises three major harmonic studies, namely harmonic modeling, simulation and measurement techniques. The harmonic modeling includes harmonic current source models, non-linear voltage–current methods, power electronic converter models, high-frequency source models and rotating machine harmonic models. The simulation techniques entail the frequency scan method, harmonic current penetration method and harmonic power flow method. The measurement techniques consist of pre-measurements, measurement and post-measurement stages. Using **Figure 1** as a typical framework, the harmonic modeling stage could employ software such as PCFLO, PSCAD or MATLAB.

The measurement procedure may not be economically viable as it may involve several single-site dedicated data acquisition systems. In order to reduce cost, traditional heuristic approaches (HA) could be used to identify potential stations most vulnerable to harmonic problems using network historic harmonic data available at limited locations and durations and the artificial neural network (ANN) techniques applied to develop the harmonic power propagation patterns. However, detailed network loading analysis can ensure that power facilities are being utilized within safe limits and not be subjected to damage.

The distribution system is commonly broken down into three components: distribution sub-station, distribution primary and secondary feeders. At the substation level, the voltage is reduced and power is distributed in smaller amount to the customers from primary and secondary distribution networks. Consequently, one substation will supply many customers with power. Thus, the number of feeders in the distribution systems outnumbers that of the transmission systems. Furthermore, most customers are connected to only one of the three phases in the distribution network infrastructure. The power flow in each of the phases is different giving rise to an adverse effect referred to as 'unbalanced system'. This is undesirable and needs to be accounted for in harmonic power flow studies related to distribution networks.

With the increasing awareness for the use of comprehensive monitoring facilities, remote terminal units (RTUs) are introduced at distribution levels. This is intended to provide automation of power network resources so as to ensure that the network is being operated within the safe margin in terms of operating parameters such as load, duty and harmonic distortions.
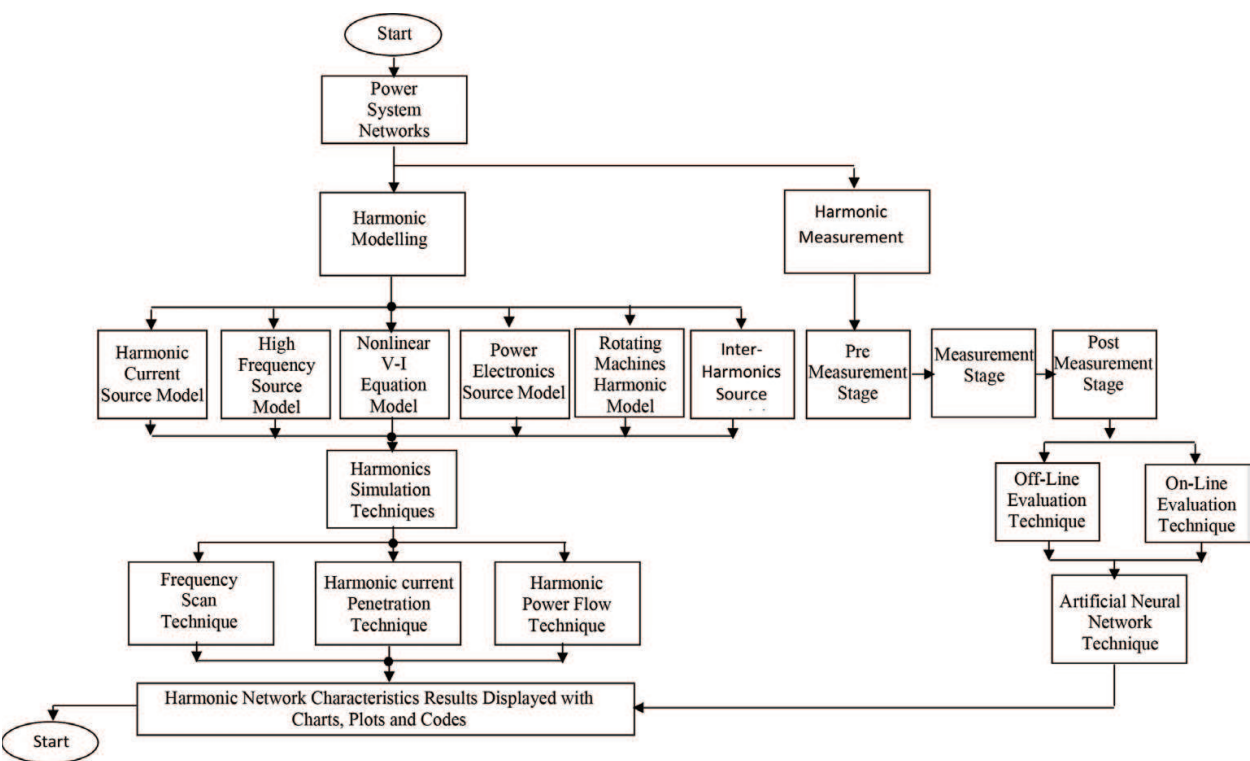

Figure 1. Framework of harmonic power flow studies.

Evaluation and simulation of planned operations using historic data will help to avoid damage to sensitive equipment due to these operations. From this standpoint, United Kingdom (UK) distribution network operators (DNO) have installed 60% of this RTU at their distribution reticulations to monitor the network conditions during different phases of operations [19] while the implementation of such automation by distribution company (DISCO) are envisaged for weak power systems.

2. Need for harmonic studies

The harmonic distortion needs to be accurately measured due to its adverse effects that include overheating, radio noise generation/interference, premature failure of sensitive equipment such as computers, hospital equipment and communication facilities. It is necessary to detect any variation in the monitored waveforms that might be due to unpredictable activities; such as system faults, customer non-linear loading, switching and so on, within the substation network outlay so as to keep the entire system safe and secure. On the other hand, the modern distribution networks are so diverse permitting the integration of New Energy Technologies (NETs), intertie AC/DC power transmission and domestic load-leveling devices as well as novel technical tools and monitoring equipment that may require new appraisal. There is a need to develop harmonic framework from the point of view of tripartite platform: modeling, simulation and prediction. This constitutes the motivation for the development of this monograph project to facilitate the documentation of pattern of harmonic distortion in some selected distribution reticulations and proffer appropriate remediation.

More importantly, the trends of harmonic studies have not satisfactorily determined whether harmonic-induced problems should be restricted to large industrial customers like rolling mills/process industries or should such harmonic monitoring framework be extended to commercial and domestic networks. This is simply accentuated due to the fact that such industries are equipped with direct current (DC) arc furnace known as major producers of harmonics. However, it may become apparent that the harmonic benchmarks set by existing standards such as IEEE519-1992, IEC 610000 need to be reviewed to capture emerging harmonic sources such as digital equipment, cell phone chargers, compact fluorescent lamps, PV inverters. This essentially represents contributions from commercial and domestic loads.

In pursuance of some specific objectives, the need for development of accurate computational engines that can replace the on-site harmonic survey and modeling of system is indispensable in modern emerging distribution systems. This is because the basic transmission network tools such as monitoring programme, contingency analysis and modern control systems aimed at improving system automation, reliability and integrity are still at developmental stages in distribution systems. More specifically, the field monitoring that is used to improve the knowledge of prevalent system operating conditions may not be cost effective at the distribution levels. It is also well known that the direct application of these techniques in the distribution systems is hampered by its unique nature, such as highly distributed and diverse loads, unbalanced phases and high R/X ratio. The high R/X ratio often requires the application of special distribution power flow solution. The unbalanced phases may need the solution

Harmonic order	Positive	Negative	Zero
1.	Yes	No	No
2.	No	Yes	No
3.	No	No	Yes
4.	No	Yes	No
5.	Yes	No	No
6.	No	Yes	No
7.	Yes	No	No
8.	No	Yes	No
9.	No	No	Yes
10.	No	Yes	No
11.	Yes	No	No

Table 1. Summary of harmonic phase sequence pattern.

of multiphase power flow and distributive loads may necessitate the deployment of several monitoring sites alongside the use of state estimation techniques on operating variables of the networks for realistic assessment of the networks. As a result, detailed distribution system analysis may not be reliably carried out especially in the development and evaluation of distribution system harmonic problems. On the other hand, it may be possible to achieve fast resolution of harmonic problems with the application of neural network, expert systems and other computational intelligence tools. These tools have the potential of minimizing the cost of multiple on-site harmonic monitoring and field recording and the rigorous harmonic modeling of the system in its entirety. **Table 1** summarizes the phase sequence pattern for harmonic orders up to 11th individual harmonic in power system.

3. Modeling of harmonic sources

It often requires serious research efforts to realistically qualify and model aggregate harmonic sources in a power system because some harmonics are non-characteristic, such as the even harmonics in transformer in-rush currents while others are non-deterministic, erratic and probabilistic in nature. Arc furnace load is one distribution load components can produce non-deterministic harmonic characteristics. Over the past two decades, significant efforts and meaningful progress have been made in the area of power system harmonic modeling. More so extensive specialized literatures are produced from time to time. In this context, the development of techniques for harmonic evaluation is often emphasized. However, according to a source [20], the tools for power system harmonic analysis are very few and as such the impact of harmonics on power quality degradation have not been fully explored.

Generally, there are four major approaches currently used for modeling of harmonics in power systems. They include:

- frequency scan analysis;

- harmonic analysis using simple current source models;

- harmonic analysis considering fundamental frequency power flow results; and

- harmonic power flow.

Harmonic studies may also be undertaken to evaluate the effects of harmonic-producing devices predictably noticed in arc furnace, large adjustable speed drives, static VAR compensators, HVDC rectifiers, flexible AC transmission systems (FACTS) devices and other equipment in the system using power quality analyser such as Fluke 435 and Fluke VR1710. Herein, the two Fluke equipment shown in **Plates 1** and **2** were used as the major monitoring device to measure and analyse power quality events in real time as well as logging the harmonic data based on preset requirements of the findings. Then, post-processing tools that could be harnessed include the Fluke 435 inbuilt DFT, MATLAB and Excel software.

(a)

(b)

Plate 1. Voltage quality recorder (VR1710) logging data. (sources: (a) installation manual of fluke VR1710 (b) at a residential power outlet in Bauchi).

Plate 2. Monitoring equipment for PQ data collection at a substation with fluke 435.

4. Neural network as harmonic computational tool

The mathematical expression formulated with respect to **Figure 2** is given in Eq. (1) which is similar to that of Ref. [21].

$$y_i = f\left[\sum_{k=1}^{n}\left(f\left(\sum_{j=1}^{M}(x_i w_{ij})\right)v_{ik}\right)\right] \quad i = 1, 2, \cdots m \tag{1}$$

where $x_1, x_2...x_n$ and $y_1, y_2...y_m$ are input and output variables, respectively, and $w_{12}, w_{13}...w_{ij}$ and $v_{12}, v_{13}...v_{ik}$ are the synaptic weights for the inputs and output, respectively. Ideally, the set of input $x_1, x_2...x_n$ and the target $y_1, y_2...y_m$ are initially known through measurements or simulation. Then, the next task is to use those data to determine the optimum values of synaptic weights, $w_{12}, w_{13}...w_{ij}$ and $v_{12}, v_{13}...v_{ik}$ that will offer tolerable error margin. The rest of work is to reuse the trained network weights for a reliable determination of unfamiliar input patterns of similar processes.

The error values in **Figure 2** can be used to directly adjust the tap weights. If the system output is y, and the desired system output is known to be d, the error signal can be defined as in Eq. (2):

$$g(e) = d - y \tag{2}$$

The error-correction learning algorithms attempt to minimize the error signal for all iterations. The most popular learning algorithm for use with error-correction learning is the gradient descent algorithm. The gradient descent algorithm is employed used to minimize an error function $g(e)$, through the manipulation of a weight vector $\bar{w}$. The cost function should be a linear combination of the weight vector and an input vector x. The algorithm is as follows:

$$w_{ij}(n+1) = w_{ij}(n) + \eta g(w_{ij}(n)) \tag{3}$$

here, η is known as the step-size parameter and affects the rate of convergence of the algorithm. If the step size is too small, the algorithm will take a long time to converge. If the step size is too large, the algorithm might oscillate or diverge. The gradient function, $g(.)$, in gradient descent algorithm, works by taking the gradient of the weight space to find the path of steepest descent as shown in **Figure 3**. By following the path of steepest descent and finding a minimum at each iterative step, the algorithm would not diverge especially if the weight space is infinitely decreasing. However, when a minimum is found, there is no guarantee that it is a global minimum. Hence, there is need for a more robust algorithm such as backpropagation technique to achieve global minimum. The backpropagation algorithm, in combination with a supervised error-correction learning rule (i.e. gradient descent algorithm), is one of the most popular and robust tools in the training of artificial neural networks. According to Ref. [22], backpropagation is used to find a local minimum in the error function. It passes the error signals backwards through the network during training to update the weights of the network. When talking about backpropagation, it is useful to define the term interlayer to be a layer of neurons, and the corresponding input tap weights to that layer. A superscript denotes a specific interlayer, and a subscript denotes the specific neuron from within that layer. These are expressed mathematically as in Eqs. (4) and (5).

$$\xi_j^l = \sum_{i-1}^{N^{l-1}} w_{ij}^l x_i^{l-1} \tag{4}$$

$$x_j^l = \sigma\left(\xi_j^l\right) \tag{5}$$

where x_i^{l-1} are the outputs from the previous interlayer (the inputs to the current interlayer), w_{ij}^l is the tap weight from the i-input from the previous interlayer to the j element of the current interlayer. N^{l-1} is the total number of neurons in the previous interlayer. x_j^l is the output of the previous layer (l − 1) which is now an input to current layer (l).
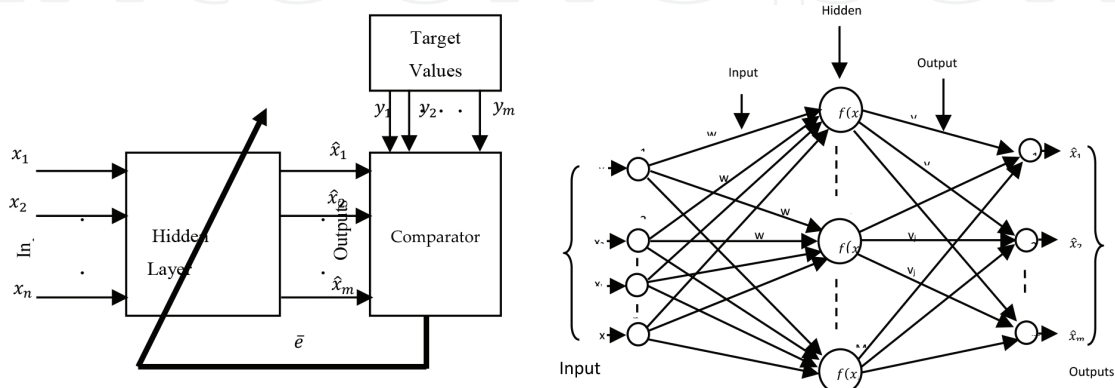
Figure 2. Input–output one hidden layer perceptron ANN.

The backpropagation algorithm specifies that the tap weights of the network are updated iteratively during training to approach the minimum of the error function. This is done via Eqs. (6) and (7):

$$w_{ij}^{l}(n) \ = \ w_{ij}(n-1) + \delta\left(w_{ij}^{l}(n)\right) \tag{6}$$

$$w_{ij}^{l-1}(n) \ = \ \eta\delta_{j}^{l}x_{i}^{l-1}(n) + \mu\Delta\,w_{ij}^{l}(n-1) \tag{7}$$

The relationship between this algorithm and the gradient descent algorithm should be immediately apparent. Here, η is known as the learning rate, not the step-size, because it affects the speed at which the system learns (converges). The parameter μ is known as the momentum parameter. The momentum parameter, μ, forces the search to take into account its movement from the previous iteration. By doing so, the system will tend to avoid local minima or saddle points, and tends to approach the global minimum. The parameter δ is what makes this algorithm a 'backpropagation' algorithm. This is given by Eq. (8):

$$\delta_{j}^{l} \ = \ \frac{dx_{j}^{l}}{dt}\sum_{k=1}^{r}\delta_{k}^{l+1}\,w_{kj}^{l+1} \tag{8}$$

The δ function for each layer depends on the δ from the previous layer. For the special case of the output layer (the highest layer), Eq. (9) can be used instead:

$$\delta_{j}^{l} \ = \ \frac{dx_{j}^{l}}{dt}\left(x_{j}^{l} - y_{j}\right) \tag{9}$$

In this way, the signals propagate backwards through the system from the output layer to the input layer. The next section presents the development of algorithmic framework for ANN harmonic predictor.
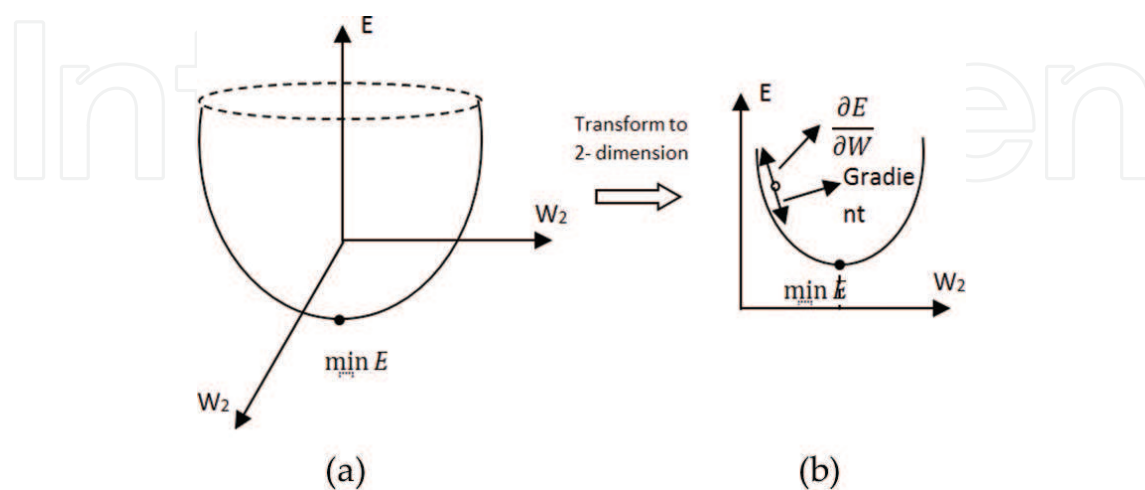
Figure 3. Iterative model for setting absolute error of ANN using gradient descent method. (a) 3-dimensional view of gradient descent. (b) 2-dimensional transform of gradient descent.

5. Development of ANN harmonic predictor

Operators of an electric power system must be able to accurately quantify the level of harmonic distortion across the system. Harmonic distortion is a system-wide problem which cannot be modelled only with an integral part of the power system. It will therefore be difficult to determine which variables are best used for ANN models. According to Ref. [23], adaptive predictive techniques generally have some implementation problems. First, how to determine the number of input signal may pose some challenges, and second, the determination of convergence factor may be done subjectively. More specifically, the harmonic distortion problem is so complicated that conventional methods do not work so well for its prediction [24]. This is apparently due to non-linearity associated with harmonic components alongside with its random-like behaviour for very short terms and a periodicity for a fairly long term.
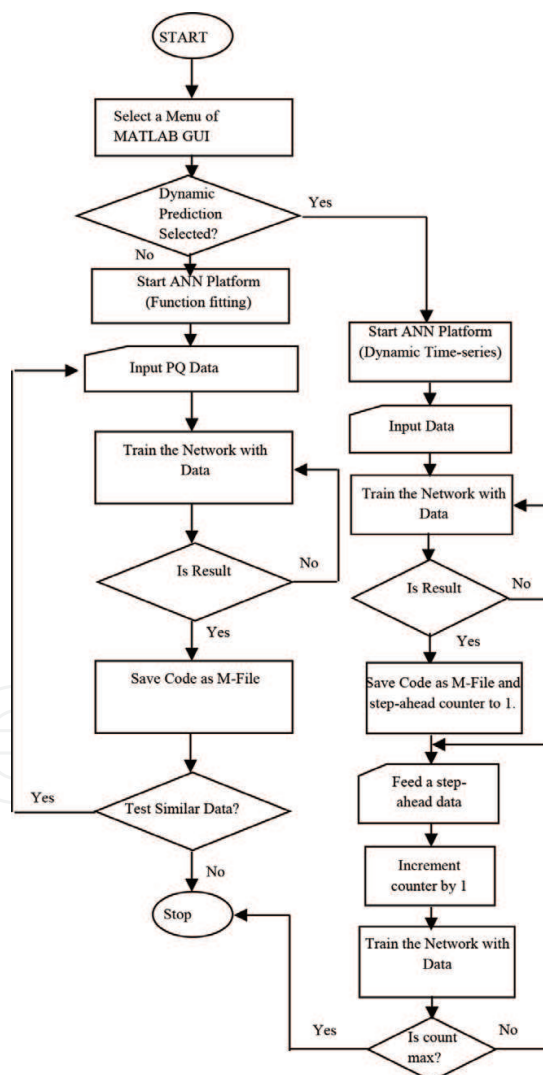
Figure 4. Flow chart for a MATLAB-based ANN function fitting and n-step-ahead prediction. (a) Training state of volt THD. (b) Performance of ANN THD$_\mathrm{V}$ tracking. (c) Tracking volt THD with ANN-Day1. (d) Tracking volt THD with ANN-Day3.

Three types of samples are presented to ANN, namely training, validation and testing samples. For the training data set, samples are presented to the network during this stage and the network is adjusted according to its error. In the validation regime, sample data are used to measure network generalization, and to halt training when generalization stops improving. Testing is used for generalization and has been said to have no effect on training performance but it is often used to provide an independent measure of network performance during and after training.

In the development of the ANN harmonics predictor, attempts were made to select the correct number of inputs for the network, optimum division of data into training, validation and testing regimes as well as their convergence indices according to acceptable best practices in the evaluation stage.

In this chapter, the ANN inputs are the RMS voltages, the RMS currents and frequency monitored in the two distribution reticulations. The outputs are the voltage or current THD and principal component indices like 3rd, 5th and 7th harmonic orders for short term comprising few seconds logged time of data up to 24 h, the long terms for daily data up to 1 week data. In the last scenario, a preconditioned non-linear harmonic network data under experimental set-up was also selected as input to ANN. The flow chart shown in **Figure 4** is proposed for the entire work in the application of neural network-based prediction technique.

The model predictor is used to train a neural network to track the harmonic data appropriately preprocessed outside the MATLAB environment with database software (POWERLOG and EXCEL). The POWERLOG is platform on which Fluke 435 power quality meter stored data into PC. However, MATLAB M-file works very well with EXCEL, serving as an interface hetween POWERLOG and ANN MATLAB programme. The ANN thus generates needful results presented in section 6. The predicted outputs of ANN are the responses/error output divided into three sub-model outputs; the training, validation and test errors. These errors are compared with the best practice error indices and fed to output evaluation unit.

6. Sample results of ANN emulator

The fitting functions established the THD for voltage and THD for current, being cumulative, using the set of input data based on selected daily harmonic data. The simulation results are as shown in **Figures 5** and **6** for harmonic estimation techniques using Malaysian university power quality (PQ) data while **Figures 7** and **8** for a Nigerian university PQ data. Each plot in these figures has three lines, because the seven inputs representing three-phase voltage and current RMS as well as nominal frequency and one target vector (output distortion index) are randomly divided into three sets as earlier stated. For all cases, 70% of the vectors were used to train the network and 15% of the matrices were used for validation whilst the remaining 15% used for testing. As a stopping criterion, the network is made to memorize the training pattern after six validations, otherwise the training is terminated. This technique has been adopted to avoid the problem of over fitting commonly experienced in the backpropagation type of optimization and learning algorithm using early stopping as observed in **Figures 5a, 6a, 7b, 8b**. Finally, after the validation was accomplished, the last 15% of the data matrix provided an independent test of network generalization process. The family of plots in **Figures 5c–d, 6c–d, 7c–d, 8c–d**, respectively, show sample results for snap-short emulators of volt and current THD in the two networks.
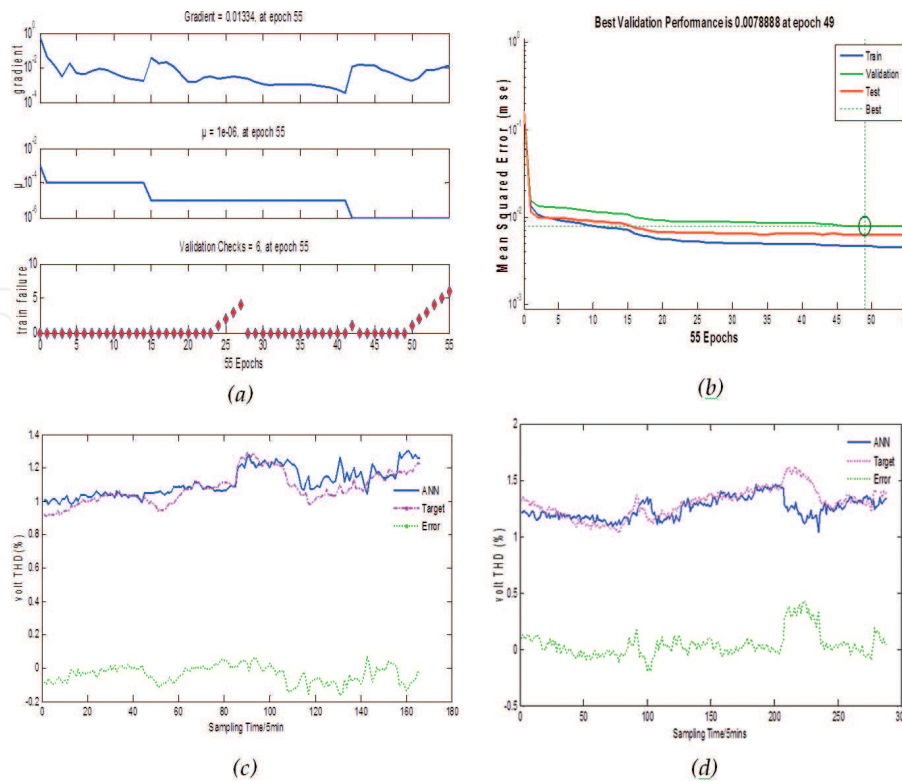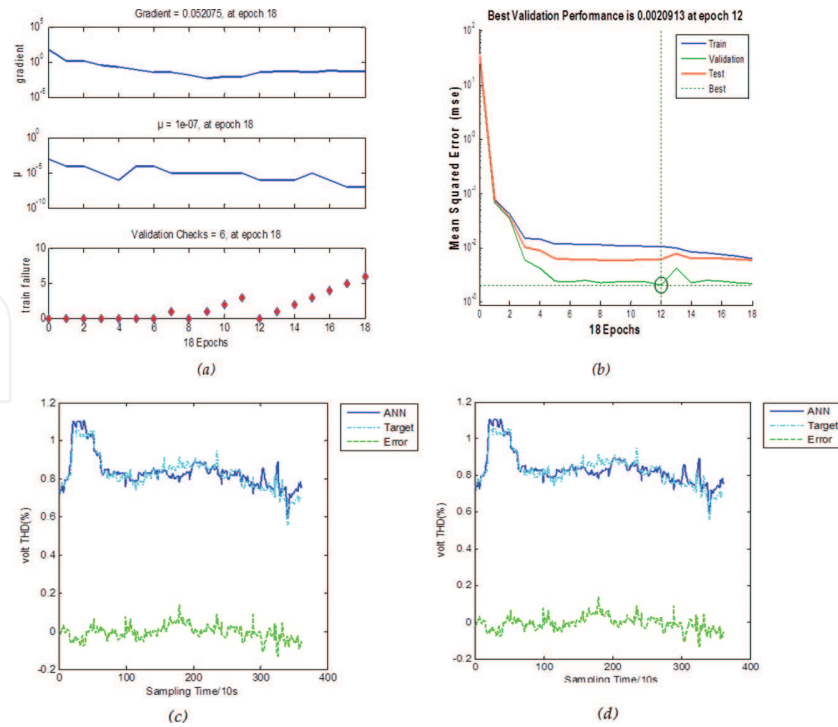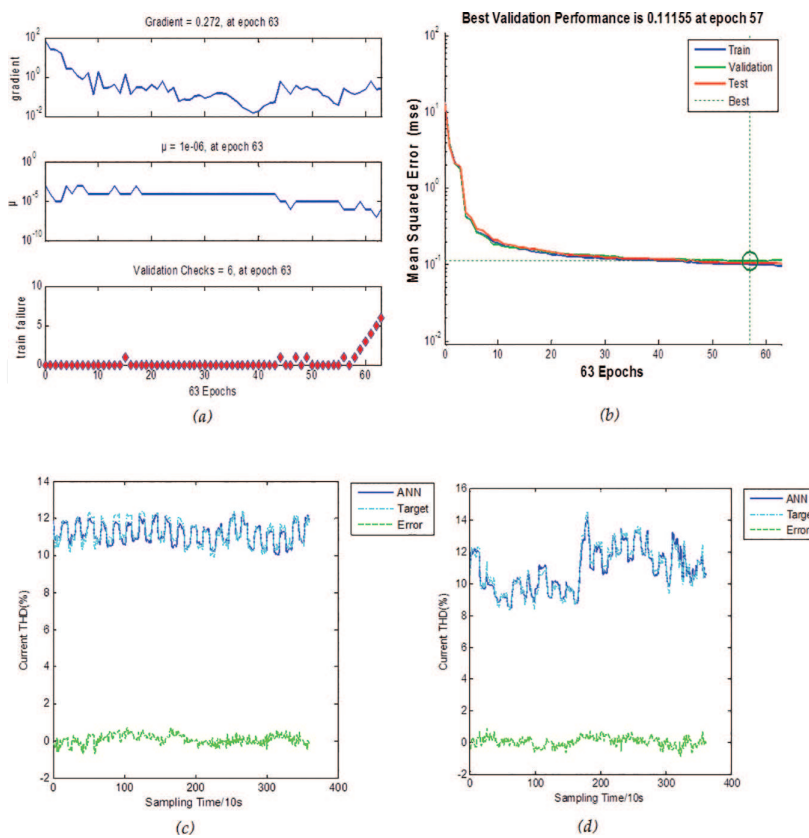
Figure 5. Field harmonic data and tracking of volt THD with ANN in Malaysia. (a) Training state of current THD. (b) Performance of ANN THD$_I$ tracking. (c) Tracking THD$_I$ with ANN-Day1. (d) Tracking THD$_I$ with ANN-Day3.
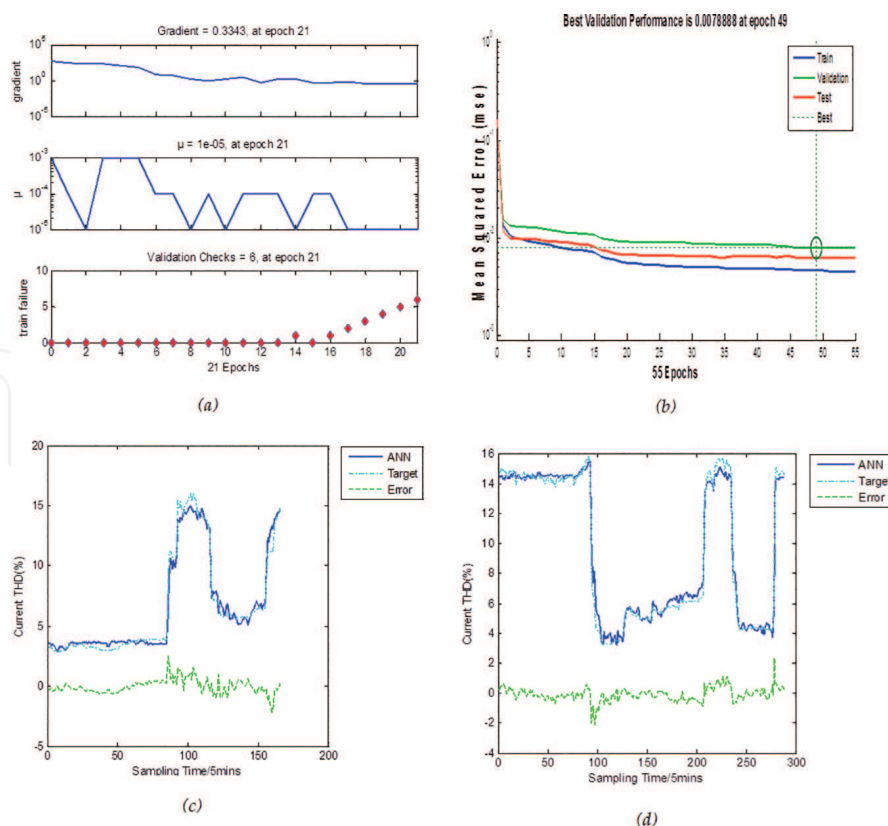
Figure 6. Field harmonic data and tracking of current THD with ANN in Malaysia. (a) Training state of volt THD. (b) Performance of ANN THD$_I$ tracking. (c) Tracking THD$_I$ with ANN-day 2 early morning (EM). (d) Tracking THD$_I$ with ANN-Day2mid day (MD).

Figure 7. Field harmonic data and tracking of volt THD with ANN in Nigeria. (a) Training state of current THD. (b) Performance of ANN THD_I tracking. (c) Tracking THD_I with ANN-day 2 early morning (EM). (d) Tracking THD_I with ANN-Day2mid day (MD).

Figure 8. Field harmonic data and tracking of volt THD with ANN in Nigeria. (a)Training State of Current THD (b) Performance of ANN THD_I Tracking (c) Tracking THD_I with ANN-day 2 early morning (EM) (d) Tracking THD_I with ANN-Day2mid day (MD)

7. Conclusion

The results have facilitated the classification of tools into simple, semi-advanced and advanced types. It also buttressed further the need for periodic investigation and harmonic assessment in a plant at least on frequency of one quarter (Q1), two quarters (Q2), three quarter (Q3) or four quarter (Q4), especially with the installation of new non-linear loads. Based on the enumerated procedures the selection of needful tools can be accomplished.

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