

CHAPTER 1

INTRODUCTION

1.1 Background

Electricity has become one of the most prominent necessities in this world today. With fast development and emerging industries worldwide, the requirement for a good and reliable power supply have become an important factor. There are many challenges in power distribution, which includes maintaining a good power quality at all time. Power quality has since become a major concern in the power networks. By definition, power quality is a set of electrical boundaries that allows an equipment to function in its intended manner without significant loss of performance or life expectancy [1]. An ideal power system is defined such when a perfect sinusoidal voltage signal is seen at load-ends. In reality, however, such idealism is hard to maintain, as any deviation from the perfect sinusoidal waveform is considered as distortion [2]. Voltage and current distortions or also referred as ‘harmonics’ has since become an active topic for researchers and entrepreneurs in finding for a solution.

Harmonics are currents or voltages with frequencies that are integer multiples of the fundamental power frequency. Harmonics current are fed by the non-linear equipments, which disrupts the desired ideal linear system [3]. These distorted current pulses, due to Ohm’s law, will also begin to distort the voltage waveforms, where it would be carried back to the distribution network [4]. Till date, the increasing use of nonlinear loads in industry keeps harmonics a rising issue in distribution network despite countless efforts being tested and implemented to obtain optimum power quality [5]. Power networks with

harmonics above tolerance deteriorate the power quality and hence cause undesired problems and issues at both generation and user-ends. IEEE Standard 519-1992 outlines the normal tolerance of harmonics voltage to be not more than 5% THD [6]. For better comprehension, decomposition of 3rd-order harmonics from a distorted waveform is illustrated in Figure 1.1. The 150 Hertz waveform is defined as 3rd-order harmonics due to its third integer multiple of the fundamental power frequency of 50 Hertz, which is the base sine waveform.

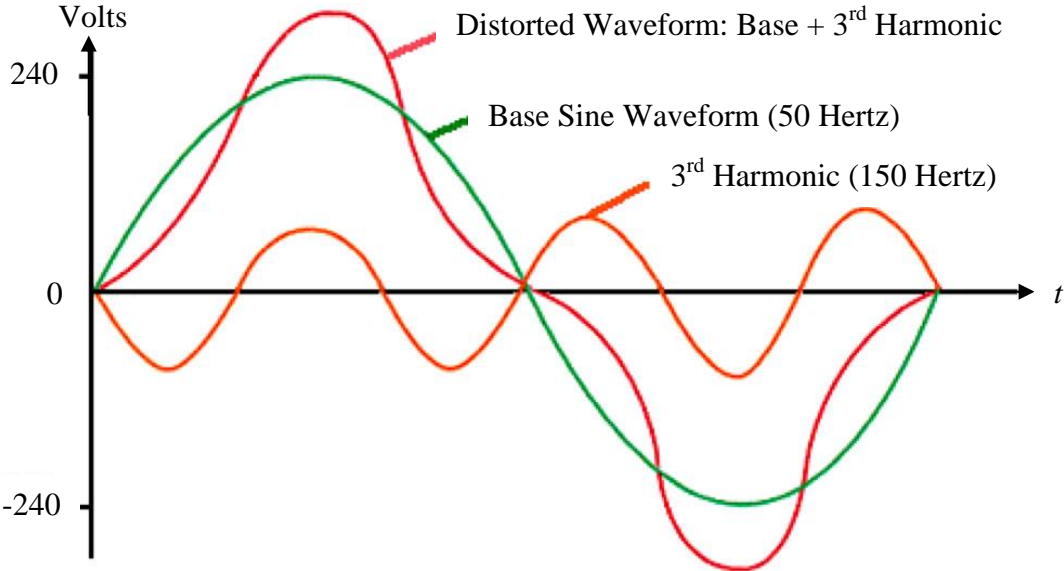


Figure 1.1 Distorted waveform composed of base sine waveform and 3rd-order harmonics

Harmonics form a very broad field of study. Hence, understanding the type and source of harmonics in each individual network is essential for a fairly accurate analysis and system optimization. In a distribution network, power is being generated and supplied to various types of equipment. The presence of harmonics in the system is an obvious problem but to which extend is the necessity to observe and minimize this distortion? Generally, harmonics can be categorized into positive sequence, negative sequence and zero sequence. Harmonics of 1st-order, 4th-order, 7th-order, 10th-order and

subsequent orders are defined as positive sequence. Whereas, the negative sequence harmonics consists of the 2nd-order, 5th-order, 8th-order, 11th-order and its subsequent orders. Zero sequence harmonics falls in a same trend as above harmonic orders, in which every order in the trend is followed by the third order from the former; harmonics of 3rd-order, 6th-order, 9th-order, 12th-order and 15th-order falls under zero sequence [7].

Harmonics with a positive sequence generally causes overheating of conductors, transformers and circuit breakers. Negative sequence harmonics can cause the same heating problems as positive harmonics plus additional problems with motors. Unlike positive and negative sequence harmonic currents, the zero sequence harmonics does not cancel but add up arithmetically at the neutral bus, causing overheating and related harmonics issues [8]. The major concern is the effect that harmonics distortion could impose; such as potential fire hazard, excessive heat, false tripping of branch circuit breakers, increased risk of faults from overvoltage state developed on power factor correction capacitors and subsequently increases maintenance cost [5,9].

The biggest challenge utilities face at present, is to provide reliable services to support the ever growing power demand. For instance, India faced critical power issue with several blackouts in 2012 due to the energy suppliers' failure to meet the growing demand [10]. The solutions are often very costly.

As part of the EPRI Reliability Benchmarking Methodology project, investigators explored the idea of estimating the voltages at locations without prior inspection. This led to the development of the power quality state estimator (PQSE), which uses feeder models and recorded data to estimate the system output [11]. There are two parts to state estimation (SE); modelling and algorithms. The overall approach is to use a model to foretell the behaviour of the system in a particular state, and then compare it with the actual telemetry from the system. This is to conclude which state is most likely to produce the observed system behaviour [12]. However, these assumptions have simplified the implementation but generate several practical problems.

Harmonics analysis consists of three main stages; harmonics pseudo-measurement or data recording, harmonics state estimation and post-fault analysis, as shown in Figure 1.2.

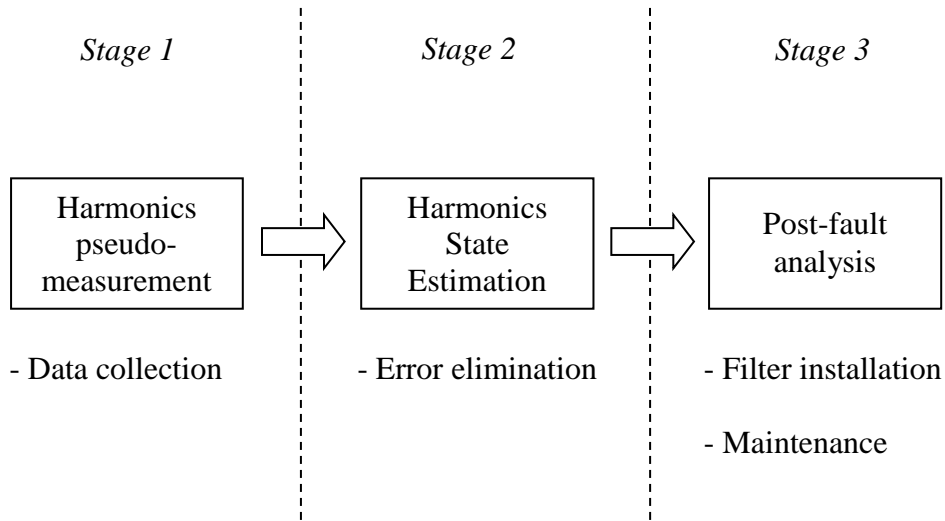


Figure 1.2 Block diagram of harmonics analysis process

Before an estimation model is being constructed, a set of known data derived from intended location is essential. These data, or also called as *pseudo-measurements*, are gathered using power analyzers. The complexity of the equipment influences its price and affordability. As an alternative, harmonic estimation and time-series prediction are being explored.

Estimation capacity is defined as logarithmic information measure [13], which provides reliable information for the analysis. Early studies suggest the usage of Global Positioning System (GPS) receiver at every local system to synchronize harmonic phase measurements with accuracy of $1\mu\text{s}$. However, the high expense of harmonic instruments and installation of communication channels limits the number of meters in network [14]. Therefore, harmonic estimations are essential to solve complex problems. Before the invention of power analyzers, harmonics estimation is carried out by measuring the load current and then computing the harmonics via Fourier series [15, 16]. The size and complexity of modern power networks makes it difficult to monitor a complete system.

Time-series prediction or often called as forecasting, on the other hand, works as a planning tool that helps management in its attempt to cope with uncertainty of the future,

relying mainly on data from the past and analysis of trends. Forecasting can be simply categorised into long-term, mid-term and short-term. A long-term forecast is usually applied by futurologists to explore the low-probability, high-impact events. For instance, this is practised by the projects on National Security Reform's Vision Working Group [18]. Whereas, mid-term forecasting concentrates on the factors that drive the evolution of power and challenges the conventional notions of waning plants or resources [19]. Short-term forecasts seek to understand the not-too-distant future, but are, all the same, enlightened by the developments occurring at present [20]. Hence, short-term forecast is the most essential forecast technique to prepare for harmonic issues, which are to occur in the not-too-distant future if left untreated.

Once pseudo-measurements are collected, they would be fed into the Harmonics State Estimation (HSE) model to economically determine the location and magnitude of harmonics in a power network and identify its source of harmonics. HSE is the fundamental for harmonics analysis in power networks. There are two main parts to state estimation (SE); modelling and algorithms. The overall idea of a HSE model is to use feeder models and recorded data to foretell the behaviour of the system in a particular state, and then compare it with the actual system [21]. Many mathematical methods, such as Fast Fourier Transform (FFT) and Least Squares (LS) have been developed over the years and have been proven that by using only partial or selected measurement data, the entire harmonic distribution of the actual power system can be obtained effectively [22].

Hence, it is important to determine the harmonics voltages in power network in order to take appropriate corrective measures. The possible solutions for power system harmonics include passive filter, active filter or hybrid filter. The most common method for harmonics filtering is by installing passive filters at power network where necessary. It filters harmonics within a selected bandwidth, while active filters shows a more sophisticated filtering concept of real-time harmonics cancelling [23]. Hybrid filter, on the other hand, combines the advantage of both active and passive filter.

1.2 Scope of study

This research focuses on a specific stage of harmonic analysis; harmonic pseudo-measurement. A real-life situation is investigated and a proposed solution is discussed. The proposed technique aims to fully utilize existing resources, and therefore leads to a novel approach. Although the system is developed with MATLAB environment on an offline network, it is fully aimed to improve power quality of the intended distribution network and prevent future undesired occurrences. This study also highlights the importance of reducing cost at the first stage of harmonic analysis to reduce the overall maintenance cost of any distribution system. A comparative study between an existing system and the proposed system is also carried out through MATLAB simulation to validate the claim that the proposed system is better than the existing system.

1.3 Problem Statement

University Teknologi PETRONAS (UTP), located in a small town Tronoh, was established in 1997 with a unique attempt to utilize gas to produce chilled water for air-conditioning and waste heat for power generation. It is configured to lower the peak load demand and reduce investment for peaking capacity especially for a large building complex [24]. A typical gas district cooling plant can be simply illustrated as in Figure 1.3.

As potential as it can be, however, this power generation does not meet its expectation in producing reliable power supply. In an online survey conducted around the campus area in May 2011, the students' response shows that harmonic issues do exist in the system (Refer to Appendix A). The survey was categorized based on students from different residential villages in UTP to identify the most troubled village. It targets students from various clusters and year of study. Out of 100 students whom participated in the online survey conducted, 86% of students agree to have experienced power failure/blackout in campus and 10% complained of frequent occurrences of such incidents. Among the 10%

of student whom complaint frequent power shortage, a surprising figure of 8% was found to be resided in residential village 3 while the remaining 2% mentioned power troubles during class and laboratory hours. Among the issues brought forward were loss of important data and documents in personal computers due to sudden power failure and long hours of laboratory due to frequent power failure, which also causes complications to the laboratory equipment.

In 2009, the research and technology division from PETRONAS, or also known as Group Technology Solutions (GTS), was invited to conduct harmonic study around the new academic complex to investigate on the multiple power failures. As an outcome, GTS reported THD_v to be 4.4% of the fundamental at every phase in selected academic blocks; Block 2, 3, 5, 13, 17, and 22. This information is vital and has led to many harmonics analysis conducts at UTP distribution network [24] - [26]. However, in recent years, despite much harmonic issues that has aroused, no proper analysis has been carried out due to limited resources. Therefore, there is a need to supervise the UTP distribution line in the most cost-efficient and reliable method.

The summary of problem statements is listed below;

- a) In midst 2011, under a research grant in UTP, a power analyzer was purchased for academic purposes. Although the analyzer has huge potentials, the usage is limited to data collection for research and academic purposes due to its cost and complexity. Only a single unit of power analyzer cannot serve the purpose of complete harmonics monitoring across the campus. Therefore, the campus clearly lacks a reliable system to monitor and prevent future harmonic-related incidents, which has also subsequently increased the maintenance costs.
- b) Since the study focuses on the harmonic issues at load-end (i.e.: power shortage at residential villages and academic blocks), a non-linear system would serve best for the harmonic monitoring due to the fact that an electric load is a non-linear function. Therefore it is indispensable for development of optimal ANN-based harmonics monitoring system to optimize the use of the existing power analyzer in UTP. Intelligent techniques on the other hand, require optimal network

structure with the most appropriate training algorithms to suit the targeted distribution network. Careful selection on these techniques will then improve the accuracy of the final product as well as the performance of the network.

1.4 Research aim and objectives

The impetus of the study is mainly to optimize the use of the power analyser and monitor as many locations as possible at a time with minimal cost. The research objectives are set to solve the problems that have been brought up, which are;

- a) to propose an intelligent system that provides complete monitoring of harmonic fluctuations at UTP distribution line,
- b) to develop a reliable algorithm for the short-term harmonic monitoring by utilizing the actual harmonics data from UTP campus, and
- c) to forecast harmonic voltages ahead, which allows preventive measure to be taken beforehand.

The proposed system shows novelty as no previous work has been recorded to neither propose nor overcome harmonic issues in UTP distribution network. Since the usage of power analyser tool currently, limits the number of monitoring station to one at a time, the proposed system is expected to increase efficiency of complete distribution network surveillance and reduce monitoring time and cost

In order to accomplish these objectives, it is very important to carry out network assessments on the bases of the average estimation and forecast error, and network performance using different training approaches. The models are carefully trained by feeding reasonable data gathered from the power analyzer. Possibilities for minimizing the error means of other intelligent-based technique are also explored and evaluated.

1.5 Assumptions

To achieve the aforementioned research objectives, a number of assumptions have to be made;

- a) it is assumed that the instrument error is below tolerance since the tool is fairly new purchase and implies to the standard calibration. Fluke 1750 power analyzer calibrated with harmonics current and voltage reading to be ± 0.5 % reading and ± 0.2 % full scale for the 1st to 20th orders, while from 21st to 50th order harmonics, the voltage and current expected to be ± 1 % reading and ± 0.3 % full scale; with current sensor accuracy of 1% from 10 mA to 5 A.
- b) The phase angle is not considered in the system since the power analyzer used to log data was not able to record the phase angle data. Therefore, the phase angle is considered stable.

1.6 Research Motivation

The residents or students in UTP currently do not enjoy the benefits of such intelligent power generation system due to the issues that occur very often. At present, no preventive measures are taken beforehand to prevent power failures in the campus area. This is mainly due to lack of tool or instrument, and also expertise to monitor the harmonic fluctuations in the distribution line. Therefore, the campus is in need for a reliable surveillance system that is not only user-friendly but also cost-efficient.

An optional tool that enables efficient harmonics monitoring in UTP distribution network would allow a virtual surveillance system to be implemented and thus, reduce probability of power failures in near future.

This is expected to reduce the maintenance cost as prior measures can be taken to avoid future power failures. Reduction in terms of equipment will also be possible as each surveillance point can be operated

1.7 Outline of the Thesis

This thesis contains five chapters, neatly divided to elaborate each section. The first chapter provides a background study on harmonics and the need for harmonics estimation at UTP's distribution network. Thesis objectives and scope of study are clearly outlined here.

Chapter 2 discusses classical methods and the state of art in general. This section attempts to provide a review on harmonics studies over time and weighs the advantages and disadvantages of several common and famous techniques.

Chapter 3 demonstrates the proposed harmonics pseudo-measurement monitoring system using AI techniques. The AI concept and techniques are also introduced and discussed further on its applications to the proposed system.

Simulation results and discussions are presented accordingly in Chapter 4. The estimated and forecast values are compared with the actual data collected from data logging using Fluke 1750 power analyzer to determine its validity. The competence of the monitoring system is clarified further by comparing the proposed system with a traditional system.

Chapter 5 concludes the thesis by providing a review on the whole work and recommendations on future works.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The presence of harmonics in distribution line was noted ever since alternating current was introduced. However, this issue of distortion that affects the power quality was not understood initially and was merely referred as a ‘mystery’. One of the first documentation on harmonics was recorded back in 1894 by Edwin J. Houston and Arthur E. Kennelly [27], where a keen understanding of harmonics as well as its effects on transformers and motors was neatly described with simple graphical interpretations. The basic idea in harmonics studies is to measure the harmonics injected by the non-linear loads and minimize the unwanted harmonics [28]. Various studies have been conducted on harmonics and distortion since 1960s. Before the invention of AI techniques, harmonics issues were treated with conventional mathematical models to detect and minimize unwanted harmonics in distribution line.

One of the most primitive methods used to calculate the steady-state solution was to integrate the accompanying system of non-linear differential equations for as many cycles as required, until the transient response disappears, leaving only the periodic, steady-state response. This is the case in any of the highly developed electromagnetic transient programs; EMTP and PSCAD/EMTDC [29]-[31]. This approach, however, does not always yield satisfying results because some power networks are lightly damped and because of difficulties in establishing suitable steady-state initial conditions [32]. This solution approach is also time-consuming and sometimes inconclusive [33].

2.2 The revolution of Harmonics State Estimation in power systems

Initial growth in power quality was the replacement of conventional analysis of harmonics by state estimations; harmonic state estimation (HSE). Early researches commonly suggest fast Fourier transform (FFT) and least-square methods for state-estimation [9, 17, 34]. Fourier transform is an old method of computation, which was developed in attempt to determine the orbit of certain asteroids [35]. It is later been adopted and tested in various fields due to its computational advantages. FFT offers reduced computations that other methods and also involves the transformation of sequences [36]. FFT methods were advantageous when computations are to be performed on a machine with limited core storage. However, FFT has been proved of its non-feasibility in a recent research. It is found that FFT enables estimation of the fundamental amplitude and its harmonics with a reasonable approximation but compels disadvantages on window dependency resolution. FFT also performs well for estimation of periodic signals in stationary state but fails to perform well for detection of sudden or fast changes in waveform [37]. State-estimation by least-squares technique uses direct solution using rectangular coordinate system. A.P. Sakis Meliopoulos [16] implements sensitivity and observability analysis to increase precision of least-square estimation. However, in the research, the confidence level computation showed the existence of constant instrument error. Huaiwei Liao [38] later, pointed out that standard least-square based method have difficulty obtaining reliable estimates when measurements are less than state variables, which are identified as underdetermined system.

In any traditional method, a common challenge often faced in harmonics state estimation issues is the underdetermined systems of equations. This issue is often solved by assuming those busses with or without loads thought not likely to contribute harmonic emission, as zero harmonic injection. In 2005, T. L. Tan [39] underlines that the problem with this technique that the voltage measurements at those buses known or assumed not to have harmonics producing devices cannot be used. Loads that are thought not likely to emit harmonics may not be true. Later, Huaiwei Liao [38] showed that underdetermined

system can be observable by utilizing the spatial sparsity of harmonic sources under proper measurement arrangement. However, this approach is rather time-consuming and expensive in meter placements.

The most common state estimation technique in industry is based on the weighted least squares (WLS) method [40]. It usually operates in a cycle of estimation-detection-elimination until an acceptable result is obtained [41]. Despite its advantages in detecting and identifying single and multiple gross measurement errors, WLS is rather time consuming to perform such bad-data detection and identification procedures online for large systems [42]. A basic Newton Raphson WLS method has a very long computational time due to the gain and Jacobian matrices associated with the basic algorithm which requires large storage and has to be evaluated every iteration. N. Mohd Nor [43], attempts to reduce the time taken to construct the Jacobian matrix by reconstructing or rearranging the H matrix and proves its effectiveness in reducing the computational-time. Though, the WLS based estimator cannot effectively detect and identify multiple interactive and conforming bad data. The most important drawback of least square method and alternatives is their high sensitivity to outliers. This is a due to the usage of *squares* as squaring exaggerates the magnitude of difference (*e.g.*, the difference between 20 and 10 is 10 but the difference between 20^2 and 10^2 is equal to 300) and therefore gives a much stronger importance to extreme observations [44].

2.3 Artificial Intelligence Techniques in Harmonic Analysis

Since the early to mid 1980s much of the effort in power system analysis has turned away from formal mathematical modelling to the less rigorous techniques of Artificial intelligence (AI) [45]. AI began with “an ancient wish to forge the gods”. Modern AI was developed by classical philosophers, back in 1940s, who attempted to describe the process of human thinking as a mechanical manipulation of symbols [46]. AI techniques have been introduced to overcome the disadvantages of non-parametric techniques, such as the Fast-Fourier transform (FFT) and wavelet transform (WT) [47].

In early years, neural network have been actively used for estimation of harmonic components in power system [48]-[53]. Various techniques were proposed. For non-linear systems, several Fuzzy Kalman filtering algorithms have been developed to extend Kalman filtering for such system. Hazem N. Nounou [54] presented multi-scale fuzzy state estimation using stationary wavelet transforms or known as multi-scale Fuzzy Kalman (MSFK) filtering algorithm. A fuzzy system is an approximator which consists of a set of IF-THEN type rules, each of which has a premise and a consequent part. Fuzzy models have been found very useful for control purposes as for their ability to describe complex system in an efficient manner. However, to achieve a good fuzzy control, reliable state estimation is essential. In terms of harmonics state estimation where measured data usually contain multi-scale features, fuzzy filtering techniques are not effective. Fuzzy filtering techniques are single scan methods where it is assumed that the measured process data only contains features with fixed contribution over time and frequency. MSFK then uses scaling function coefficients of the data obtained using Stationary Wavelet Transform (SWT), and then selecting the optimum fuzzy Kalman filter, which minimizes a cross-validation estimation error criterion [54]. Although Kalman Filter is fairly accurate, it has high mathematical burden which limits its use for on-line tracking [55]. Wavelet-based signal processing algorithm in general, introduces lag that is equal to the length of the used window and hence, impose limitation on on-line applications.

Adaptive perceptron approach in neural networks has been tested and applied successfully for power systems harmonic estimation [56]-[57]. The neural estimator was based on the use of an adaptive neuron called ADALINE. Adaptive tracking of harmonic components of a power system could easily be done using this algorithm [58]. However, ADALINE network is limited to only one output neuron. The convergence of ADALINE slows as the number of harmonics included increases and it is also subjected to fall in local minima [59]-[61].

Another common method is the back-propagation neural network, which uses supervised training approach to identify selected harmonics. This method treats harmonics detection problem as a pattern recognition problem [62]. ANN is one of the

earliest methods used in AI. In 1990, R.K. Hartana [63] had published a patent work using ANN method for harmonic source monitoring and identification, while in 1992, another patent [64] has been recorded to implement ANN based method for power systems harmonics voltage prediction. Due to its reliability regarding many other techniques available, ANN is still a popular technique in current researches; in harmonic estimation [65] and also harmonic analysis [66]. A review by M. Tarafdar [67] shows that application of ANN in power systems have shifted from analysis to the operation phase, where forecasting of systems has a special interest.

However, a common drawback is seen in a basic back propagation approach where the time taken for convergence is fairly long and the solution often stuck at local minima [68]-[70]. M. Gupta [55] introduced a faster training algorithm for estimation purposes, which utilizes particle swarm optimization (PSO) combined with gradient descent (GD) to train weights of neural network. This hybrid algorithm has also been proved to be more advantageous than genetic algorithm (GA), PSO or GD on stand-alone. The advantage of this hybrid algorithm is fast convergence with no possibility of getting stuck in local minima. The surety of not getting stuck in local minima is due to PSO and fast convergence is because of GD. The NNs are trained to uniquely identify various types of devices using their distinct harmonic “signatures” as their input.

In 1994, while ANN technology was actively being explored in harmonic studies, D.K.Ranaweera [71] highlighted the concern that the ANN methods applied for load-forecasting problems do not flag mathematically when they are extrapolating from the training data, and therefore creates room for invalid forecast as a result. Classical ANN techniques concentrate on global fit, while gives poor fit on local regions [72]. Therefore, it underlines the main unmet need of users who wishes to use ANN techniques in forecasting; the determination of confidence intervals for each load forecast. Newer generation Radial Basis Function (RBF) techniques employs hybrid algorithms, in which varies nonlinear time-varying techniques are adopted when training the RBF neural network (RBFNN) [73]. Real time experiment of time-series prediction on different practical load types of Taiwan power system (Taipower) were carried out to compare between an RBFNN network with nonlinear time-varying evolution PSO (NTVE-PSO)

algorithm and existing PSO algorithm [73]. Simulation results proved NVTE-PSO algorithm has better forecasting accuracy and computational efficiency for different electric demand.

The idea of RBF was drawn from the theory of function approximation. An RBF network is similar to a feed-forward neural network, only with slightly different approach [74]. RBF methods were tested on harmonic studies for over a decade and has gained popularity in time-series prediction in early 1990s [75] and have since continuously applied and enhanced to suit various needs [46], [76]-[77]. In general, it is capable of approximating highly nonlinear functions, the training can be done in a sequential manner, and the use of local approximation gives better generalization capabilities [66]-[68]. However, this method seems to show the same disadvantages found in a back propagation neural network approach [46].

2.4 Artificial Intelligence in Harmonic Estimation

Each system display unique attributes and therefore, a suitable problem solving method need to be identified before evaluating its performance. D.O. Abdeslam [65] proposes a new approach to improve the performance of conventional Active Power Filters (APFs) by using ANN for harmonic estimation. The separation of powers is implemented with an Adaline NN based on *a priori* knowledge of frequency waveform, in which, a multilayer NN was used to generate reference currents to cancel the unwanted harmonics. To test the effectiveness of the proposed method, a common power quality environment was created mathematically, with nonlinear loads to create distortion. The method is justified by showing estimation error to be 0.01%, whereas the THD parameter reduced to 0.85% after the neural estimation compensation currents are applied.

Although M.J. Ringrose [78] in his paper aims to monitor multiple harmonic sources using state estimation, the initial measurements or pseudo measurements are provided using NN. NN serves the purpose well due to the highly complex and poorly defined input-output relationships between the harmonic and power flow measurements and the

harmonic sources. Using this technique, harmonic sources could be monitored using only a few harmonic-monitoring stations. Similar approach was used by R.K. Hartana [63] back in 1990. NN used to make initial estimates of harmonic sources, which are then used as pseudo measurements for harmonic state estimation, which further improves the measurements.

Another recent research [79] exploits the few real-time measurements from distribution systems to provide an initial estimation of harmonic currents. Bayesian approach was used to estimate the source of harmonic distortion in the tested distribution network; laboratory scaled small low-voltage single-phase network. However, similar to earlier researches, *a priori* knowledge about the harmonic behavior of the load was determined. The *a priori* information was modeled with Gaussian distributions so that a closed-form solution of the estimation problem was possible. To evaluate the quality of these estimates, *a posteriori* check on the coherence between the obtained results and the initial assumptions. The proposed technique was validated by performing tests on a small-sized low-voltage distribution network in a laboratory scale.

Other applications of ANN in harmonic estimation include [80] extraction of selective harmonics contents in the signal based on separated and sequential training with RBFNN technique. It demonstrates the capability of RBFNN to estimate the harmonics with half fundamental cycle. To train the algorithm, desired output were computed using FFT on several fundamental cycles of source current waveform.

In short, most researches aims to efficiently estimate harmonics in order to reduce error at HSE. Although PQ analyzers are easily available in market today, attempts to develop virtual analyzers to replace these equipment are being looked at. The virtual PQ analyzer, which is developed with ADALINE technique, provides a flexible analytical and measuring platform without taking hardware requirements into account. The performance was later tested with a series of test signals generated via the arbitrary waveform generator (AWG).

2.5 Artificial Intelligence in Harmonics Time-series Prediction

ANN based approach have also gained popularity in prediction of power system harmonic voltages in early 90's. Mori. H [81] tested the effectiveness of recurrent neural network back in 1991. Unlike the conventional feed-forward ANN, the recurrent neural networks have the advantage of being able to consider the dynamics of a time-series. In early 1995, [82] applied RBFNN model and a back-propagation model to provide peak and total load forecasts for the next day and showed strong results indicating RBFNN to perform better than the back-propagation model. Pacific Gas and Electric Company's (PG&E) load data for 1985 were used to train the networks and holidays were excluded from both training and testing data sets to ensure that the observations were free from any irregular load patterns.

Most researchers develop approximation tools using a lab or MATLAB-based model. [83], for the first time, utilize a practical power distribution offered by Thaipower Company. The actual hourly load data was used for the time-series prediction of one-day (24-hr) ahead and five-days ahead. Three different schemes were introduced with 504 numbers of training data for each scheme; to forecast weekdays for spring season, weekdays for autumn season, and weekends across two seasons respectively. Simulation results of the proposed non-linear time-varying evolution particle swarm optimization as the training phase of radial basis function neural network (NTVE-PSO-RBFNN) has better forecast accuracy, superior convergence rate, and shorter computation time than other PSO-RBFNNs in time-series prediction.

2.6 Summary of Chapter

Each network has its own limitations. To overcome these drawbacks, hybrid algorithms were formed and tested for their effectiveness. Although the techniques used in these researches appear to be similar, they were each designed for different problems and conditions. Hence, problem identification is merely as important as choosing the

technique for solving. In short, feed-forward neural network with back-propagation training method is the most anticipated approach in estimating harmonics, whereas RBF technique is more widely selected for harmonics prediction. In the following chapter, harmonics estimation in UTP distribution network is carried out using back-propagation neural network technique. Whereas, harmonics time-series prediction uses RBF approach.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter will provide an insight of the solution proposed to overcome the problem as stated in Chapter 1, as well as abide with the objectives of the study. The tools used to measure and develop the proposed system are also defined carefully to provide better understanding. Before presenting the proposed system, it is important to understand and learn on the research background, the tools to be used along the process, and the research design that includes data collection technique and interpretations. In short, this chapter discusses on the knowledge acquisition and pre-processing, data collection, in-depth discussion on the proposed algorithm and the algorithm developments. A comparative study is also proposed at the end of the chapter between Virtual Harmonic Analyser and Forecaster (V-HAF) system and a typical system with a forecast network to evaluate the reliability of the proposed V-HAF system.

3.2 Establishing a Research Territory

This research is systematically organized to enable reader to understand the experiments carried out, their purposes and the outcome recorded, with discussions along the chapter for better understanding. The experiments and data logging were carried out

at student residency village in UTP, in which powered by Gas District Cooling (GDC). GDC system will be further discussed in following section as research background. An academic-based tool, MATLAB is proposed due to its user-friendly interface, reliability, and flexibility to compare with other research works.

The techniques used in this research are merely adoption from previous successful research works. After a careful analysis on the most suitable techniques for this study, they are developed with the aid of MATLAB version 7.1 software, and implemented for the case of harmonic distortion in UTP distribution network. A well-known estimation model, which was proven to have shown successful results, is picked for harmonic estimation. The model is briefly known as feed-forward Neural Network. As for time-series harmonic prediction, which forms the second proposed network in V-HAF system, the RBF technique is chosen based on qualities that are discussed further in this chapter. Section 3.5.1 brings in depth the process of data collection; from meter placement to data segregation.

A systematic research framework is then applied to present the proposed system. Section 3.5.2 to 3.5.4 discusses on the knowledge acquisition, development of basic block diagram and development of proposed model for each system. Technique validation, experimentation and data collection, analysis and documentation are presented in the following chapter. In short, the research is strictly guided by research framework shown in Figure 3.1.

Upon establishing the two-network system, known as V-HAF, a comparative study is conducted to compare the performance of V-HAF based on the predicted future harmonic voltages. A Non-linear Auto-Regressive with eXogenous (NARX) dynamic recurrent Neural Network is used for the comparative study. The results are evaluated based on MAPE, correlation coefficient and the execution time.

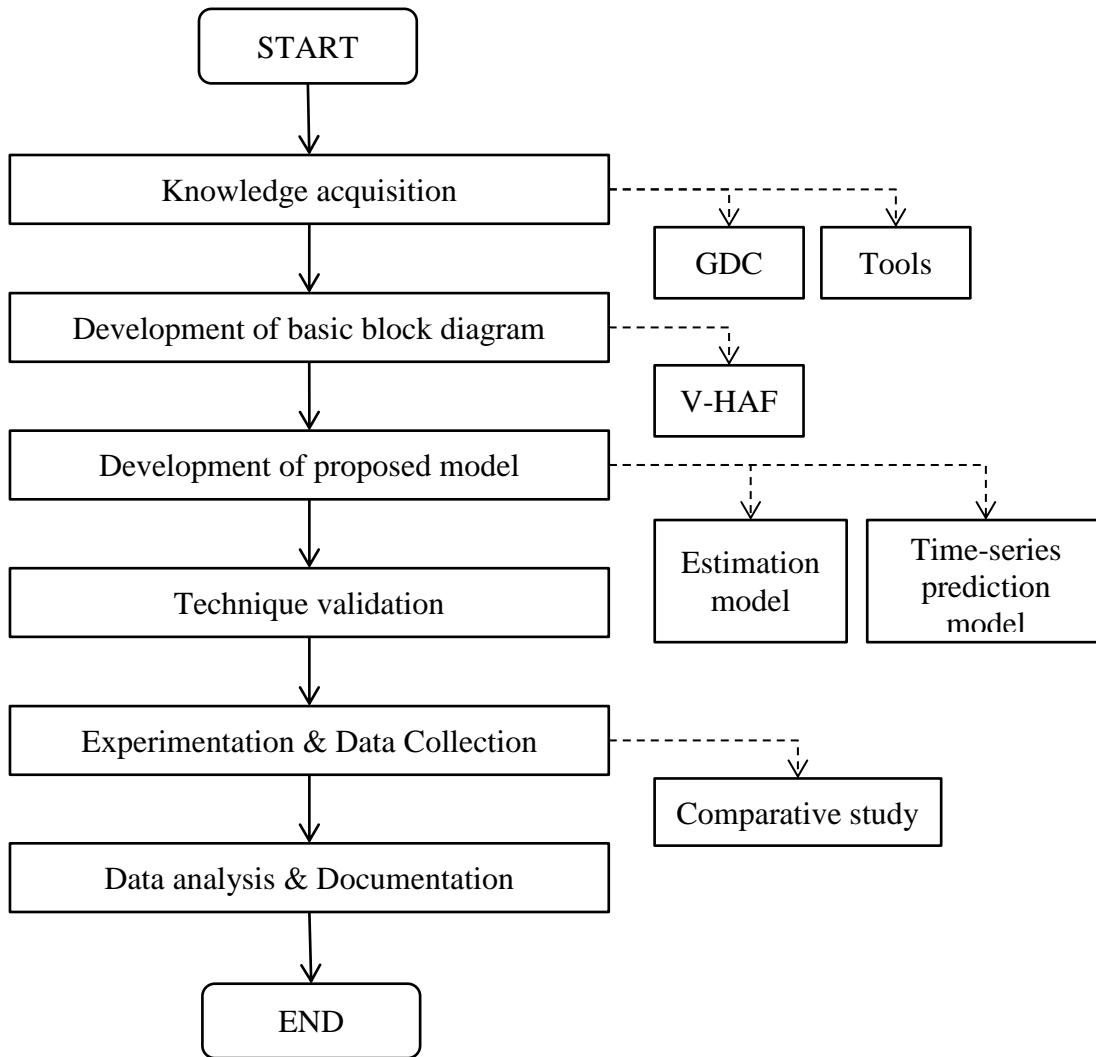


Figure 3.1 Research framework flow-chart for research presentation

3.3 Research Background – Gas District Cooling (GDC)

GDC is a co-generation system that utilizes gas to produce chilled water for air-conditioning and waste heat for power generation. Such a configuration helps to lower the peak load demand and reduces investment for peaking capacity especially for a large building complex [86]. There are a total seven districts cooling systems in Malaysia that

are all fuelled by natural gas, with two standalone operations and five are cogenerated. The GDC systems were pioneered in Malaysia by Gas District Cooling Sdn. Bhd. (GDCSB), with the first plant established in 1997. The plants are located in major cities; Kuala Lumpur City Center, Putrajaya Plant 1, Kuala Lumpur International Airport, Putrajaya Plant 2, and UniversitiTeknologi PETRONAS (UTP). Unlike other plants, the GDC plant supplying UTP was build out of necessity. The campus is located at the end of power distribution lines in industrial surroundings and therefore, the quality of the available power was not complying with the university’s requirements [84]. Figure 3.1 provides a good illustration of a GDC system, which uses gas and diesel fuel.

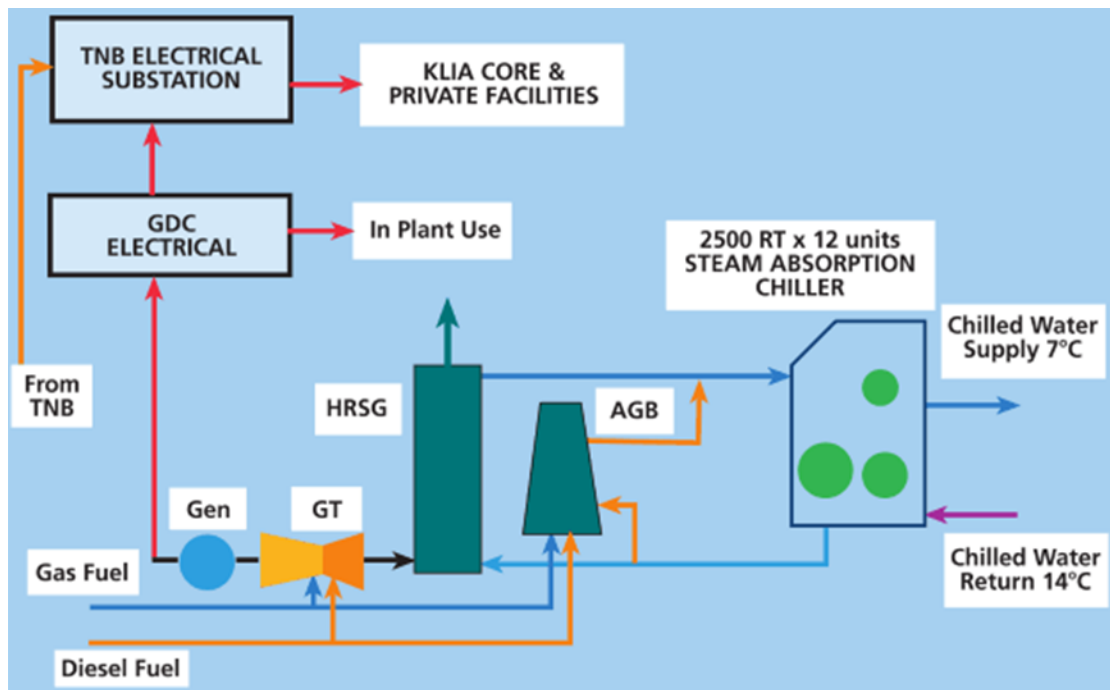


Figure 3.2 A typical Gas District Cooling System Schematic for the Kuala Lumpur International Airport Plant [84]

However, it can be said that, to a certain extent, all power plant components possess the undesirable property of introducing distortion into the AC power circuit.

3.4 Programming tool

This study utilizes MATLAB's interactive tools and command-line functions to develop various approximation tools to cater the research's need. MATLAB is a program originally designed for solving linear algebra type problems using matrices. Today, it has become a useful tool for prototyping AI projects due to its large library functions, useful data visualization, focuses on high-level details and also allows quick prototype development of algorithms.

MATLAB offers a huge range of AI tools that also enables its users to integrate different techniques to achieve the simulation goal. It is a good tool for demonstration purposes, which is the main objective of this study. It is also a common tool used by researchers worldwide.

3.5 Approximation Tool

Based on literature review, as discussed in Chapter 2, intelligent system based models have proven to be more advantageous than any classical methods. The challenge in applying intelligent method in problem-solving is to determine the best possible method for the intended problem. Since demonstrating an organised monitoring system is the main objective of this thesis, analysis on the most suitable method with high dependability will be purely based on previous studies. Algorithm optimization will NOT be focused in this study. Hence, the literature review would underline the techniques that would be proposed for this research on various grounds, which would be discussed further.

To develop any approximation tool, a prior in-depth understanding on the tools is crucial. Hence, basic architectures of the proposed approximation tools will be further investigated to allow appropriate parameter adjustment to find the best fit. For model parameters selection, a systematic approach with regards to number of hidden layers,

number of nodes, epochs, network performance, desired activation functions, and training period has to be unambiguously formulated.

3.6 Research Design

Underlining a good research design is a primary need for successful research work. This study concentrates in proposing a solution for the UTP's distribution network, which is currently troubled with harmonics issues. Hence, an intelligent and reliable system needs to be implemented in UTP distribution system to reduce on the maintenance cost. The main cause of increasing maintenance cost with the electrical system maintenance in UTP is due to lack of proper surveillance on the harmonics at the distribution line. Maintaining a good power quality would eliminate unwanted costs due to damages caused by poor surveillance. This also reduces probability of damages of private and laboratory equipment due to poor power quality. Figure 3.2 suggests the overlook on the proposed monitoring system.

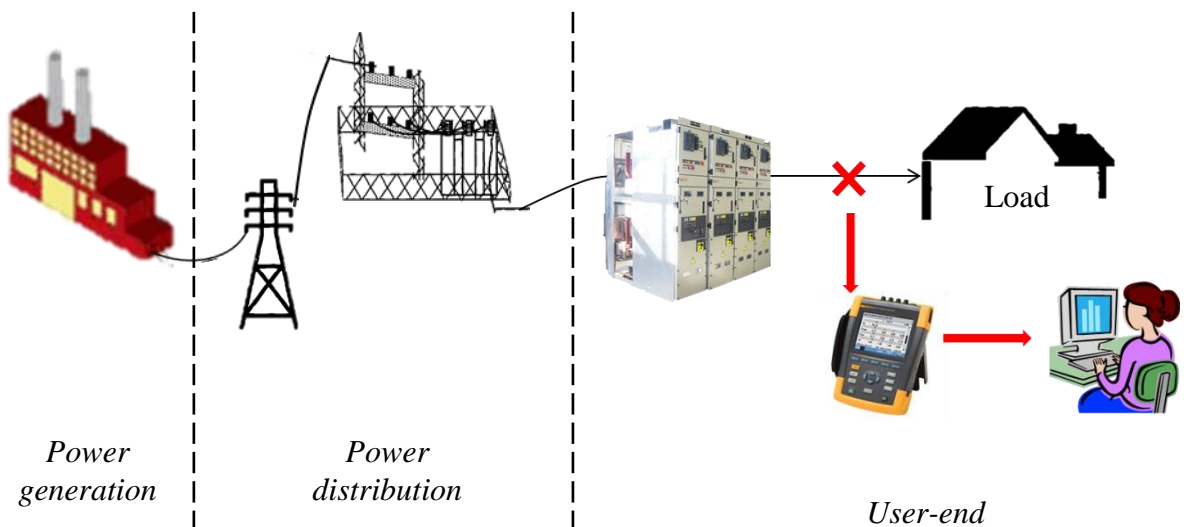


Figure 3.3 Complete overlook on the proposed intelligent system for UTP distribution network

This section brings into detail on the development of the proposed Virtual Harmonic Analyser and Forecaster (V-HAF) system. A dual-function system is expected to reduce instrument cost, which will be discussed further in Chapter 4's comparative analyses. The research proposes an offline system that enables monitoring of fluctuations in recent and future harmonic readings using intelligent techniques.

3.6.1 Data Collection

This section provides a thorough insight on the data collection and interpretation, which is used to directly train and develop the approximation tools. To ensure data gathered for the research is valid, verifications were done prior to training algorithms.

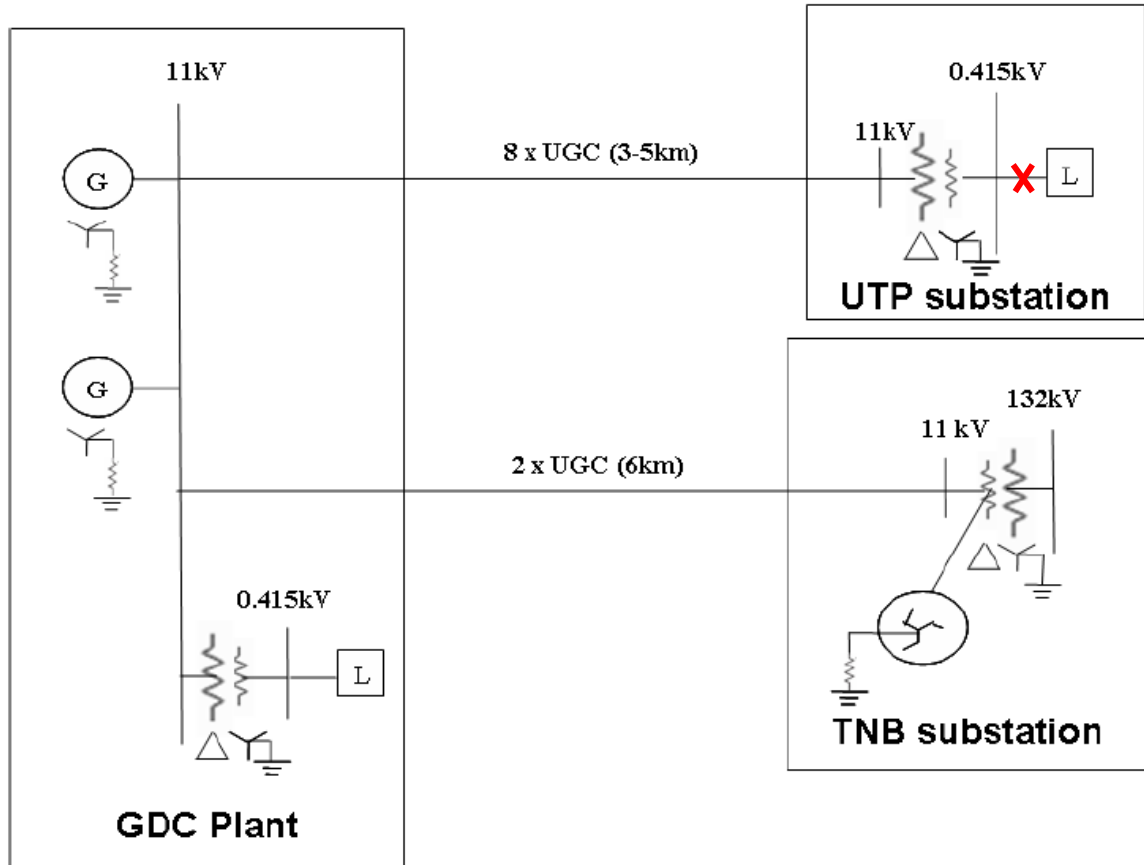
3.6.1.1 Meter Placement

The study focuses on the user-end of the distribution line, in which several harmonic issues had been encountered. Figure 3.2 shows a simple illustration of the UTP distribution network. It consists of two gas turbine generators located at the GDC plant that generates 11 kV and distributes along the 3-5 km distribution line before stepped down to 415 V, which supplies the offices, academic buildings and residential villages.

The bold 'X' as marked in the Figure 3.2 and 3.3 shows the location targeted to gather necessary data for proposed system training and development. Figure 3.3 is a single-line diagram of UTP distribution network, which shows a more detailed diagram of data logging location for the targeted distribution network. The primary location identified through student survey and repeated harmonics issue were recorded at student residential village 3, located in the centre of the students' accommodation area. It accommodates approximately 1200 students. Hence, the data logger was fitted at SSB V31 switchboard to record voltage, current, and harmonics behaviour in this particular student residential village. The sub-station distributes 240 V, 800/5A current at load-end.

3.6.1.2 Data Logger Tool

Raw data are gathered using Fluke 1750 Power Analyzer, which allows data logging for an intended period. The equipment measures voltages at each phase, and 5-Amp



current clamps used to gather phase currents from current transformer (CT).

Figure 3.4 GDC-UTP embedded distribution network

The algorithm is trained and tested using data from phase A (red); phase B, phase C and neutral line estimation can be done using a similar algorithm with sufficient training. Figure 3.4 show the instrument on-site, while logging data. The instrument was attached at each location's switchboard for 10-days.

The clarity of data recorded is assured by a hand-held digital clamp meter that enables instantaneous voltage and current readings. A comparison is made between measures shown on both meters before data logging are initiated.



Figure 3.5 Fluke 1750 power analyser logging data at SSB V31

3.6.1.3 Analysis of Data / Data Interpretation

Based on logged data at student residential village in UTP, the existence on harmonics can be seen from the event on the logged voltage plot. The surges on various random locations on the voltage waveform plot at Figure 3.5 prove the presence of disturbance in the line and calls for immediate attention to overcome the issue.

Let; fundamental frequency is 50Hz, harmonics data (multiples of the fundamental frequency) are recorded from the first-order, which is the fundamental order, up to 50th harmonics order. For instance, the third order harmonics is measured as;

$$3^{\text{rd}}\text{-order harmonics} = \text{Fundamental harmonics (50 Hz)} \times 3 = 150 \text{ Hz} \quad (3.1)$$

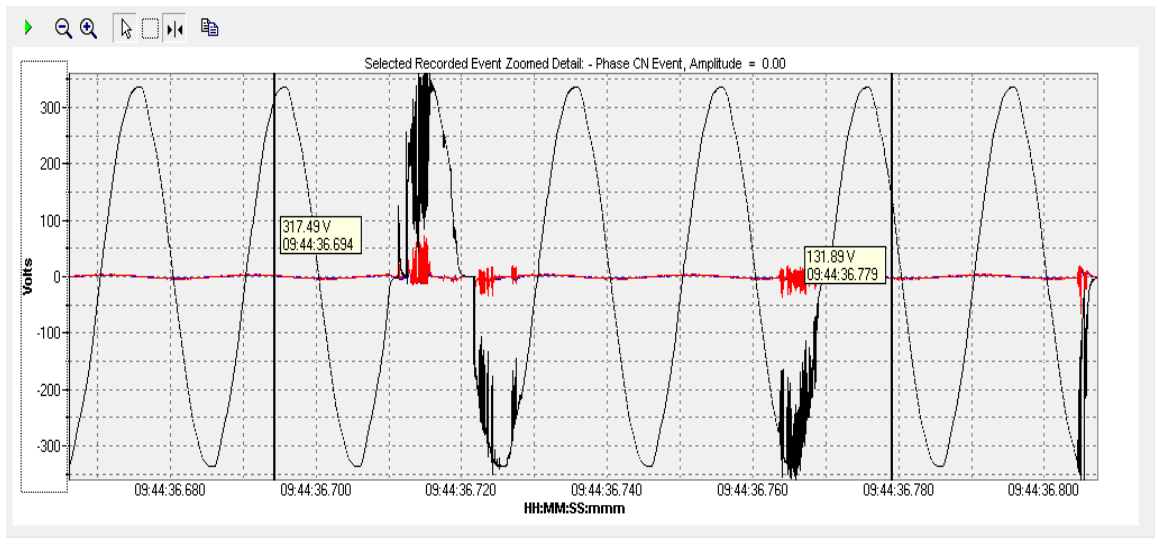


Figure 3.6 Voltage waveform recorded from Fluke Power Analyser at student residential village in UTP

The data shows significant decrease of harmonic voltages as the order increases. Table 3.1 shows the maximum recorded harmonic voltages in percentage of fundamental harmonic voltage from data logging site. It only shows till the 15th-order of harmonics since the following orders does not show significant harmonic voltages recorded and, therefore, can be ignored for this case.

Table 3.1 tabulates maximum harmonics voltage ($V_{h(max)}$) in percentage of the fundamental harmonic voltages. The first order shows almost 100% measurement as first order of harmonics records voltages at 50 Hz, which is the fundamental measure. The following harmonic orders show percentage of harmonic distortions. Based on gathered data, seventh-order harmonic records the highest distortion. Therefore, the proposed system is tailored to estimate and predict the seventh-order harmonic voltages (V_{h7}). It is important to identify the distorted harmonic orders, since the system proposed could only

Table 3.1 Percentage of fundamental harmonics voltage in Phase A

<i>Harmonics order</i>	$V_{h(max)} [\%]$
1	102.60
2	0.86
3	0.95
4	0.50
5	1.41
6	0.39
7	2.42
8	0.42
9	0.85
10	0.39
11	1.21
12	0.30
13	1.02
14	0.30
15	0.46

content a single order estimation and prediction. Similar systems need to be developed and trained in respective of different harmonic orders.

3.6.1.4 Data Segregation for Training, Validation, and Testing

Data were taken in percentage of fundamental harmonics. Sampling period of 3 seconds executes 3806 rows of data between 1.48 pm to 5.00 pm of the same day. This data is then divided into three sets; training data set, validation data set, and test data set. A ratio of 60:30:10 was proposed or in another word, 60% of data set for training, 30% for validation and 10% for test data set. Table 3.2 simplifies the mentioned data segregation according to logged data set;

Table 3.2 Data segregation for training, validation, and testing based on logged data

<i>Data Set</i>	<i>Percentage of total data set (%)</i>	<i>Data rows, m</i>
Training	60	2284
Validation	30	1142
Testing	10	380

In terms of MATLAB coding, the above data segregation are done as per MATLAB coding below. For estimation network;

```
% TRAINING DATA
pC = data(1:2283,1:2);
t = data(1:2283,4);
% VALIDATION DATA
pCV = data(2284:3425,1:2);
```

```

tV = data(2284:3425,4);
% TEST DATA
pCT = data(3426:3806,1:2);
tT = data(3426:3806,4);

```

where ‘pC’, ‘pCV’, and ‘pCT’ indicates input data for training, validation and testing respectively, whereas ‘t’, ‘tV’, and ‘tT’ refers to the targeted measures. For time-series prediction models, data segregation were done to fit accordingly;

```

% TRAINING DATA
p = data(1:1141,4);
t = data(1142:2282,4);
% VALIDATION DATA
pV = data(2283:2854,4);
tV = data(2855:3426,4);
% TEST DATA
pT = data(3427:3616,4);
tT = data(3617:3806,4);

```

where ‘p’, ‘pV’, and ‘pT’ indicates input data for training, validation and testing respectively, whereas ‘t’, ‘tV’, and ‘tT’ refers to the targeted measures. The ‘data’ referred in both set of MATLAB codes calls the collected measures from instrument logging, which is then saved in MATLAB work folder as ‘data.xls’.

3.6.2 Proposed System: Virtual Harmonic Analyser and Forecaster (V-HAF)

The main objective of this thesis is to demonstrate harmonics estimation based on RMS voltage and RMS current of the measurement point, and forecasting harmonics data for the next 24-hours. Therefore, two separate networks are proposed to execute the tasks individually. These networks form a system or ‘black box’.

While conventional techniques generally suggests data logging of preceding data, prior to forecasting, the proposed V-HAF system enables forecast of harmonics voltages using preceding fundamental measures. The main advantage of the proposed system is that it does not require the usage of a more expensive tool such as harmonic power analyser, but allows fundamental data logger to provide sufficient inputs. This indirectly reduces cost of instrument. This is further justified at the end of Chapter 4. The fundamental data gathered from instrument are then processed as in Figure 3.6.

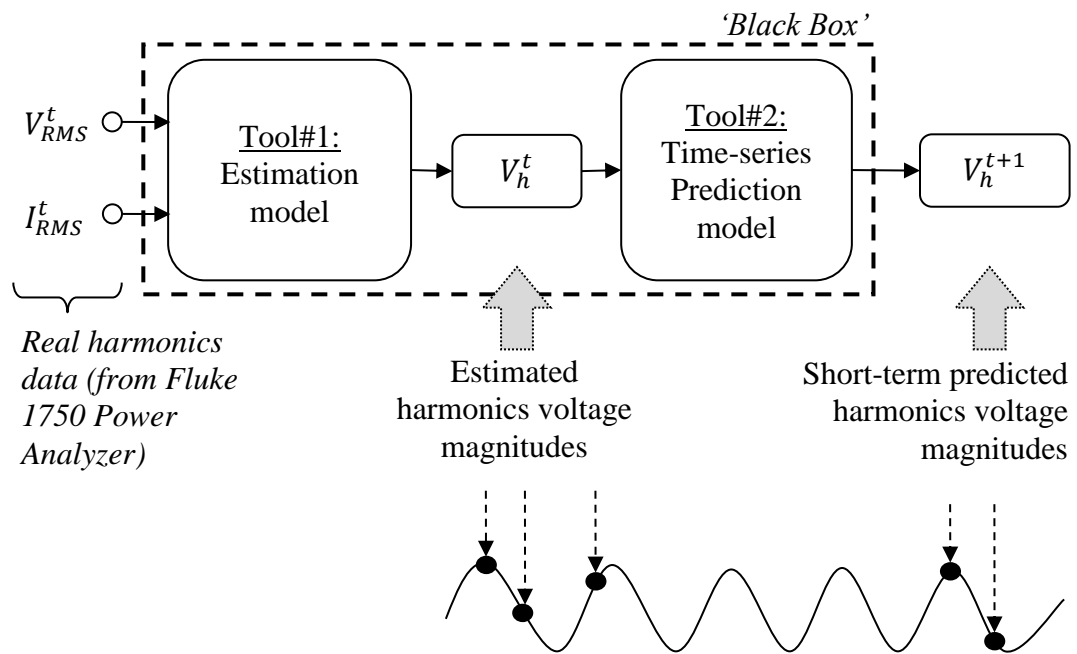


Figure 3.7 The overall proposed system which comprises estimation and time-series prediction models in a 'black box'

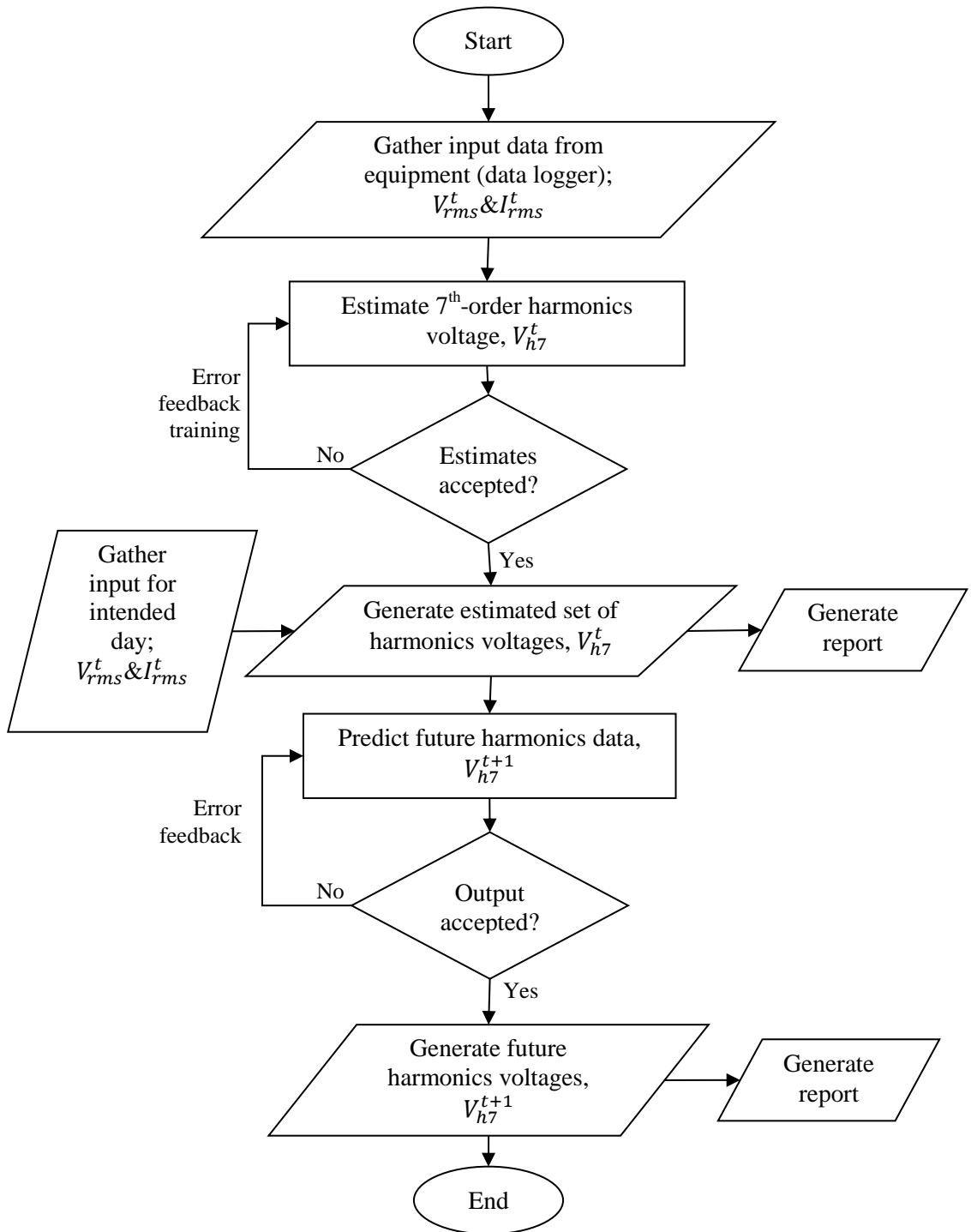


Figure 3.8 Proposed 'Black Box' systems operating flow-chart

Figure 3.6 shows the overall proposed system that feeds RMS voltage and RMS current from location and able to produce harmonics estimation for the same time period and predicts harmonics voltages for the next 24-hours. The ‘Black Box’ takes V-rms and I-rms recorded at targeted location and provides current and future harmonic voltages to cater the need of UTP’s distribution network for a reliable harmonic monitoring system. The first tool serves as an estimation model and second tool as short-term time series prediction model. The flow chart in Figure 3.7 below provides a better understanding on the system flow.

Both networks are neatly written in MATLAB M-file using build-in functions from MATLAB library and will be further discussed along with basic knowledge acquisition on the techniques proposed.

3.6.3 Feed-forward Neural Network for Harmonics Estimation

In harmonics studies, NN is one of the earliest tested AI techniques [78], and is still used in recent researches due to its adaptive nature and high approximation accuracy. Its recursive nature makes it possible to be used in real-time measurements. Figure 3.8 provides an insight on the network architecture for harmonics pseudo-measurement estimation at UTP distribution network using feed-forward neural network.

To begin with, parameter selection is done by multiple simulations using different sets of inputs to identify the best performing network. Once the appropriate inputs are identified, they would be fed into the harmonic pseudo-measurement estimation tool, in this case, neural networks. The network developed for this estimation purpose is a feed-forward neural network with back-propagation learning algorithm. Real harmonics data logged using the power analyser instrument will be utilized as the benchmark for the network training and error calculation. In general, network development of the estimation model will strictly abide to the following process flow-chart.

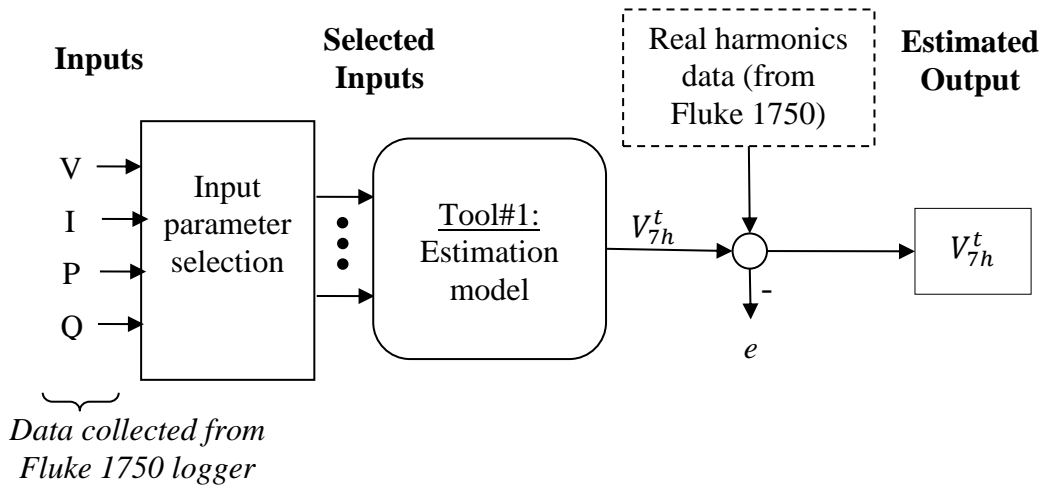


Figure 3.9 Overall process of harmonic pseudo-measurement estimation.

As illustrated in the flow chart in Figure 3.9, network inputs and targets are set; m -by- n matrix, where m is number of data rows and n is number of inputs/target. Once inputs determined, neural network parameters are set and designed to suit the problem and weights are trained to optimize the estimation using back-propagation training method.

3.6.3.1 Fundamentals of Feed-forward Neural Network

ANN is a concept adapted from the human brain system. In a human body, signals or ‘tasks’ are being carried by neurons. A typical neuron collects these signals through a host called *dendrites*, which then travels (spikes of electrical activity) along *axon*. Once the signal reaches its desired destiny, *synapse* converts it into electrical effect and induces reactions. Learning occurs when a neuron receives larger excitatory input than its inhibitory input and forces the neuron to change its effectiveness of the synapses [21]. Based on this knowledge acquisition from simple logical operations, ANN-based models in different fields were discovered.

ANN is a part and parcel of intelligent based system to distinctively improve the conventional computing techniques. The evolution of harmonics analysis techniques from conventional methods to ANN-based solutions clearly proves the statement above.

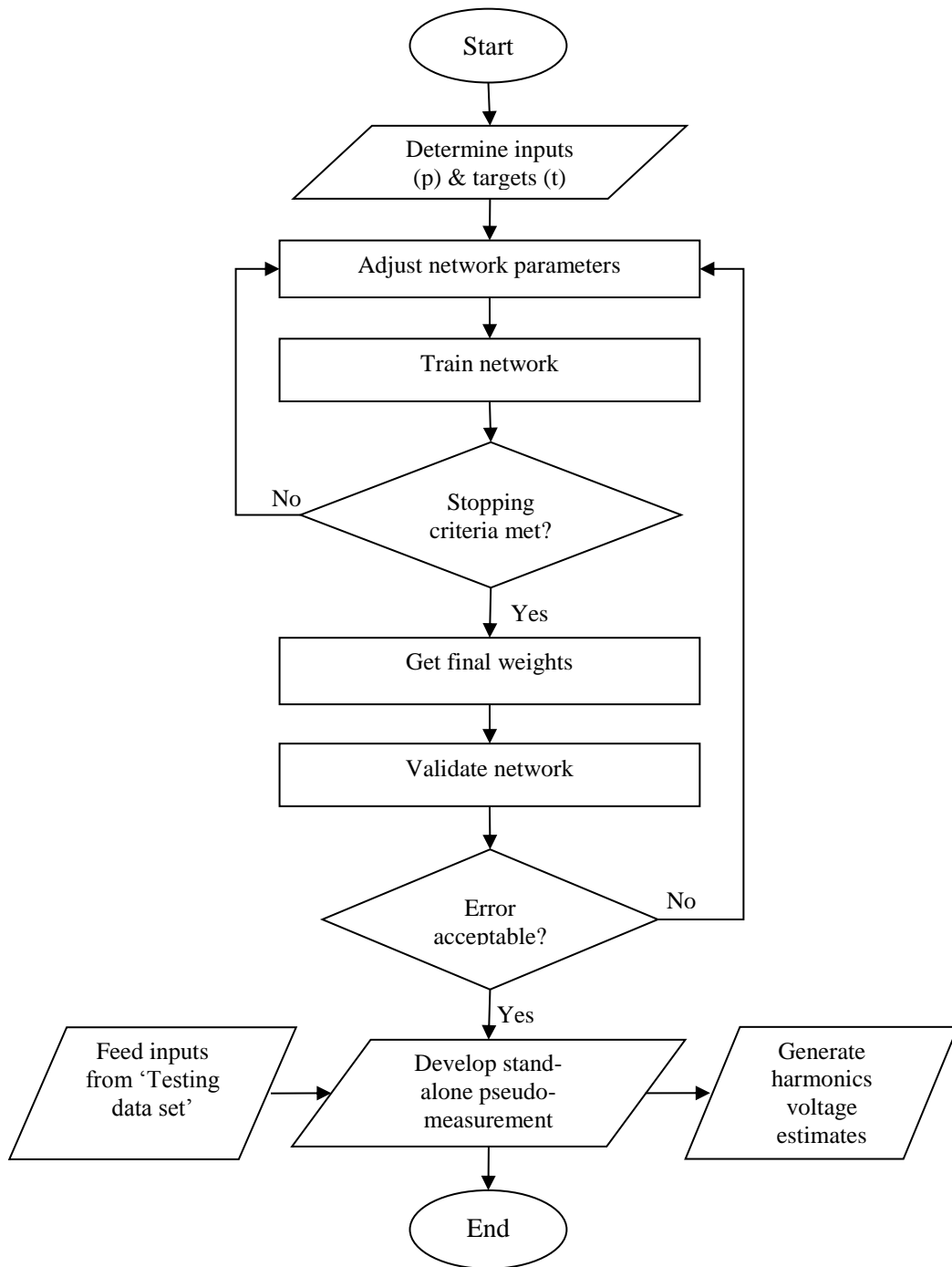


Figure 3.10 Proposed system flow-chart for estimation model

Similar to the neuron behaviour in a human body, ANN consists of neurons, while signals are passed through weighted links [52]. Figure 3.10 shows a graphical illustration of a typical architecture of a feed-forward ANN, which is proposed in this study.

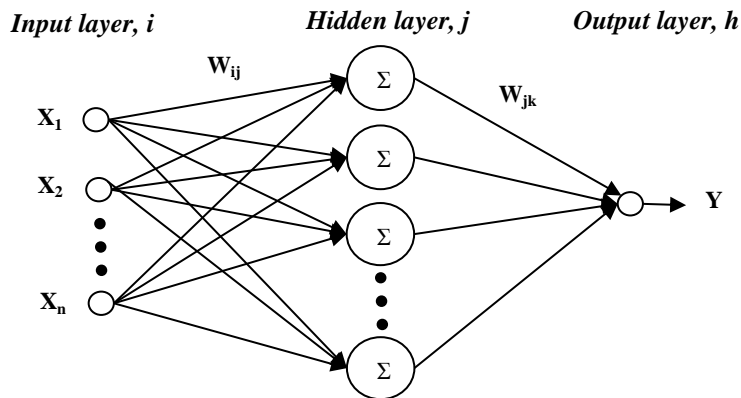


Figure 3.11 A typical architecture of a feed-forward neural network.

Three layers are seen in the ANN architecture as shown above; input layer (i), hidden layer (j), and output layer (h). Multilayer neural network is selected in this study due to the non-linearity behaviour of the observed system.

INPUT LAYER: Input layers neurons represent the data fed into the network, inputs of hidden layer neurons defined by the sum of weighted inputs, while weighted sum of outputs of the hidden layer neurons decides on the network output. This type of network is more often referred to as feed-forward network. An important application of the feed-forward neural network is pattern recognition; extracting and detecting trends that are too complex for classical computation or even for human observation. As discussed, the training data set contains 2,284 data samples or data rows, m .

Network inputs are determined by trial-and-error method where several combinations of input parameters were fed and tested for minimum error at simulation (estimation as close as possible to real data). Input set tested were;

- a) Set A: RMS voltages ONLY

- b) Set B: RMS currents ONLY
- c) Set C: RMS voltages and RMS currents (TWO parallel inputs)

The most advantageous set of inputs are determined by calculating the lowest mean square error with cross-validation technique. Cross-validation technique will be discussed further as this thesis writing progresses.

HIDDEN LAYER: The most important criteria to be determined in this layer is the number of neurons. For this, trial-and-error based technique is proposed. Another important parameter in a neural network structure is determining the activation functions. For the hidden layer, activation function chosen should introduce nonlinearity into the network. Considering the neural network is trained by back-propagation, the most advantageous activation function is a sigmoid function. Sigmoid function is easy to differentiate, which reduces computation burden [88].

Activation functions are employed to decide if the neuron either fires or does not fire. B. Karlik [89], in his paper, performed analysis of various activation functions in generalized multilayer perceptron (MLP) architectures of ANN. In an experimental comparison made between Bi-polar sigmoid, Uni-polar sigmoid, Tanh, Conic Section, and RBF; Tanh (hyperbolic tangent) function performs better recognition accuracy with an error of 0.002 that is 99% accuracy with 40 neurons at hidden layer. Therefore, this study suggests a combination of “Tanh-Tanh” activation functions for both neurons of hidden layer and output layer for good results. However, the real accuracy of these activation functions can differ with different applications and conditions in which the ANN is composed to cater. The following MATLAB plot in Figure 3.11 is a graphic of the hyperbolic tangent function for real values of its argument x over the domain $-5 \leq x \leq 5$.

For this purpose, the network is tested with two different sigmoid functions; hyperbolic tangent sigmoid transfer function (`'tansig'`) and logarithmic sigmoid transfer function (`'logsig'`). Hyperbolic tangent sigmoid transfer function returns squashed elements between -1 and 1, while the latter transfer function returns squashed elements between 0 and 1. For output layer, where targets (harmonics voltage

magnitudes) are positive values and have no known upper bound, a pure linear function is sufficient.

In this study, network weights initialization is made random, while activation functions are pre-determined, as mentioned above.

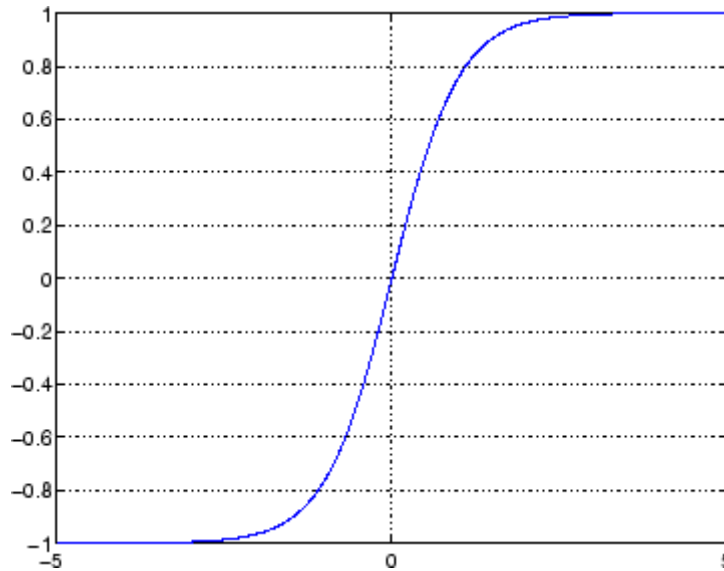


Figure 3.12 Hyperbolic Tangent Function

OUTPUTLAYER: The outputs solely depend on the firing ability of the network; firing rule determines how one calculates whether a neuron should fire for any input pattern. On the other hand, to provide a good firing ability, the hidden layers are equipped with computational neurons which detect the neuron weights and adjust it at each iteration to find the best fit at output.

Mathematically, general ANN output can be simply written as;

$$Y = \varphi\left(\sum_{j=1}^n W_j x_j + b\right) \quad (3.1)$$

where x_n is n number of inputs, W is weight matrix, b is the bias value, often 1, and φ is the activation function [21]. The desired output is harmonic voltage measures that are close as possible to the actual data gathered from the power analyser equipment; with m -by-1 matrix.

The evolved models need to be trained to accomplish realistic targets. Thus, the selection of training algorithm and parameters needs to be explicitly understood. Generally, ANN can be categorized to supervised and unsupervised learning network. Supervised training uses external teacher, while paradigms of unsupervised learning are Hebbian learning and competitive learning; in which learning is based on only local information [87]. The following network development issues or points need to be clearly understood to enable good training command: learning rate, momentum factor, local and global minima of the network.

Hence, in forward pass, the outputs and the errors at the outputs are calculated. Whereas in backward pass, the output and hidden unit errors are used to alter the weights on the output and hidden units respectively. In short, the estimation accuracy is based on the efficiency of training; error feedback and weight adjustments.

3.6.3.2 Back-propagation Training and Control Parameters

Back-propagation technique, or also called as error feedback training technique, can be simply described as illustrated in Figure 3.12. The block diagram in Figure 3.10 shows approximation outputs obtained from a feed forward network are compared to the set of targeted values. The difference or error obtained would be feed back to the training algorithm and this process is repeated till training goal reached. The goal of back-propagation algorithm is to find a new set of weights and biases that generate outputs closer to the actual target values. The process of finding the best weights are often referred to as ‘training’. As long as training goal has not been reached, back-propagation training continues.

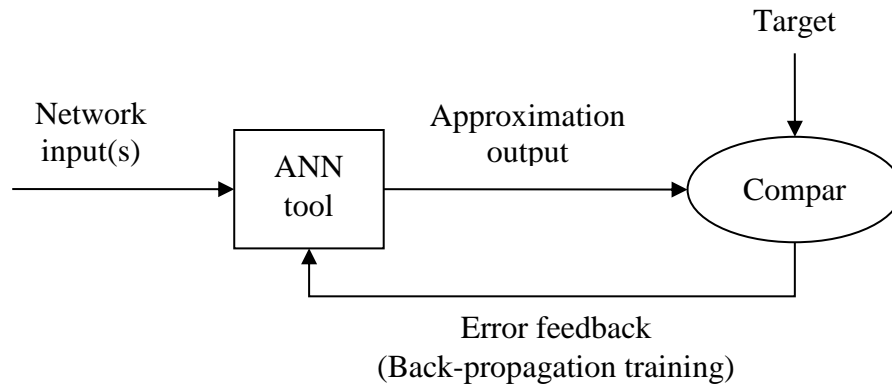


Figure 3.13 A simple block diagram of ANN structure with back-propagation training

Foremost, suitable back-propagation techniques need to be identified and tested. This is because one network cannot be suited for different problem background. Therefore, proper problem identification is important to determine the best solution to be proposed. The system as proposed will be fitted at the user-end, in which is a low-voltage distribution line. There are various function optimization techniques to provide numerical solution to a problem of minimizing a function.

Similar to finding suitable number of neurons at hidden layer, there is no direct law or formula to determine the right training function to be used. A trial-and-error method can be used in this case. The different possibility can be carried out and the best will be chosen. For example the fastest training function is generally ‘trainlm’, and it is the default training function for feed-forward neural network. ‘trainlm’ or Levenberg-Marquardt (LM) is a well-known non-linear optimization algorithm. Application of LM back-propagation method in power system dates back to as early as 1980 [88], whereas the technique initially was found back in 1963 [89]. In power systems, LMBP technique is widely used for various purposes; i.e. peak load forecasting [90], reducing harmonic distortion in supply system [91], and estimation of harmonic current produced by Grid-connected PV system [92]. Is it easily chosen over GD as LM shows faster performance. It has been popularly used due to its good accuracy and compromise between the speed of Newton method and stability of the steepest descent method [93]. Similar to quasi-

Newton method, LM was designed to approach second order training speed without having to compute Hessian matrix.

The quasi-Newton method, 'trainbfg', is also considerably fast. These methods tend to be less efficient for large networks (with thousands of weights), since they require more memory and more computation time for these cases [96]. Also, 'trainlm' performs better on function fitting (nonlinear regression) problems than on pattern recognition problems (Matlab, 2010).

STOPPING CRITERIA: The training stops if any of the stopping criteria met; number of iteration reaches maximum epochs or performance function meets the goal. The effect that each input has at decision making is dependent on the weight of the particular input.

Training stops when any of these conditions occur:

- 1) The maximum number of epochs (repetitions) is reached.
- 2) The maximum amount of time has been exceeded.
- 3) Performance has been minimized to the goal.
- 4) The performance gradient falls below mingrad.
- 5) mu exceeds mu_max.
- 6) Validation performance has increase more than max_fail times since the last time it decreased (when using validation).

Once training goal reached, the applicability of the trained algorithm is then evaluated based on mean square error (MSE). To enable direct comparison to other researches, MSE is often being used to evaluate the neural network's performance [95]. MSE is computed by taking the differences between the targets and actual output, squaring the errors and averaging over all the samples [96], or can be written mathematically as;

$$MSE = \frac{1}{n} \left(\sum_{j=1}^n (\hat{\theta}_j - \theta_j)^2 \right) \quad (3.2)$$

where θ is real vector and to estimate it, we use an estimator with a function of our observation $\hat{\theta}$, which is a function of n random variables. Number of neurons in hidden

layer is adjusted by trial and error to obtain the best mean squared error (MSE). To reduce error at validation sample estimation, cross-validation approach is proposed in this study to train the networks efficiently; algorithm is run on the training set until MSE starts to decrease on the validation set, which usually occurs long before the minimum MSE is reached on the training set.

The network is acceptable when MSE is sufficiently small at validation ; training algorithms iteratively adjust its parameters in the direction of the negative gradient of mean squared error. Simulation errors are evaluated in MSE due to its continuous error metric, where errors will be summed over the validation set, and then normalized by the size of validation set.

3.6.4 Radial Basis Function for Harmonic Time-Series Prediction

Time-series prediction or forecast means to estimate or calculate in advance. This is essential in power systems field as preventive measures to secure the power quality can be planned ahead before unnecessary losses occur. The second algorithm in the V-HAF system aims to demonstrate time series prediction of harmonics pseudo-measurement based on values estimated using ANN. It is developed for short-time forecasting, in which the model is only able to forecast harmonic voltage measure for the next 24-hours. To simplify, the proposed forecasting algorithm is as Figure 3.13.

It is seen in figure above that the output from Tool #1 or also the estimated harmonic voltages will be fed as inputs into the time-series prediction tool to forecast future harmonic voltages. Similar to the previous algorithm, real harmonics data logged using the power analyser instrument will be utilized as the benchmark for the network training and error calculation. This, however, only applies to the network training. A well trained network can work independently.

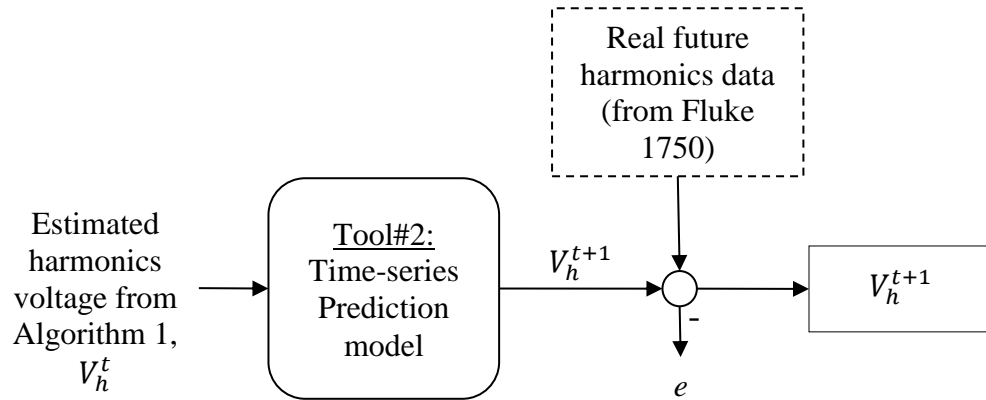


Figure 3.14 Overall process of time-series prediction of harmonic pseudo-measurement.

For time-series prediction, the method proposed by Chien-Cheng Lee [76] in his paper will be adopted. He had proven that an RBF network, trained by contaminated training data with fifty percent of the outliers performs better than an ordinary back-propagation neural network even though no outliers included. Flow chart in Figure 3.14 gives an understanding on a typical RBF network formation using MATLAB software.

For reliable and more accurate measures that are closer to the actual values, the proposed tool is trained with data gathered from the power analyser instrument. Since error from instrument is neglected, measured values are assumed to be actual values. Once inputs are determined, neural network parameters are set and designed to suit the problem and weights are trained to optimize the estimation using back-propagation training method.

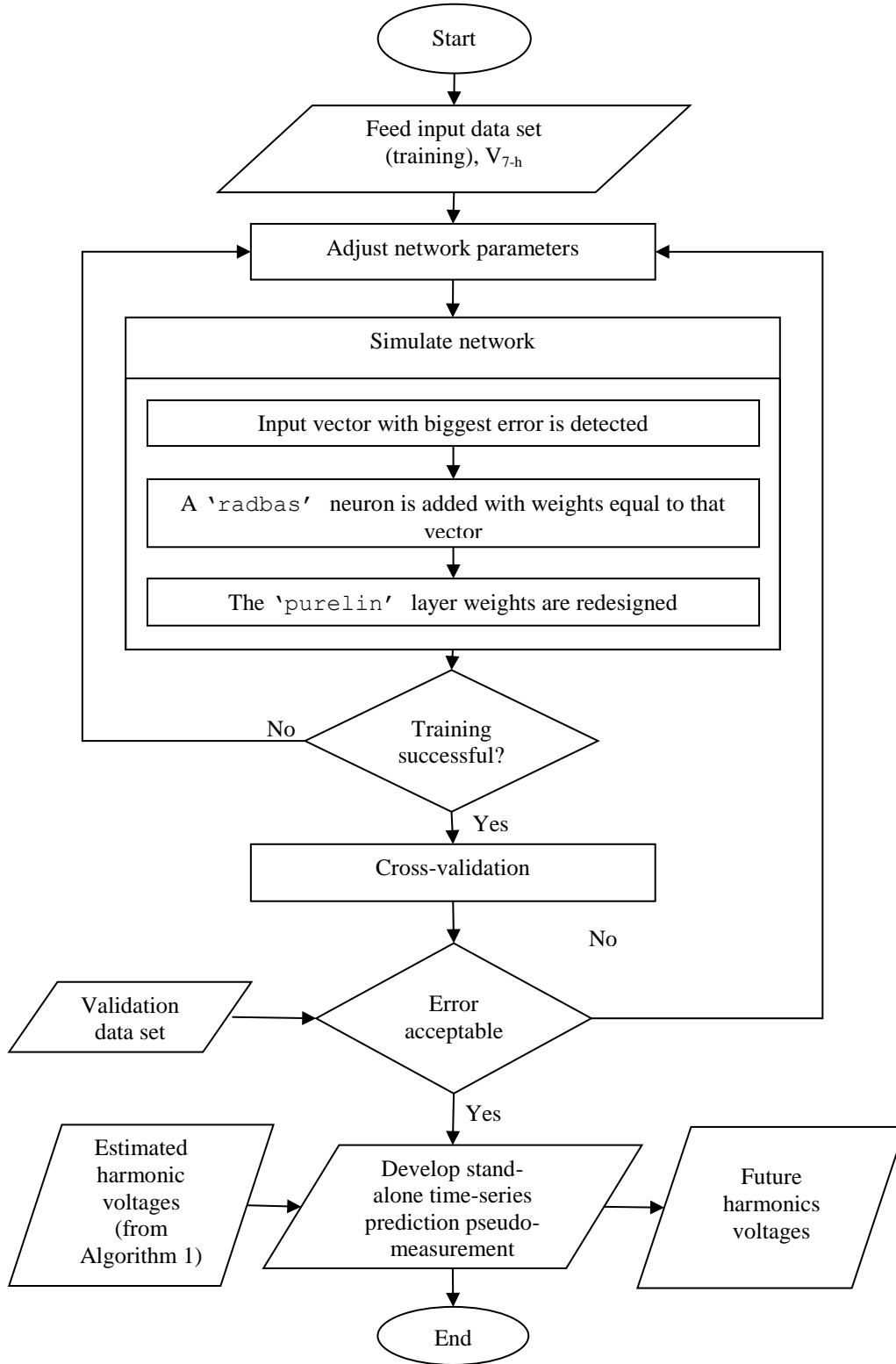


Figure 3.15 Proposed system flow-chart for time-series prediction model

3.6.4.1 Fundamentals of Radial Basis Function

Radial Basis Function (RBF) is a type of commonly used technique for time series modelling and pattern classification problems [97]. Similar to the feed-forward neural network architecture, an RBF network consist of input, hidden, and output layers. Although NN can involve more than one hidden layer, RBF network is limited to only a single layer of hidden neurons. Figure 3.15 illustrates a time-series RBF system, with n number of inputs (x_1, x_2, \dots, x_n) and output, y .

The network is composed using MATLAB M-file, which offers reliable build-in functions in its library; 'newrb', which creates a two-layer RBF network.

INPUT LAYER: The network input is m -by-1 matrix, where m is the number of data rows. Similar to estimation model, the training data set proposed contains 60% of the whole data collected; 2,284 data samples. However, it is important to note that the training data set is divided in 50:50 ratios to serve as inputs and targets respectively. Number of inputs, n is 1,142 and set to forecast the following 1,142 data rows.

HIDDEN LAYER: The first layer has 'radbas' neurons, and calculates its weighted inputs with `dist`, and its net input with 'netprod'. Typical shape of a radial basis transfer function is as in Figure 3.16. However, in an RBF network, only one hidden layer is used with each node having a 'centre'. These centres are compared with the network input vector to find a symmetrical response; also referred to as Euclidean distance [98].

At this step, a trial-and-error method need to be implemented to find the fairly appropriate number of neurons that gives the best network performance with validation data set.

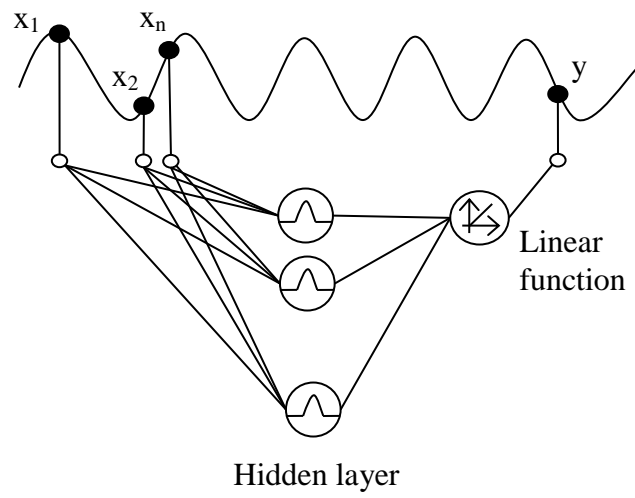


Figure 3.16 A simple time-series RBF topology

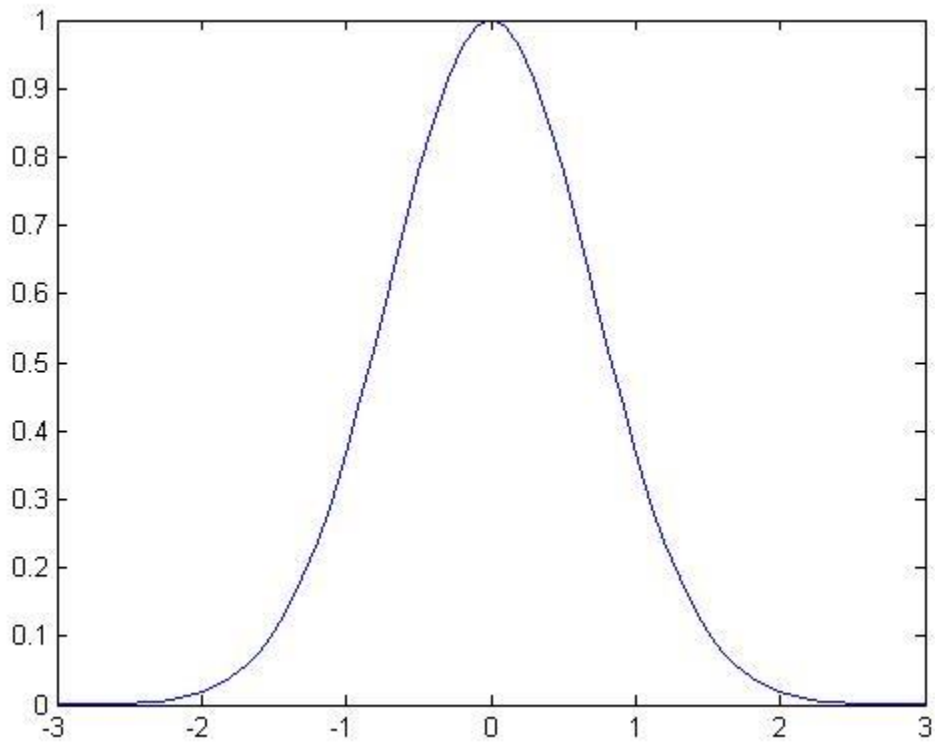


Figure 3.17 Typical shape of a radial basis function

OUTPUT LAYER: The second layer has 'purelin' neurons, and calculates its weighted input with 'dotprod' and its net inputs with 'netsum'. The output of each neuron in the hidden layer is computed with the Euclidean distance, using a nonlinear function. A commonly used nonlinear function here is the Gaussian function. Gaussian function decreases the response monotonically with distance from the central point. With the output of each neuron, the network output can be mathematically describes as follows;

$$Y = \sum_{k=1}^n w_k \phi_k \quad (3.5)$$

where n is the number of neurons in the hidden layer, w is the weight vector between hidden and output layers, and ϕ_k is the basis function of the network.

Both layers have biases. Initially the 'radbas' layer has no neurons. The complete MATLAB coding for prediction model using RBF network is attached as Appendix B.

3.6.4.2 Network Training

In order to forecast harmonics pseudo-measurement, an RBF network is trained with raw harmonics data gathered using Fluke 1750 Power Analyzer. A well trained algorithm is then used as a tool to forecast harmonics voltages based on estimated harmonic voltages.

The network training is similar to an ANN back-propagation technique, where, the steepest gradient descent learning rule continuously adjusts the network parameters until stopping criteria or error target is reached; until the network's mean squared error falls below goal or the maximum number of neurons are reached. The main issue in RBF modelling is to determine an appropriate number of basis functions to achieve a good bias-variance compromise [99]. In short, the following steps are repeated in the MATLAB simulation process until the stopping criteria met;

- 1) Network simulated with random weights

- 2) Identify input vector with greatest error
- 3) A neuron, or also referred as basic function, is then added with weights equal to that vector
- 4) Output layers weights redesigned to minimize network performance error.

However, the RBF 'spread' value is determined by trial-and-error method. Every trained network is evaluated by feeding a test data set and the forecast is compared to the actual data set obtained from instrument. The 'spread' is network parameter that controls the smoothness of its function approximation. Repeated simulations were carried out to find the best 'spread' value. Training is considered complete when the trained network is able to process a new set of data with minimum error.

The network performance is evaluated using mean absolute error (MAE). MAE is a network performance function. Unlike the back-propagation training algorithm, which attempts to minimise the MSE, MAE is used to measure accuracy of forecasts. It is a common measure of forecast error in time-series analysis that corrects the 'cancelling out' effects by averaging the absolute value of the errors;

$$MAE = \frac{1}{n} \sum_{i=1}^n |f_i - y_i| \quad (3.6)$$

where f_i is the predicted value, y_i is the actual measures and n is the number of variables.

To determine how well the estimation and time-series prediction values really represented the actual data set, a simple regression is proposed. The correlation coefficient, r , can be formulated as below;

$$r = \frac{n \sum ty - (\sum t)(\sum y)}{\sqrt{(n \sum t^2 - (\sum t)^2) \cdot \sqrt{n \sum y^2 - (\sum y)^2}}} \quad (3.7)$$

where n is the number of data sets, t is the targeted data set or the actual measures from instrument logging, and y is the harmonic voltage output from respective intelligent techniques used. The value of r is expected to be in $-1 \leq r \leq +1$ range to show a good correlation between the actual and outputs generated from the intelligent techniques. A

correlation greater than 0.8 is generally described as strong, whereas a correlation below 0.5 can be considered as weak.

3.7 Comparative Study Between V-HAF and NARX Forecast

A system that integrates TWO separate intelligence methods arise questions on the system's dependability and error tolerance. Hence, the performance of the proposed system is compared with a time-series prediction method or a typical system. A typical system here is defined as a system that feeds x^t to generate x^{t+1} . Hence, for this purpose, a Non-linear Auto-Regressive with eXogenous (NARX) dynamic recurrent neural network is proposed. This approach has been verified in a recent research in 2008, to predict chaotic time-series and proven to achieve a correlation coefficient estimated for the original and generated (1000 points) time series close to 1. Figure 3.17 further illustrates the proposed comparative study between V-HAF system and NARX time-series prediction.

The network, or simply known as NARX, is an important class of discrete-time non-linear system. It is simply an architectural approach of recurrent neural network (RNN) with embedded memory, which is proven to have the potential to capture the dynamics of nonlinear dynamic system [100].

Besides RNN, a NARX model can be implemented in various approaches. A simple approach that implements NARX technique is the classic feed-forward neural network with an embedded memory. Figure 3.1 illustrates a typical NARX model tapped with delay line at input.

A distinguished attribute of the NARX model is well illustrated in Figure 3.14, where input is usually referred as a "time window" since it only provides limited reflection on part of the series;

$$y(t) = f(u(t - D_u), \dots, u(t - 1), u(t), y(t - D_y), \dots, y(t - 1)) \quad (3.7)$$

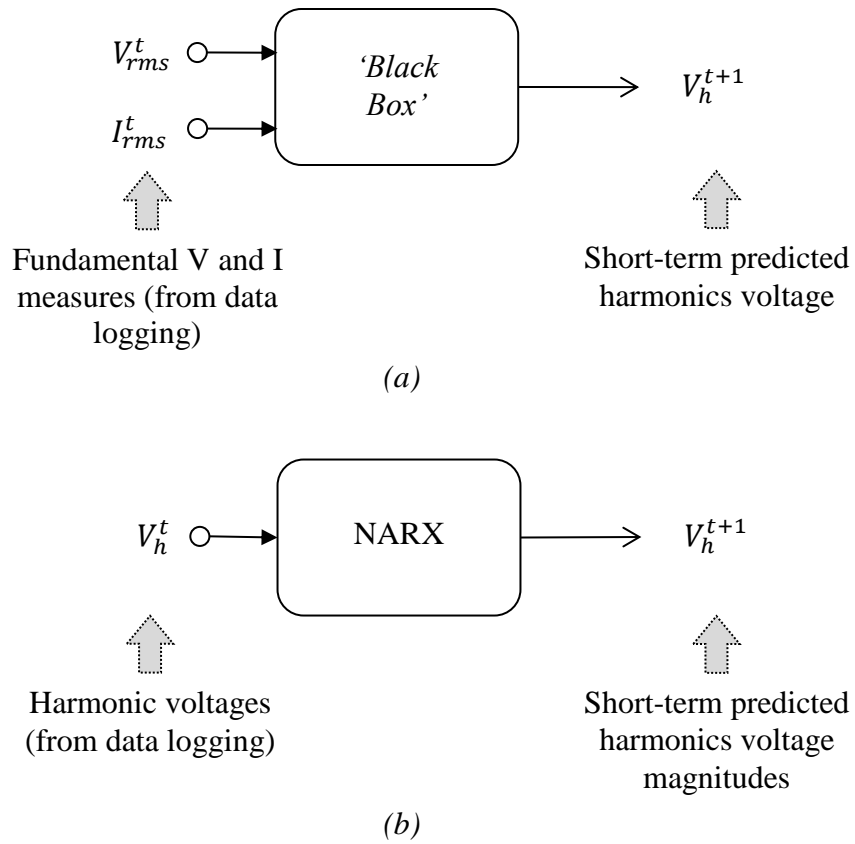


Figure 3.18 Illustration of (a) proposed V-HAF system, and (b) NARX system.

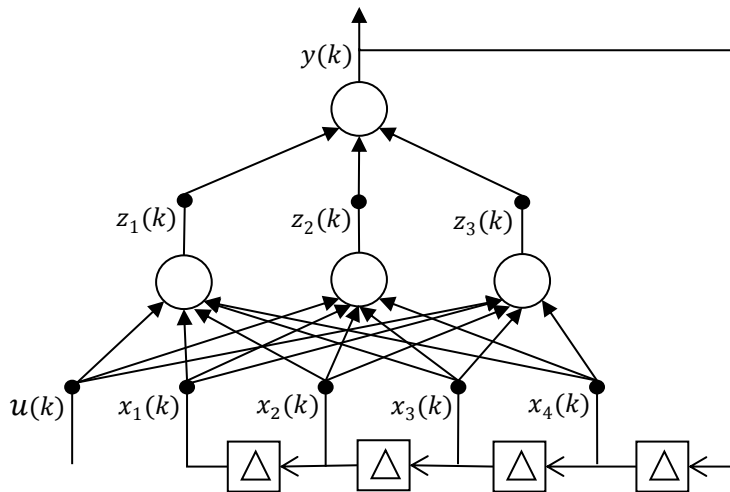


Figure 3.19 NARX network architecture with four output delays

where $u(t)$ and $y(t)$ represents input and output respectively, at time t , D_u and D_y are the input and output order, and f nonlinear function [101]. The advantage this network carries is that the embedded memory can help to speed up propagation of gradient information, and hence help to reduce the effect of vanishing gradient.

The NARX system is trained by 1142 sets of sample data as proposed to train the RBF network in Section 3.5.4.1. For comparative study, both V-HAF and NARX system will be evaluated based on error produced when simulated using test data set. The simulation execution times for both systems are measured by using ‘*tic*’ and ‘*toc*’ MATLAB function. The execution time of the codes that embodied by these two functions are measured in unit of second. The results of the simulation are tabulated in Chapter 4.

The NARX model is trained until best performance was obtained. To test and compare this technique against the proposed system, test data set is used. A total data row of 380 rows of data used as test data set, which yields 190 rows of input set and another 190 rows of target. Whereas, fundamental RMS voltage and current from the test data set will be used as input for the developed V-HAF system and both simulation results will be compared in terms of time-series prediction outputs, relative to the raw data. This enables direct comparison to be made on the time-series prediction error, correlation coefficient and computational time in seconds. To compare between methods, mean absolute percentage error (MAPE) is proposed since it does not depend on the series’ magnitude or unit of measurement, and can be averaged across series and can be used for comparing methods. MAPE can be formulated as below;

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{t_i - y_i}{t_i} \right| \times 100 \quad (3.8)$$

where t_i is the actual harmonic measures, y_i is the network outputs and n is the number of data sets. A MAPE of below 5% is considered highly accurate [102].

3.8 Summary of chapter

This chapter explains in detail on the proposed system to resolve harmonics issues faced in UTP distribution network. A prior understanding of the approximation tool is vital before evaluating the best fit intelligent system method for the problem. Chapter 3 carefully explains on the method and parameter selection for proposed models. The complete system is presented and a comparative study suggested evaluating the proposed system.

The research, however, concentrates only on a residential village that is experiencing repeated power issues. A ‘Black Box’ is proposed to overcome the main issue identified in this thesis; excessive maintenance cost that occurs recently at UTP distribution due to poor network quality surveillances.

The novelty of this research lies on the proposed solution or system to overcome the harmonic issues in UTP distribution network. No such efforts have been taken or put in practise before to monitor UTP distribution network. Current solution for the power issues experienced is far too costly to be implemented frequently; inviting third party (GTS) to provide a complete quality observation and report on affected areas. The proposed stand-alone algorithms are hassle-free and user-friendly too, as it would not require a third-party’s expertise for handling.

Therefore, the ‘Black Box’ or V-HAF as proposed, is tailored to fit the purpose of developing a reliable harmonics monitoring system that not only provides complete monitoring of harmonic fluctuations at UTP distribution line, but also expends the usage of the currently available power analyser. The advantage of the proposed system is that it requires only a fundamental (RMS voltage and RMS current) data logging in order to estimate and forecast harmonics voltages as accurate as a power analyzer instrument.

In the next chapter, the precision of the algorithms and their ability would be tested and verified, in order to support the proposed system’s dependability. The proposed algorithms will also be compared to other selected researches for clarification.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

Simulation results of each algorithm in the ‘Black Box’ system, or referred as V-HAF system, are presented individually using MATLAB programming tool as in Chapter 3. These results are tabulated for best interpretation and necessary plot are inserted in this chapter in attempt to visualize the simulation results. Three sets of simulation results have been presented accordingly in this chapter. The comparative performance between the proposed V-HAF system and NARX forecast method is analyzed in terms of forecast accuracy. At the end of chapter, advantages and disadvantages of proposed system against existing systems and approaches have been evaluated and compared.

4.2 V-HAF Simulation Results

First of all, it is important to note that the proposed system are trained and developed based on assumption that harmonic measures recorded using the instrument are error-free. Therefore, the efficiency of proposed technique would be compared to the actual measures from Fluke 1750 Power Analyzer. Simulation of the proposed V-HAF system is shown and discussed in two parts to present the estimation and time-series prediction model respectively, before conducting a complete demonstration of the system using test data set.

4.2.1 Part 1: Simulation Results for Tool#1 - Short-Term Estimation using Feed-forward Neural Network with LM Back-propagation

To ensure optimum performance of the network, appropriate parameter adjustments need to be identified. Table 4.1 show simulation summary on trial-and-error based method to find best-fit network parameters for neural network with LM back-propagation. Three set of inputs are tested, as discussed in Chapter 3 previously. Amongst the three sets, Set B simulations show the highest error, ranging from 1.0578 to 1.3086. This is due to the usage of current (Ampere) data, which is not consistent and fluctuates in a more uneven manner than the voltage measures. Hence, Set A with voltage measures as input shows a more accurate estimation. However, the results show that Set C, which consists of TWO parallel inputs, records least estimation mean square error at cross-validation. It is observed that each node at the input layer typically represents a single attribute that may affect the estimation.

Figure 4.1 shows network training performance versus training goal that was set as 0.023 SSE. The intersection of these plots marks the convergence of the network and training stops as stopping criteria met. The network training using training data set converged in 7 iterations, with goal achieved at 0.022917 SSE.

Table 4.2 shows a quick comparison of estimation accuracy and number of iteration between the classical NN with GD back-propagation and the proposed estimation technique for demonstration in this study.

The system performs better estimation using LM training method, compared to the standard GD method integrated with feed-forward neural network in MATLAB programming tool. This evaluation is important as not to overlook the performance of LM, which promises a better result based on literature. Several trial-and-error simulations using GD training method leads to it best fit result, in which the network shows near convergence or at goal 0.029 SSE, as shown in Figure 4.2 below. The back-propagation training algorithm attempts to minimise the MSE.

Table 4.1 Simulation summary on hidden layer adjustment for NN with LM back-propagation

Num. of neurons at hidden layer	Hidden layer activation function, ϕ	Error (MSE)		
		SET A	SET B	SET C
10	Tansig	0.9101	1.0578	0.9371
	Logsig	0.7952	min. gradient reached	1.0031
20	Tansig	0.652	1.1732	0.0301
	Logsig	0.6713	min. gradient reached	0.0917
30	Tansig	1.5078	1.2549	0.8455
	Logsig	0.9469	min. gradient reached	1.0240
50	Tansig	0.9982	1.2548	1.0266
	Logsig	1.0891	min. gradient reached	0.0963
100	Tansig	0.9163	1.3086	0.1160
	Logsig	1.1664	min. gradient reached	0.9816

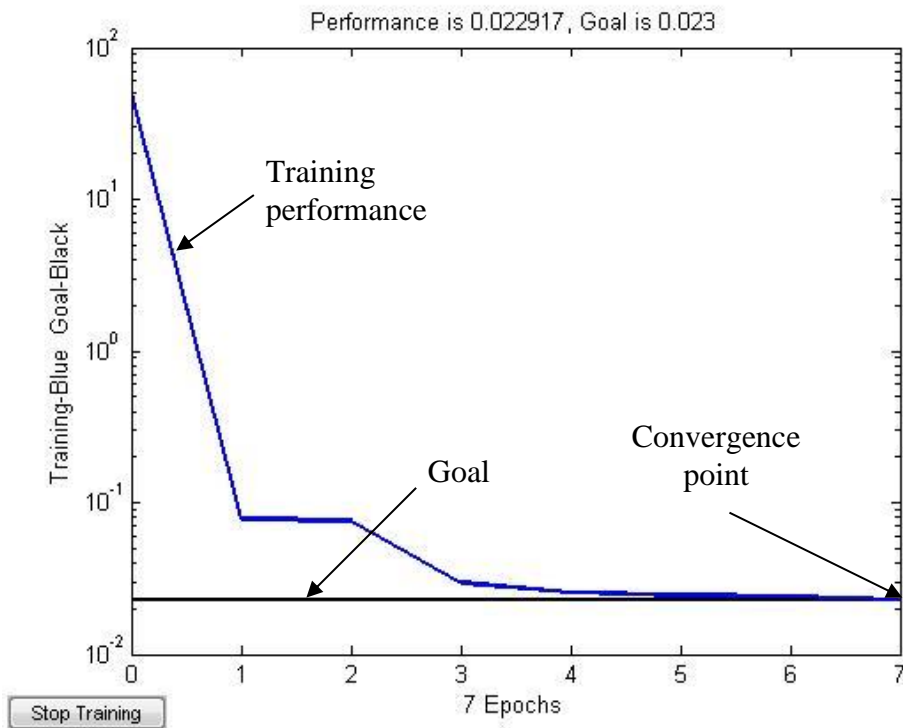


Figure 4.1 Network training performance for NN with LM back-propagation

Table 4.2 Summary of estimation network comparison

Back-propagation Method	MSE (%)	Number of iteration(s)
Gradient Descent (GD)	3.7402	> 100
Levenberg-Marquardt (LM)	0.0301	7

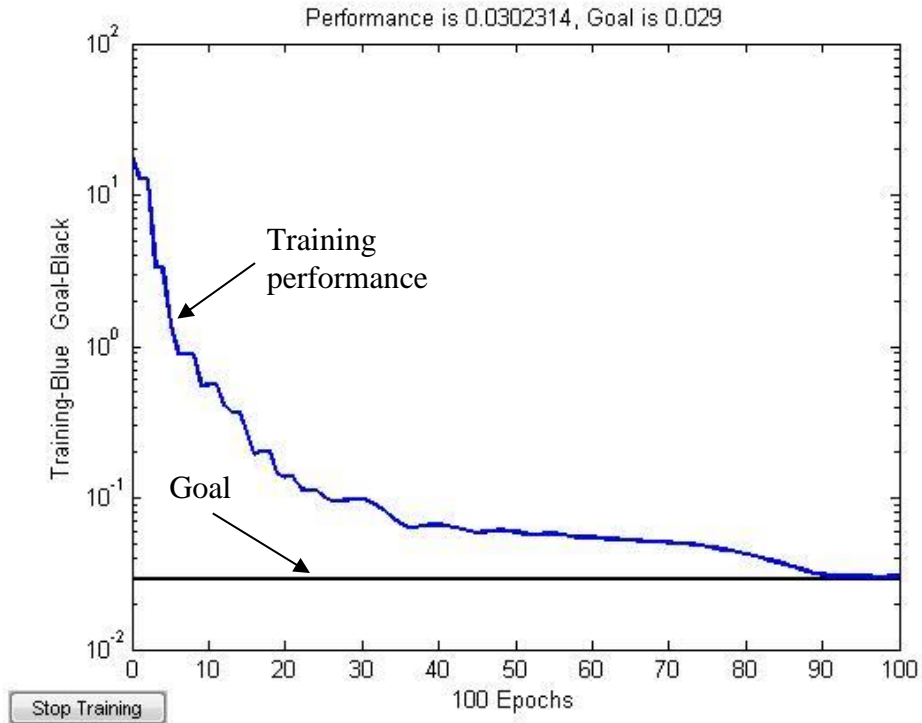


Figure 4.2 Network performances for NN with GD back-propagation

Hypothesis is proven true as GD training takes longer time to converge compared to LM method and performs poor estimation. This shows that the quadratic approximation of error function is reasonable with LM training. The network training could find proper step size for each direction in order to display convergence very fast. If the error function has a quadratic surface, it can converge directly in the first iteration. The LM algorithm blends the steepest descent method and Gauss-Newton algorithm, in which it exhibits the speed advantage of Gauss-Newton algorithm and the stability of the steepest descent method.

Due to NN behavior which yields different results at every simulation, multiple simulations were carried out using the chosen estimation network. Table 4.3 tabulates 15 simulation trials with error at cross-validation used as the comparison measure to determine the least error producing network before converting into stand-alone simulation network.

Table 4.3 Multiple simulation error summary

Trial(s)	Error at cross-validation (MSE)
1	0.0301
2	0.0701
3	0.0098
4	0.1710
5	0.0103
6	0.0027
7	0.0230
8	0.0067
9	0.0931
10	0.0080
11	1.302
12	0.0207
13	2.186
14	0.0111
15	1.009

Hence, the best-fit estimation model with MSE of 0.0027 at cross-validation is determined from multiple trainings and network parameters are as presented in Table 4.3. The parameters are specifically designed for feed-forward neural network using LM back-propagation. By running several tests, as shown in Table 4.1 and 4.3, with learning rate of 0.3 and 0.2 momentums, ‘tansig’ activation function at hidden layer and 20 neurons at hidden layer are seen to produce network with least MSE of validation simulation. Table 4.4 summarizes the network parameter for estimation model as proposed.

Table 4.4 Parameters for proposed estimation model

Parameters	Value(s)
Input(s)	i. RMS voltages ii. RMS currents
Num. of neurons at hidden layer	20
Activation function at hidden layer	Tangent sigmoid
Activation function at output layer	Linear
Training method (back-propagation)	Levenberg-Marquardt (LM)
Epoch(s)	7
Goal	0.023
Learning rate	0.3
Momentum	0.2

The complete MATLAB coding for estimation model using feed-forward neural network with Levenberg-Marquardt back-propagation is attached as Appendix B. To visualize the quality of the developed network, the estimation at cross-validation and error evaluations are presented below. Figure 4.3 shows the estimated harmonic voltages at cross-validation and error plot which indicates the difference between estimation and actual value measured using power analyzer instrument.

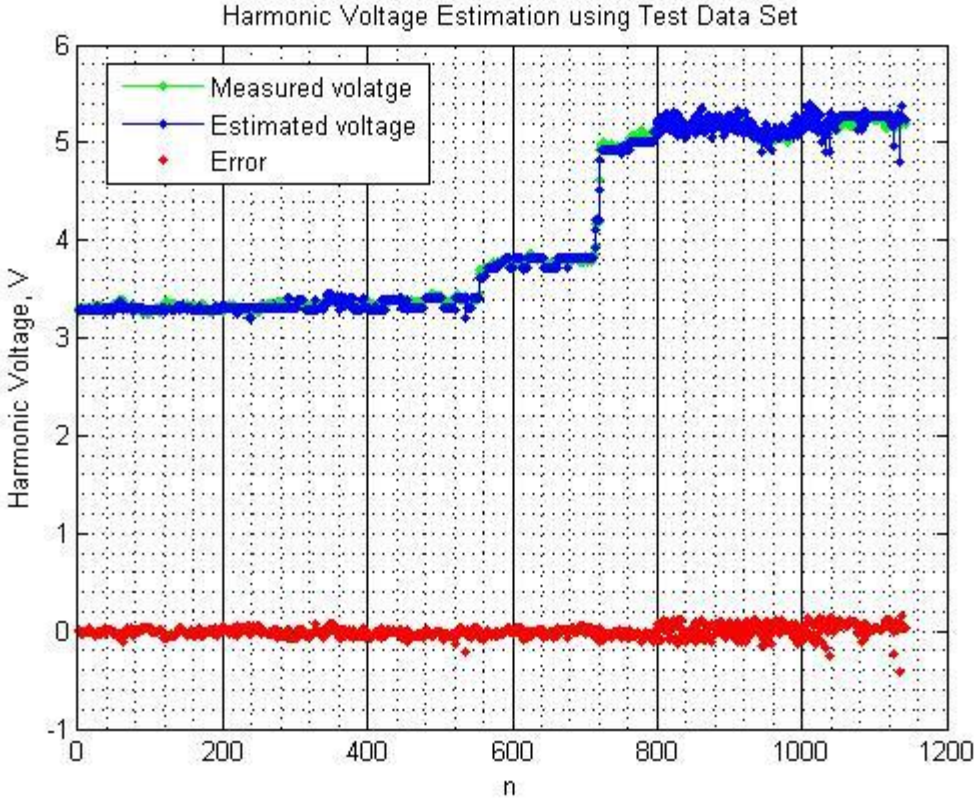


Figure 4.3 Harmonic voltage estimation using validation data set

Analysis of error at validation data (cross-validation) simulation plot shows that an average of $\pm 2\%$ error or difference observed between the measured and estimated harmonic voltages. Figure 4.4 highlights the percentage error of simulation using validation data set (cross-validation), with two horizontal lines which indicating area within $-2 \leq y \leq 2$ as the average error range of the simulation.

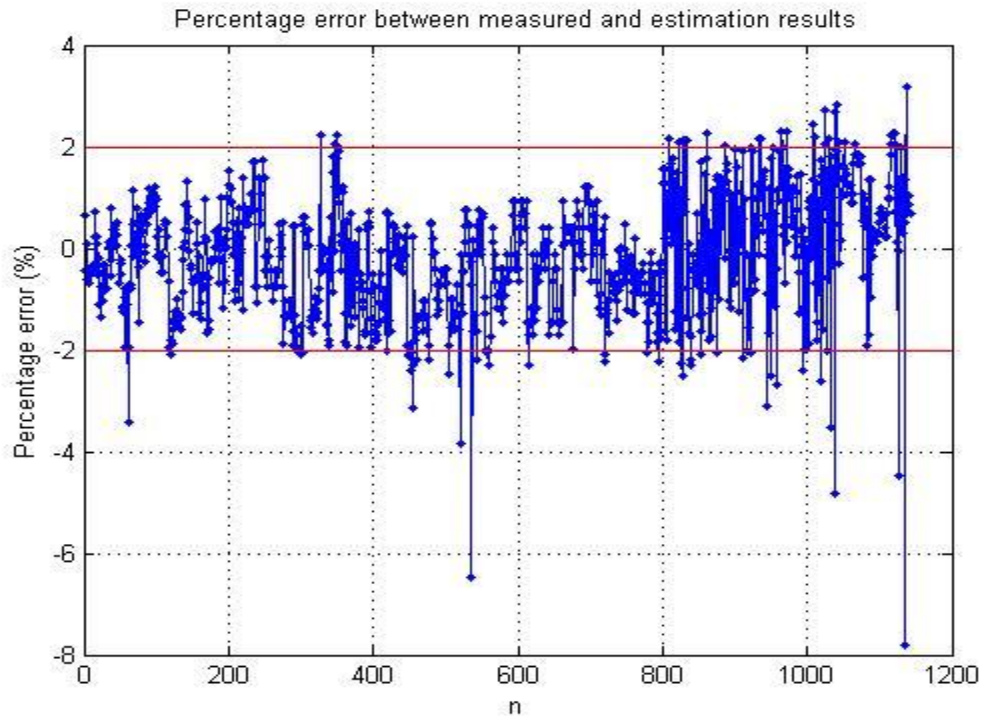


Figure 4.4 Percentage errors between measured and estimation results using validation data set

To further analysis the quality of estimated outputs, estimated regression analysis was performed between the actual and estimates, as shown in Figure 4.5. Discrete values of estimated voltage at the intended measured values are seen to construct a linear pattern. This show the estimated values are close to measured, with error as discussed previously. The coefficient of correlation is computed to be;

$$r = 0.998256 \quad (4.1)$$

Hence, positive correlation obtained close to +1 that indicates a strong correlation between the actual and estimated harmonic voltages.

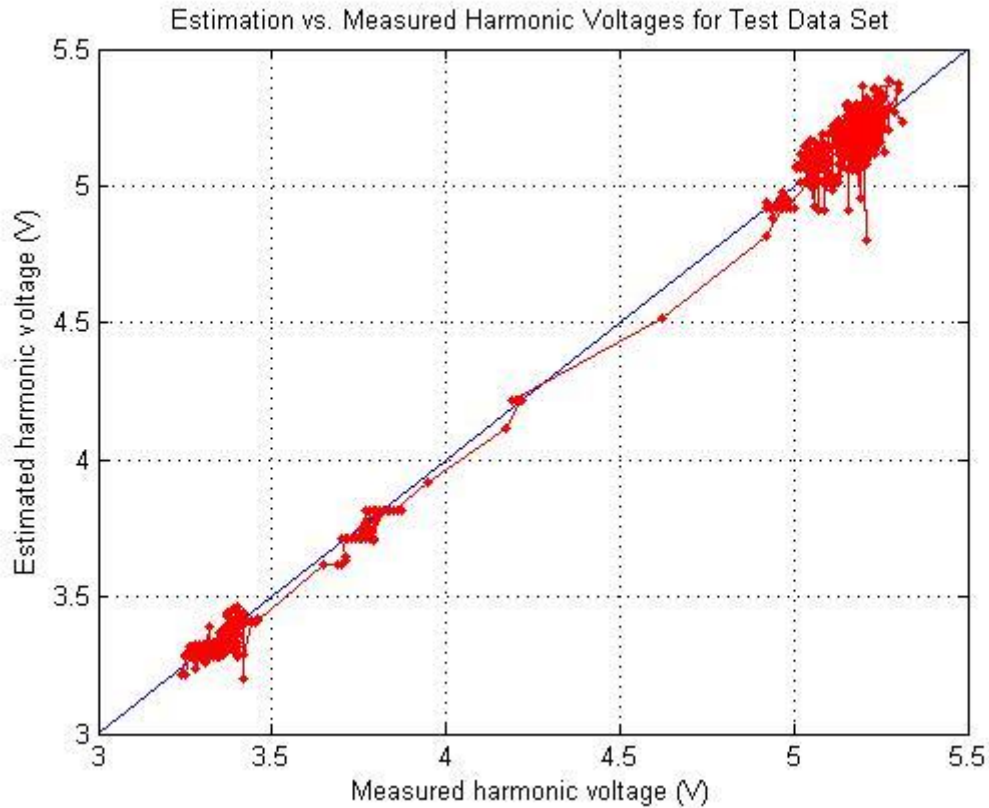


Figure 4.5 Regression analyses between the actual and estimated harmonic voltages using NN with LMBP

4.2.2 Part 2: Simulation results for Tool#2 – Time-series Prediction using Radial Basis Function (RBF)

Similar cross-validation training technique is used for the development of ‘Tool#2’. Parameter adjustment for the time-series prediction model is presented in Table 4.6 and error summaries tabulated accordingly. Trial-and-error based simulations carried out to identify the best-fit ‘spread’ value with carefully adjusted maximum number of neurons (mn) and goal parameters. Training stops when training goal reached.

Table 4.5 Trail-and-error simulations for RBF network

Trial Num.	'spread'	Error (MAE)	
		Training	Cross-validation
1	0.0	2.433101	13.311526
2	0.25	1.074674	6.323349
3	0.5	0.223373	1.902273
4	0.75	0.000985	0.285001
5	0.8	0.078512	0.109363
6	0.9	0.003914	0.076445
7	1.0	0.931441	4.337120

The value of spread parameter that ensures the best generalization is chosen. At spread value 0.9, the least absolute error was observed at cross-validation, and the network performance can be judged by analyzing the performance as plotted in Figure 4.6. The network goal was set to 0.6 SSE and the mentioned parameters in Table 4.6 were adjusted to meet this goal. Complete MATLAB coding for RBF time-series prediction model is attached as Appendix C.

This accuracy is reached in only six iterations with a measured performance of 0.599506 SSE, as shown in Figure 4.6. RBF network is generally classified as a high-accuracy network with fast convergence.

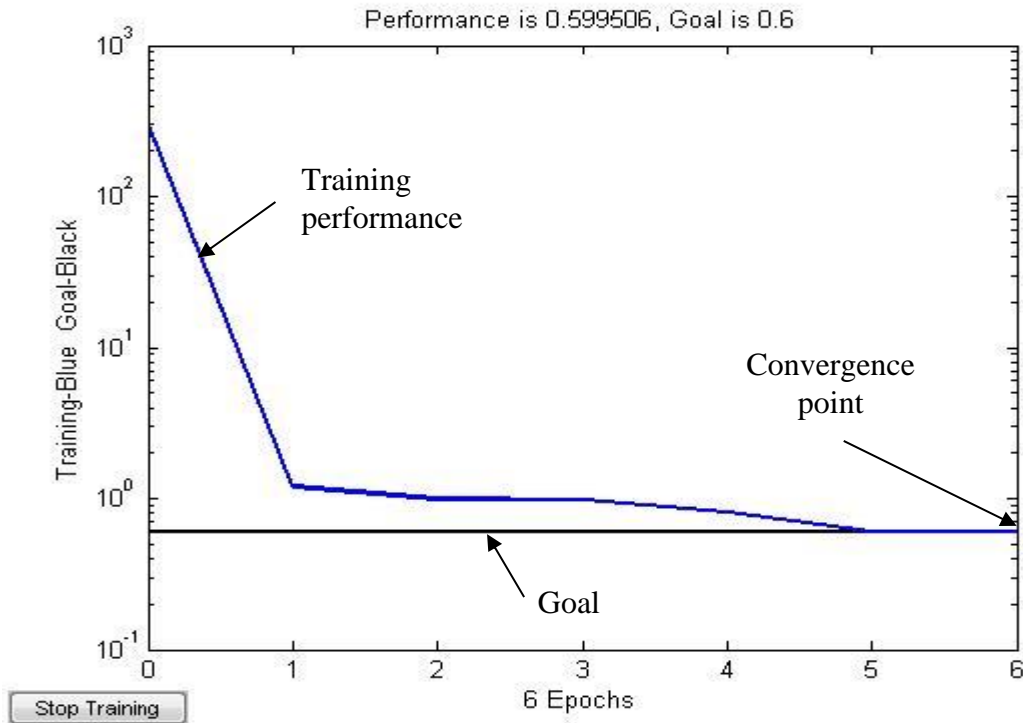


Figure 4.6 Training performance for RBF network

The network performance is compared with a standard NN time-series prediction model and the simulation results are tabulated as in Table 4.7. From the simulation results tabulated, RBF network shows better generalization property, hence, better time-series prediction.

Table 4.6 Summary of time-series prediction network comparison

Time-series prediction model	MAE (%)	Number of iteration(s)
Radial Basis Function (RBF)	0.076445	6
Neural Network (NN)	0.899340	143

Based on Table 4.7 above, it is proven that an RBF network would be a wise choice to be able to demonstrate the time-series prediction for harmonic voltages for UTP distribution network, with reliable accuracy and hence, fluent demonstration.

Figure 4.7 plots the predicted harmonic voltages, the actual data set as gathered from Fluke 1750 power analyzer data logging, and error between the prediction and actual. From this plot, one can observe a consistent prediction result when a new set of data fed as cross-validation.

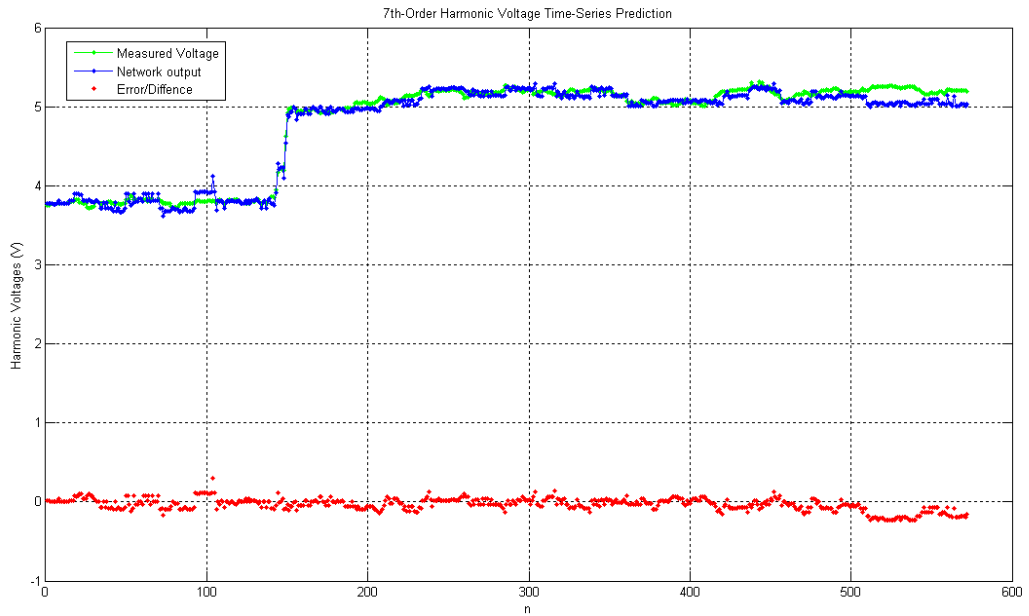


Figure 4.7 Time-series prediction results versus real measures and difference in voltage

From Figure 4.7 and 4.8, it is observed that there is an increase of error towards the end of prediction and also error fluctuation present at $n = \pm 100$. The error range can be seen in Figure 4.8, where error or difference between the prediction and actual falls at an average of -0.6501% . This increase in error is due to change of input range and insufficient training of the network. This can be overcome by providing sufficient training for the network by feeding more raw data for training. For this case, the training will be considered acceptable if regression analysis shows satisfactory results. Figure 4.8 also highlights an average percentage error of the training to be -0.61706 , which means less than $\pm 1\%$ error.

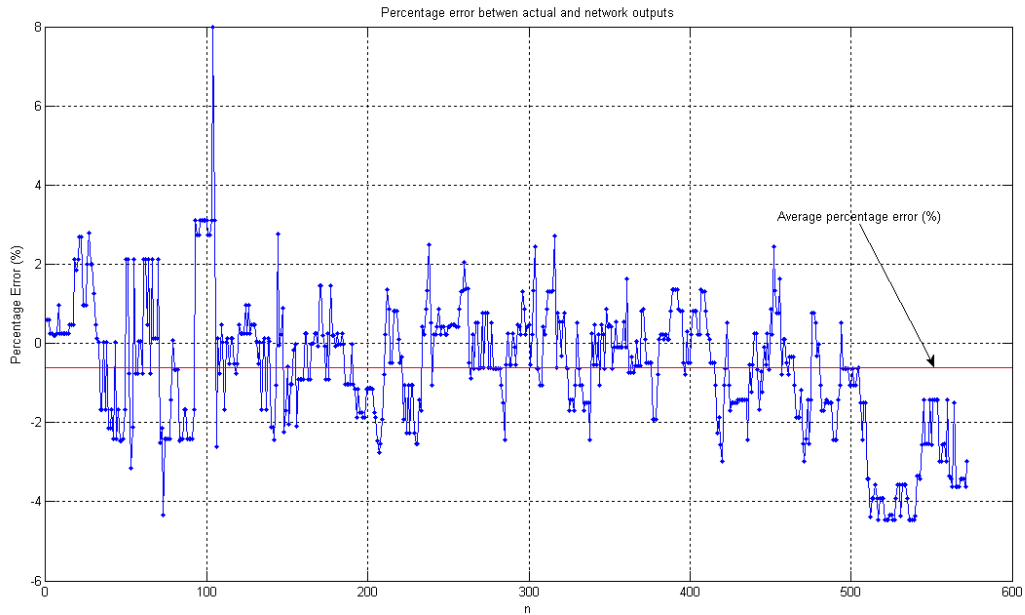


Figure 4.8 Error observations in percentage error for time-series prediction using RBF network

In general, validation data simulation generates an MAE of 0.0632 at validation simulation. From the regression analyses as shown in Figure 4.9, it can be clearly seen that the predicted harmonic voltage measures follows the trend of the real harmonic data. The coefficient of correlation is computed to be;

$$r = 0.987788 \quad (4.1)$$

Hence, positive correlation obtained to be higher than 0.8 and considered as a strong correlation between the actual and predicted harmonic voltages.

Hence, the error is negligible. Therefore, network training is complete and the trained network is developed into a stand-alone forecast model using MATLAB compiler (mcc);

`mcc-mcompiled_network`

in which “compiled_network” calls a MATLAB function that captures the RBF network parameters and create a trained stand-alone network.

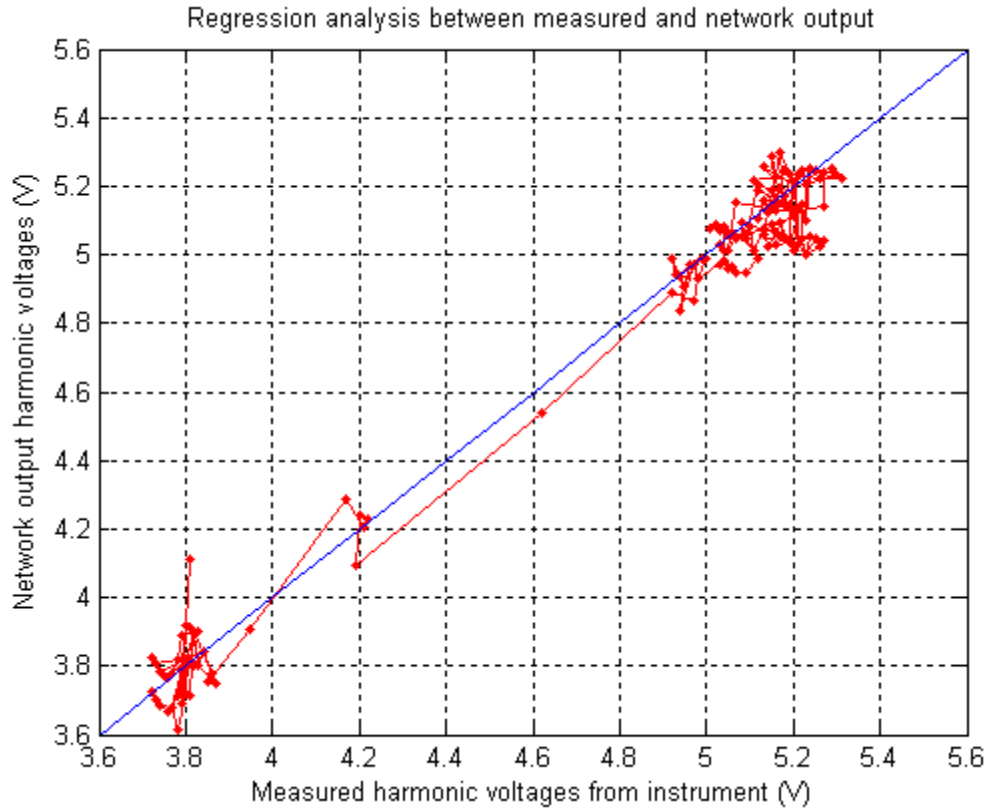


Figure 4.9 Regression analyses between the actual and estimated harmonic voltages using RBF network

4.3 Results of Comparative Study between V-HAF and NARX systems

A comparative study was proposed in Chapter 3 earlier to determine if the proposed system to monitor harmonic in UTP distribution network is indeed a reliable method. Hence, this section presents comparative simulation results between the proposed V-HAF system and NARXsystem, which was developed using MATLAB and simulated using inputs from UTP distribution network.

Table 4.8 shows the error in mean absolute percentage error (MAPE) and the code's execution time needed using the proposed V-HAF and NARX systems. The execution time is measured by using *tic* and *toc* MATLAB functions. The code structure is as followed;

tic;

(Simulation code as per algorithm)

x=toc;

Table 4.7 Comparing simulation results between proposed V-HAF system and NARX technique

Intelligent System	MAPE	Correlation Coefficient, r	Execution time (sec)
V-HAF	4.4487662	0.998139	7
NARX	4.003541	0.998266	5

Based on tabulated results above (Table 4.8), it is observed that both V-HAF and NARX simulations generate similar error range, which is below 5%. Hence, error is acceptable for both systems. This is further verified by computing the correlation coefficient, which falls near +1%.

However, a NARX simulation result shows a lower error compared to the proposed V-HAF system. This is due to direct time-series prediction using harmonic voltages as input data at NARX model, while the time-series prediction inputs in V-HAF were obtained from the estimation model.

Hence, it has been demonstrated that the V-HAF system, which consists of two separate algorithms, gives similar results of time-series prediction with those obtained using direct prediction (only one algorithm utilized). Prediction error can be decreased further if more accurate estimated values could be fabricated. Therefore, the proposed V-HAF system is acceptable in terms of simulation error, based on acceptance line drawn from previous study, by E. Diaconescu [103]. In order to determine if the system is worth being implemented, further analyses are done to weigh the pros and cons of the proposed method in the following section.

4.4 Advantages and disadvantages of the proposed V-HAF system

In order for this system to be implemented in UTP distribution network, a thorough consideration has to be done on both its advantages and disadvantages. While the novelty of this study lies at proposing the system itself which has never been done in UTP distribution network, the proposed system has to be competent and reliable enough to be implemented. The main advantage of this system is its ability to monitor harmonics voltages continuously in UTP and reduce maintenance cost due to damages experienced due to high harmonic range in distribution line.

Conventional method 1 here is referred to the time-series prediction method that utilizes raw harmonic data for model trainings, while conventional method 2 refers to classical technique in which harmonic voltages are computed based on fundamental measure.

Table 4.8 Comparison between implementation of V-HAF and conventional methods

Comparison criteria	V-HAF system	Conventional method 1	Conventional method 2
Cost of instrument to collect raw input data	USD500 – USD2,500	USD6,000 – USD6,500	USD500 – USD2,500
Computational burden	Low	Low	High

A copy of cost of instruments can be found attached as Appendix D & E at the end of this thesis. Therefore, the proposed V-HAF system also imposes advantages such as;

- i. lower instrument cost for input data collection, and
- ii. low computational burden, which allows fast estimation and time-series prediction with intelligent techniques.

4.5 Summary of Chapter

The proposed V-HAF system comprises two tools, which are Tool#1 for the estimation and Tool#2 for time-series prediction, in a successful manner. Tool#1 and Tool#2 simulation results are presented accordingly in this chapter. All simulations were generated by MATLAB. The system is evaluated using cross-validation technique, with a 60:30:10 ratio of training, validation and test data set respectively. Training is considered complete when error at cross-validation is acceptable. Simulation results of Tool#1 are first presented, and a stand-alone model developed once training is successful. The same process was repeated for time-series prediction using Tool#2. For comparative study, both stand-alone models were fed with test data set and evaluated accordingly. The same set of data was also used to test a pre-developed NARX model to compare the accuracy of the models based on time-series prediction output.

The results from comparative study between V-HAF and NARX shows that V-HAF system performs similar to a classical time-series prediction technique, which in the downside, uses raw harmonic data from power analyser instrument as inputs. Hence, V-HAF system allows a significant reduction in instrument costs since it only need fundamental voltage and current to generate the harmonic voltages and future data that enable reduction of maintenance cost due to harmonic issues as previously recorded in UTP distribution network.

Chapter 5 summarizes the whole study and highlights on the significant contribution of the study and recommendations for future work.

CHAPTER 5

CONCLUSION AND DISCUSSION

5.1 Introduction

In the power industry, advances of technology and equipment do not solve the current harmonic issue, but indeed multiplies it. Continuous maintenance plan and ability to monitor the power quality has since become the focus of many researchers worldwide. For a maintenance technician to neither underestimate nor overestimate the harmonic fluctuations in the distribution line, convenient harmonic monitoring technique with reasonable degree of accuracy need to be developed.

In this modern era, Artificial Intelligence (AI) has surpassed all classical techniques in proving its reliability in various aspect and field. Artificial Neural Network is a working tool employed to solve real-time problems. Feed-forward neural network with back-propagation training and RBF are among the most successful and common techniques utilized in harmonic estimation and prediction respectively. Therefore, these techniques are employed to demonstrate the usage of AI technique in replacing PQ meter to reduce cost in data collection phase. A detailed introduction of harmonics estimation and prediction, and its need in UTP distribution network is presented in this thesis.

Chapter 2 gives an overview of the state of art of harmonics estimation and forecasting in power systems field and weighs the advantages and disadvantages of each method discussed. It also clarifies the methods selected to estimate and forecast harmonic voltages. This led to the selection of fee-forward neural network with Levenberg-

Marquardt back-propagation for harmonics pseudo-measurement estimation, and RBF for short-term time-series harmonic prediction, which are further discussed in the next chapter.

Simulations and tests were done to identify best fit and to understand the behaviour and adaptability of the developed networks. Throughout the network development and simulations, many challenges had occurred; insufficient professional assist in handling the equipment, the clarity of gathered data, instrument error, and the quality of network trainings. In neural network training, when a network shows a near-perfect fit in-sample but poor prediction out-of-sample, it is the attribute of “overfitting” plot. This occurs in neural network training due to their flexibility in approximating different functional forms. To avoid “overfitting”, network training must be stopped before it reaches local minimum. With good training, the network’s performance is more reliable and minimizes error.

In short, the thesis meets its objective, which is to propose and develop a reliable intelligent system that provides a complete monitoring of harmonic fluctuation in UTP distribution network. The system, which consists of an estimation and a time-series prediction model, not only reduces measuring instrument cost, bu also allows preventive measures to be taken beforehand by forecasting future harmonic voltages. Hence, all research objectives stated in chapter 1 has been achieved with sufficient experiment and presentation of results.

5.1 Summary of Contribution

In conclusion, the main contributions of this thesis are:

- i. Development of an alternative method to measure harmonics with reduced cost.

- ii. Short-term time-series harmonic prediction allows corrective measures to be taken beforehand or prepared before unwanted losses occur and saves maintenance costs.
- iii. With this system in place, it is possible to monitor more locations at a time since cost of instrument is subsequently reduced. This enables more accurate HSE without the need to neglect or choose measurement point due to restrictions in number of instruments available.

5.2 Recommendations

Some of the problems that have aroused for future investigation are outlined below.

- i. For a more satisfactory harmonic estimation, the network must be tested with other techniques as well, such as hybrid algorithms to overcome the disadvantages each network carries.
- ii. Since instrument error is neglected in this study, results obtained from estimation and prediction may not be close enough to the actual harmonic measures. Therefore, error elimination using harmonic state estimation (HSE) tool should be included into the system to minimize error.
- iii. The proposed system should be available online to enable real-time observation.

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LIST OF PUBLICATIONS

i. International Journal:

- (1) U.Arumugam, N.M.Nor, and M.F.Abdullah, *A Brief Review on Advances of Harmonic State Estimation Techniques in Power Systems*, International Journal of Information and Electronics Engineering, Vol. 1, No. 3; 2011, pp. 217-222.

ii. Paper Proceedings:

- (1) Ugasciny Arumugam, Nursyarizal Mohd. Nor and Mohd Faris Abdullah, *A Review on Various Methods of Harmonics State Estimation*, Proceedings of The 3rd Int. Conf. on Software Technology & Engineering: 2011, pp. 705-711.
- (2) U.Arumugam, N.M.Nor, and M.F.Abdullah, *A Review of Triplen Harmonics Estimation and Forecasting Techniques Applied to GDC-UTP Distribution Network*, in National Postgraduate Conference 2011.

APPENDIX A

Student Survey Form on Electricity Conditions in UTP

Electricity condition in UTP

*All data collected in this survey will be held anonymously and securely. All results will be presented in an aggregated and anonymised form. Demographic data collected at the end of the survey will only be used for the purpose of an individual study conducted for master's degree research and will not be used to identify any individuals.

Current year of study? *

Which student residential village you reside in?

1. Have you experiences a power failure/blackout in campus? If yes, please rate on the frequency of occurrence (blackout).

- never
- once in a while
- frequently

2. If yes, when do you mostly experience the power failure?

- 8am till 5pm
- 5pm onward

3. Are you satisfied on the electricity services you have received?

- yes
- no

4. Have you been through any complication caused by electric supply disturbance in UTP ?

- yes
- no

If yes, please specify

5. Do you think UTP should seriously look into providing better power supply?

- yes
- no

Submit

APPENDIX B

MATLAB Simulation Code for Neural Network with Levenberg-Marquart

backpropagation

```
%=====
% NN (LMBP) - Pattern recognition / Estimation
% Author    : Ugasciny Arumugam
% Date      : Spetrember, 2012
% Description : to estimate harmonics voltage
%=====
%train_set : 28.08.2012 Tues  SSB VC1 <-- estimation.m
%test_set  : 29.08.2012 Wed   SSB VC1 <-- est4.m
%val_set1  : 04.09.2012 Tues  SSB VC1
%val_set2  : 05.09.2012 Wed   SSB VC1
%val_set3  : 30.08.2012 Thurs SSB VC1
%val_set4  : 11.09.2012 Tues  SSB B-L
%val_set5  : 31.08.2012 Fri   SSB VC1
%val_set6  : 01.09.2012 Sat   SSB VC1
%val_set7  : 10.09.2012 Mon   SSB B-L
%
%=====
fprintf('=====\n');
fprintf('  Harmonics Pseudo-Measurement Estimation TRAINER  \n');
fprintf('=====\n');

train_set = xlsread('C:\Program Files\MATLAB71\work\train_set.xls');
test_set  = xlsread('C:\Program Files\MATLAB71\work\test_set.xls');

ptrain = train_set(:,1:2); % |V avg|I avg|S avg| PF |
ttrain = train_set(:,5);  % |Vh max|

% Set network (NN with Levenberg-Marquardt bp) :-
fprintf('Please wait. Network under training...\n');
net = newff(minmax(ptrain),[10 1],{'tansig','purelin'},'trainlm');

% Adjust NN parameters :-
net.trainParam.epochs = 1000; % iteration
net.trainParam.show = 100;
net.trainParam.goal = 0.001; % Perf. minimized to goal(based on target)
%net.trainParam.goal = mean(var(t1'))/100;
net.trainParam.lr = 0.3; % learning rate
net.trainParam.mc = 0.6; % momentum

% Training :-
```

```

net = init(net);
net = train(net,ptrain',ttrain');
fprintf('Training complete...\n');
ytrain = sim(net,ptrain');
etrain = ytrain' - ttrain;
train_error = mse(etrain)

% Test network :-
ptest = test_set(:,1:2); % |V avg|I avg|S avg| PF |
ttest = test_set(:,5); % |Vh max|
ytest = sim(net,ptest');
etest = ytest' - ttest;
test_error = mse(etest)
x = [ytest' ttest etest];

% Plot :-
%input('\nPress ENTER to plot estimation vs. target...');
input('Press ENTER to plot test simulation');
close all
plot(ttest, 'b')
grid on
hold
plot(ytest,'r')
xlabel('n');
ylabel('Harmonics Voltage, V(h)');
plot(etest,'p--')
%title('7th-order harmonics voltage estimation(red) vs. target(blue)');
%=====

```

APPENDIX C

MATLAB Simulation Code for Radial Basis Function

```
%=====
% RADIAL BASIS FUNCTION (RBF) - Time-series prediction
% Author    : Ugasciny Arumugam
% Date      : Oct. 09, 2012
% Description : to forecast future harmonics voltages
%
%=====
%train_set : 28.08.2012 Tues  SSB VC1
%test_set  : 29.08.2012 Wed   SSB VC1
%val_set3  : 30.08.2012 Thurs SSB VC1
%val_set5  : 31.08.2012 Fri   SSB VC1
%val_set6  : 01.09.2012 Sat   SSB VC1
%val_set4  : 11.09.2012 Tues  SSB B-L
%est_set   : test(29.08.12)||val1(04.09.12)||val2(05.09.12)||val3(30.08.12)
%=====
fprintf('=====\\n');
fprintf('          RBF Time-Series Prediction          \\n');
fprintf('=====\\n');
close all

% DATA FEED
train_set = xlsread('C:\Program Files\MATLAB71\work\train_set.xls');
test_set  = xlsread('C:\Program Files\MATLAB71\work\test_set.xls');
est_set   = xlsread('C:\Program Files\MATLAB71\work\est_set.xls');
val_set3  = xlsread('C:\Program Files\MATLAB71\work\val_set3.xls');
val_set5  = xlsread('C:\Program Files\MATLAB71\work\val_set5.xls');
val_set6  = xlsread('C:\Program Files\MATLAB71\work\val_set6.xls');
val_set4  = xlsread('C:\Program Files\MATLAB71\work\val_set4.xls');
val_set7  = xlsread('C:\Program Files\MATLAB71\work\val_set7.xls');

p = train_set(:,5); % 28.08.12 (real)
t = test_set(:,5); % 29.08.12 (real) <-- test
ptest = val_set3(:,5); % 30.08.12 (real)
ttest = val_set5(:,5); % 31.08.12 (real)
pval = est_set(:,1); % 29.08.12 (est) <-- simulation
tval = val_set3(:,5); % 30.08.12 (real)
pvalL = val_set(:,5);
tvalL = val_set4(:,5);

% TRAIN NETWORK
spread = 0.9; % 0.0 - 1.0 (for network smoothness)
goal = 0; % performance goal (SSE)
```

```

mn = 50;           % choose max num of neurons
df = 5;           % number of neurons to add between displays
net = newrb(p',t',goal,spread,mn,df);
ytrain = sim(net,p');
etrain = ytrain' - t;
mae(etrain)
out_train = [ytrain' t etrain];

% TEST NETWORK
input('press ENTER to test network..');
ytest = sim(net,t');
etest = ytest' - ptest;
%mse(etest)
mae(etest)
out_test = [ytest' ttest etest];

% PLOT
input('Press ENTER to plot test simulation');
plot(ytest,'r');
grid on
hold
plot(ptest,'b');
plot(etest,'p--');
% xlabel('n');
ylabel('Harmonics Voltage, V(h)');
%plot(p1,y,'b');
legend('Forecast','Actual','Error(MAE)');
%=====

```

APPENDIX D

Price Quotation for a standard Current and Voltage data logger

10/16/13 Current And Voltage Data Logger - Buy Current And Voltage Data Logger, Calibration And Testing Device, Machine Calibration And Measurement Produc...

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Products Search or
Advanced Search

About 384 results: [Temperature Instruments \(83\)](#), [Other Measuring & Analysing Instruments \(13\)](#), [Voltage Meters \(17\)](#), [Testing Equipment \(13\)](#), [Multimeters \(4\)](#), [More...](#)

Home > Products > Measurement & Analysis Instruments > Temperature Instruments (227778)

Multi-Language Sites



See larger image

Current and Voltage data logger

Add to Inquiry Cart Add to My Favorites Share to: 0

FOB Price: US \$500 - 2,500 / Piece [Get Latest Price](#)
 Port: Shanghai
 Minimum Order Quantity: 1 Piece/Pieces
 Supply Ability: 600 Piece/Pieces per Day
 Payment Terms: L/C, T/T

Verified Supplier - Jiangsu Huahai M & C Technology Co., Ltd.

[Jiangsu, China (Mainland)]

Business type: **Manufacturer, Trading Company**

Onsite operations checked and legal status confirmed

[Contact Details](#) | [Company Profile](#)

Outline
 Ms. Emily Xu
[Start Order](#)

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[Product Detail](#) [Company Profile](#)

[Report Suspicious Activity](#)

Quick Details

Place of Origin: **Jiangsu China (Mainland)** Brand Name: **Haihai** Model Number: **HHTX-1815**
 Usage: **Industrial** Theory: **Temperature Sensor** IP67: **220V**
 24V power supply: **COM/terminal**

Packaging & Delivery

Packaging Detail: **Export carton and plastic**
 Delivery Detail: **7-10 days**

[TradeManager](#)

Specifications

1. Source of voltage, current and frequency.
2. Measure of voltage, current, loop current and frequency
3. Manual stepping

Function

1. Source of voltage, current and frequency.
2. Measure of voltage, current, loop current and frequency.
3. Manual stepping and automatic stepping and ramping.

Summary of Source and Measure Functions

Function	Measure	Source
DC V	0~30 V	0~10 V
DC mV	0~100 mV	0~100 mV
DC mA	0~24 mA	0~24 mA
Frequency	1.000Hz-99.999kHz	0.00Hz-20.000kHz
Others	24V power supply, Step, Ramp.	

Advanced Application

1. Setting 0% and 100% output parameters

www.alibaba.com/product-gs/697873572/Current_and_voltage_data_logger.html?s=

1/3

APPENDIX E

Price Quotation for a standard Power Quality Analyzer

10/16/13 Power Quality Analyzer - Buy Power Quality Analyzer,Power Quality Meter,Power Quality Test Instrument Product on Alibaba.com

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Products Please Input a keyword Search or Post Buying Request Advanced Search

About 24748 results: Power Meters (787) , Testing Equipment (482) , Other Analysis Instruments (289) , Other Measuring & Analyzing Instruments (161)

Home > Products > Measurement & Analysis Instruments > Testing Equipment (466968) Multi-Language Sites

Zhenhuan.en.alibaba.com

SGS

Power Quality Analyzer

Add to Inquiry Cart Add to My Favorites Share to:

FOB Price: US \$6,000 - 6,500 / Set | [Get Latest Price](#)

Port: Shanghai

Minimum Order Quantity: 1 Set/Sets

Supply Ability: 10 Set/Sets per Month

Payment Terms: L/C,T/T,Western Union

Offline

Ms. Aileen Chen [Contact Supplier](#)

[Start Order](#)

Not exactly what you want? [Post a quick Buying Request!](#)

Verified Supplier - Nantong Zhenhuan Trade Co., Ltd.
[Jiangsu, China (Mainland)]
Business type: Trading Company
Main Markets: Eastern Europe 47.86% , ...

Comprehensive capabilities verified by **TÜV Rheinland**

Onsite operations checked and legal status confirmed

17.6% Quick Response

[Contact Details](#) | [Company Profile](#)

See larger image

Product Detail Company Profile Report Suspicious Activity

Quick Details

Place of Origin: Jiangsu China (Mainland)	Brand Name: Zhenhuan	Model Number: PQA-3561
Power: Electronic	Usage: power quality testing	Input Impedance: 1MΩ, 20PF
Voltage range: 10-700V rms	Current range: 5A,10A,100A,1000A,1500A,3000A	Weight: 1.6kg (3.53lb)
Package: wooden case special for export	Guarantee: one year since the date of B/L	Lead time: within 15 working days

Packaging & Delivery

Packaging Detail: **wooden case**

Delivery Detail: **within 15 working days**

[TradeManager](#)

Specifications

power quality analyzer

- 1) 5.7" color LCD touch screen
- 2) Digital oscilloscope
- 3) USB port, li-battery powered

power quality analyzer

5.7" color LCD touch screen

Digital oscilloscope

USB port, li-battery powered

portable, light, 1.6kg

Description

This PQA-3561 is 3P3W and 3P4W testing and analyzing device for the quality of power grid. It provides multiple analyzing for electric harmonic, voltage/current/frequency, 3-phase unbalance, power and energy, data recording and so on. It helps you locate, predict, prevent and troubleshoot problems in power distribution systems. It is featured with big size memory, suitable for long-time analyzing & collecting data of power grid; Featured PC software can analyze data collected and uploaded into PC.

Applications

- Frontline troubleshooting - quickly diagnose problems on-screen to get your operation back online
- Predictive maintenance - detect and prevent power quality issues before they cause downtime
- Quality of service compliance - validate incoming power quality at the service entrance
- Long-term analysis - uncover hard-to-find or intermittent issues
- Load studies - verify electrical system capacity before adding loads
- Energy assessments - quantify energy consumption before and after improvements to justify energy saving devices.

Main features

- Light weight, small size, portable

www.alibaba.com/product-gs/485941736/Power_Quality_Analyzer.html