An Analytical Framework for Power Quality Monitoring in Smart Power Microgrid

by

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Proposal for PhD Dissertation

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Chapter 1

Introduction

1.1 Why Power Quality Monitoring?

Electrical power networks are one of the critical infrastructures of our society. Due to our high dependence on electricity, the issue of reliability in electric networks has become a core research interest in the area of smart grid [4]. Reliability evaluation of power grid, however, is challenging due to the existence of multiple electric utilities and the potential of cascading failures of power distribution systems [5]. One of the most influential factors impacting the reliability and energy saving of power networks is the power quality delivered to, and experienced by, critical electric equipment. Poor power quality, such as voltage sags/swells, harmonics, fast impulses etc, may lead to power outage and service interruptions. Service unavailability caused by power losses is a serious problem for many companies and organizations, e.g., it may result in a significant revenue loss for Internet service providers or even loss of lives in hospitals. To improve the reliability of power networks, organizations and large companies (e.g., Google data centers) adopt smart microgrid, and closely monitor the power quality in different segments of the microgrid. Hence, the monitoring of power quality is a crucial component of assessing and maintaining reliability in power grids.

Monitoring power quality, however, is not an easy task. Since the power measurement devices [6, 7] (termed as smart meters in this proposal) are expensive, it is financially impractical to monitor every segment of a power network. The overhead of interconnecting these power meters and developing the power management system further increases the cost. In addition, in many cases direct monitoring of power quality is difficult, e.g., it is hard to install smart meters after power lines were sealed in hard-to-reach areas in a building. We identify various research challenges in power quality monitoring.

1.2 Open Challenges

In order to effectively monitor the power quality in the grid, this work is intended to tackle the following challenges:

1. Based on a limited small number of monitored points in a power network, how can we effectively estimate the power quality of other unmonitored segments of the network?

2. Given a fixed number of available power meters, which grid segments should be selected for monitoring such that power quality can be inferred as accurately as possible in the remaining non-monitored segments of the network. A relevant research problem is to device a mechanism that calculate the optimal number of meters required to get an acceptable level of network reliability.

3. Based on readings from the meters placed on various segments of the power grid, how can we accurately identify a potential malfunction device.

4. Which power characteristics need to be measured by the power meters to effectively monitor the power quality in the power grid?

In order to tackle the above challenges, we take a unique perspective and propose an analytical framework which help us represent the power grid at an abstract level as a data-driven network. Modeling the power grid as data driven network help us utilize the best available techniques of data network to solve the relevant research problems in the power grid domain. Specifically, we believe that the above identified power quality challenges can be best tackled if targeted as data network problems. We detail our novel analytical framework in Chapter 3. In the next section, we give further detail on the identified challenges and represent them as potential research problems in the power quality monitoring era.

1.3 Possible Research Problems

The power quality meters are recently being used to improve the reliability of power grids networks. We identify four research problems related to smart meters' placement and power quality estimation in the power grids as follows:

1.3.1 Power Quality Estimation

The reliability evaluation of enterprise-level power grid seems to be much simpler compared to the large-scale power grid which is notoriously difficult due to the existence of the multiple electric utilities and the cascading failures of power distribution systems [5]. Nevertheless, to tackle the practical challenges, the power quality and operational status of electric devices in the micogrid must be monitored and recorded. On the other hand, due to financial and other practical in-feasibilities, each device in the network cannot be monitored. We need to tackle the challenge as: *Based on a limited small number of monitored points in a power network, how can we effectively estimate the power quality of other unmonitored segments of the network?*

We propose to use a Maximum-Entropy (MaxEnt) [8] approach to power quality estimation. The basic idea of MaxEnt is that out of all probability distributions consistent with a given set of constraints (i.e., the known measure values in our case), we should choose the one that has the maximum uncertainty to be the estimated power quality values. Intuitively, the principle of MaxEnt implies that we should make use of all the information that is given and avoid making (biased) assumptions about information that is not available.

In order to tackle the identified research problems, we first propose an analytical framework where we represent the power grid as data-driven network (see Chapter 3 for details). We then model the identified research problems on the top of our analytical framework. The problem of estimating power quality be modeled in such a way where we can effectively get the benefit of MaxEnt approach to correctly estimate the power quality values at links where we do not have any measuring device installed. We solve the formulated MaxEnt problem and validate its effectiveness and efficiency with a simulated microgrid system using our analytical framework. Proposed solution and simulation results of the power quality estimation is detailed in Chapter 4.

1.3.2 Intelligent Meter Placement

To effectively measure the power quality on power lines of the grid networks, smart meters are being deployed to closely monitor the power quality. Power meters are expensive devices [6, 7] and it is impractical to monitor every segment of the electric network. Instead, power quality in non-metered grid locations must be inferred given data obtained from the measured locations. Here, the research question is *where to place the meters in the power grid network?*

We propose an iterative approach for identifying network segments suitable for power meter placement. During each iteration of the algorithm we identify in a greedy manner the network segment that suffers from the most unpredictable power quality given the meters deployed so far. We then deploy the next power meter at that location.

A relevant challenge here is to identify the optimal number of meters to reduce the uncertainty and hence the overall reliability of the network to an acceptable level. Formally, we tackle the problem of *how to device a mechanism that calculate the optimal number of meters required to reduce the uncertainty of power quality in the power grid to an acceptable level?* We propose to model the above issue as an optimization problem to minimize the number of meters while maintaining the desired level of network reliability.

For above two problems, the detailed problem definitions, the proposed solutions, and results from an experimental study are presented in details in Chapter 5.

1.3.3 Detecting Malfunctioning Device

The main objective of this work is to increase the reliability of power networks in terms of power quality. The two research problems discussed above address how to accurately estimate the state of the network. Since the power quality readings (exact readings from monitored links, estimated readings from unmonitored links) are available now, we can use this information to estimate the state of the network and identify any potential malfunctioning device. Our research problem becomes: *how to detect a potential malfunctioning device in the power network based on available PQ readings.* The problem is further investigated in Chapter 6.

1.3.4 Power Meter Choices

The main causes of power quality problems include voltage sags/swells, fast/sub-cycle impulses, harmonics, and high frequency noise. Some of these causes occur frequently while the others occur rarely. Depending on the users' requirements and financial budget, the capabilities of the power meters varies. We plan to conduct a detailed research study to identify the required capabilities of a power meter based on: 1) user types; 2) financial budget; and 3) the environmental factors.

Currently, many measurement devices use the level of voltage on electric lines as the measurement parameter to classify power quality. In addition to using the voltage level as a measure, we propose to consider physical power characteristics like level of current as well. We formulate our research question: *which power characteristics should be considered in choosing a smart meter for classifying power quality in smart grid*. Chapter 7 give a brief proposal on the meter selection criteria and our plans about conducting a detailed study on the issue.

1.4 Planned Contributions

The proposed thesis work is intended to investigate various algorithms to tackle the research challenges in the area of power quality monitoring in power grid. We first propose an analytical framework and then build various algorithms corresponding to different research problem in the domain. Our analytic framework and proposed algorithms are detailed in separate chapters in this document.

We have already investigated the first two research challenges (i.e., the PQ estimation, and the meter placement in power grid) to an appropriate level. Our proposed algorithms on the two issues are recently published in IEEE SmartGridComm 2013. References are available in Chapter 9. We plan to further investigate the issues and address the limitations of the existing solutions. The extended work will address the scalability issues of our proposed algorithms.

Our positive initial findings toward the possible extensions of the two problems motivated us to further investigate the issues. Specifically, we plan to address the scalability issue of our PQ estimation approach and propose an extension of the work. The guideline is to divide the larger subnets in logical components where each logical component represent several physical components. We then estimate the transfer functions of the logical components. Based on the logical transfer functions we then estimate the actual transfer functions of each physical device in a logical component. The idea is discussed at the end of Chapter 4.

We also plan to address the scalability limitation of our proposed Bayesian network based solution for meter placement in smart grid by proposing a conditional-entropy based extension. We believe that the conditional-entropy based approach for calculating uncertainty of PQ values on segments in the power grid network is much faster than Bayesian network based approach. We will also look into the possibility of proposing a hybrid approach using both our proposed Bayesian network and the prospective conditional-entropy based solution. This possible extension is discussed as future work in Chapter 5 of this document.

The third and fourth research problems (i.e., detecting malfunctioning devices, meter selection) are the key parts of the work to be investigated. Our proposed ideas to address these issues are immature and they serve as guidelines for our future solutions to be proposed as part of this work. Specifically, to address the issue of detecting a malfunctioning device, we will identify various characteristics which may differentiate a malfunctioning device from a normal one. We plan to further mathematically model the identified characteristics and propose algorithms which will accurately detect the potential malfunctioning devices in the power grid network. On similar fashion, our plans include to conduct a detailed research on identifying various parameters which play a key role in the power meter selection for the effective measurement of power quality in the power grid. These plans are discussed in Chapters 6 and 7.

1.5 Proposal Outline

The rest of the proposal is organized as follows. Chapter 2 provides review on power quality in smart grid and discusses the available literature related to our proposed work. The proposed analytical framework is outlined in Chapter 3. Based on the proposed analytical framework, we build various algorithms to address the identified research issues. The research issue of estimating power quality values on unmonitored links is investigated and its future extensions (to be investigated as part of this proposal) are discussed in Chapter 4. In Chapter 5, we propose algorithms that intelligently place the power meters in the grid network on high information locations. A relevant research problem of identifying optimal number of meters is also formulated in the same chapter. In Chapter 6, based on the known power quality values from our proposing algorithms, we give a proposal on how to detect a potential malfunction device. We plan to conduct a detailed study on smart mater choices and our plans are briefly discussed in Chapter 7. The summary of expected research contributions is given in Chapter 8. Some of our research work has published very recently in a prestigious avenue of my research area; their references are itemized in Chapter 9.

Chapter 2

Background and Related Work

Due to our hight dependency on electric power, reliability of power networks has become critically important. A variety of hardware and software tools for measuring and monitoring power and power quality are available. Before we detail the cutting-edge research work in the area, we detail the most important causes of power quality problems as follows.

2.1 Main Causes of Power Quality Problems

2.1.1 Voltage Sags/Swells

The voltage sags are brief reductions in voltage while the voltage swells are brief increase in voltage level which may last from a cycle to a second. Voltage sags are caused by faults, sudden increases in loads or device impedance, short circuits or faults. Causes of voltage swells are an abrupt reduction in load on a circuit or a damage in neutral connection. Sag or swell is the largest cause of problems from the utility side. Sags or swells can occur in the power distribution network or at the point of use. These types of disturbances can lead to loss of production or electronic device failures. Measurement devices being used should be able to detect these events. A standard reference for measuring the power quality events largely used by industry is the Computer Business Manufacturers Association (CBEMA) also known as ITI Council profile curve [9]. Power quality monitoring devices use the ITI curve as a reference to highlight if the voltage events may result in any potential problem.

2.1.2 Harmonics

A harmonic is a periodic, an integer multiple wave of the fundamental frequency. They are caused by non-linear electric loads. Technically, voltage harmonics are caused by the combination of line impedance and current with a frequency other than the fundamental frequency. Harmonics in power grids are the main cause of power quality problems. A lot of harmonics in the power systems can cause malfunctioning or damage to the electric devices. Power quality measurement devices use the technique of Fourier Analysis to detect the magnitude and frequency of of voltage harmonics.

2.1.3 Interharmonics

Interharmonics are distortions in the current or voltage waveforms. They are different from ordinary harmonics in that it refers to voltages or currents having frequency components that are not integer multiple of the fundamental frequency. They can be found in networks of all voltage classes.They can be found in networks of all voltage classes. They can affect power-line carriers, lighting, computer displays, heating of transformers and motors, mis-operation of electronic devices etc. However, due to their small amplitude and uncertain frequency, they are difficult to detect.

2.1.4 Transients

Transients (also known as *surges* or *spikes*) are momentary changes in voltage or current that last for a very short period of time. The interval is usually less than $1/16^{th}$ of a voltage cycle or about 1 milliseconds. The typical duration of voltage transients is 50 microseconds while the duration of current transients is 20 microseconds. Transients can come from external sources as well as from within the system. The external sources include lightning, switching of facility loads, poor or loose connections in the distribution system, opening/closing of disconnects, tap changing on transformers, environmental changes. The main culprits within the system causing transients include device switching, arcing, static discharge, and adding or removing loads. If left unchecked, transients can lead to device degradation over time.

2.1.5 Other Causes

As discussed earlier, the life time of electric/electronic devices is dependent on the electric power quality. There are many other causes which effect the power quality in the electric network. In order to improve the reliability of the electric power network, the causes of the power quality problems need to be addresses. Some of the main other causes are as follows.

Over/Undervoltage

When the RMS value of the voltage in a power system raises above 110% for a duration of greater then 1 minute, it is classified as an overvoltage. It happens when the system is either too weak to support the desired voltage or the voltage controls are sufficient. They are usually the result of switching off a large load. The overvoltage is usually protected using bulk capacitors.

An undervoltage is a decrease in the RMS voltage value when it falls under 90% of its original level for a duration of greater than 1 minute as classified by the CBEMA curve [9]. Its causes include overload circuits, load switching, and capacitor bank switching off. Undervoltages may result in premature shutdown of circuits, loss of important data, restart of electronic equipments.

Sustained Interruptions

It is a decrease in the voltage level to zero for a period of more than 1 minute as defined by IEEE standard [2]. They are often permanent in nature which requires manual intervention to restore the system. This type of interruptions are caused by permanent faults caused by storms, equipment failures, trees striking lines, and other environmental factors. If not tackled on time, these faults may result in a complete shutdown of the facility.

Voltage Unbalance

It is defined as the largest difference of the RMS voltage value (or phase angles) on a line from its average value. It is quantified in terms of ratios of the negative and zero components to the positive sequence. Voltage unbalance is usually caused by uneven distribution of voltage between the phases of an n-phase (usually 3-phase) system. It may also caused by mismatch of the impedance of a transformer, a blown fuse, or a bad capacitor. The problem may cause premature equipment aging, power supply ripple, insulation degradation, decrease in mean time between failures (MTBF).

Table 2.1: Electromagnetic Disturbance Phenomena Categories [1]

1. **Conducted low-frequency phenomena**
   - Harmonics, interharmonics
   - signaling systems
   - Voltage fluctuations
   - Voltage dips and interruptions
   - Voltage unbalance
   - Power frequency variations
   - Induced low-frequency voltages
   - DC in AC networks
2. **Radiated low-frequency field phenomena**
   - Magnetic fields
   - Electric field
3. **Conducted high-frequency phenomena**
   - Directly coupled or induced voltages or currents
   - Unidirectional transients
   - Oscillatory transients
4. **Radiated high-frequency field phenomena**
   - Magnetic fields
   - Electric fields
   - Electromagnetic fields
5. **Electrostatic discharge phenomena (ESD)**
6. **High-altitude nuclear electromagnetic pulse (HEMP)**

Frequency Variations

Frequency variation is the deviation of fundamental frequency from its nominal value. The size and duration of the frequency shift is dependent on the load characteristics. It is usually caused when a large load is disconnected or when a large power generator goes off-line. It can cause data loss, device crash/damage, or erratic operation in the electronic system.

2.2 Classification of Power Quality Disturbances

It is a known phenomena that when a power system is disturbed either by a short circuit, sudden increase in load, or any other relevant cause, the balance of energy is disturbed. During the disturbance, energy exchange between the electric and magnetic fields occurs which deviates the waveshapes of voltages and currents in the power system. This electromagnetic phenomena is standardized by two leading knowledge bodies in the field by standards: 1) IEC/TS 61000-2-5; and 2) IEEE Std. 1159-1995.

2.2.1 The IEC Classification

The International Electrotechnical Commission (IEC) classifies various phenomenas that cause electromagnetic disturbances through their standard IEC/TS 61000-2-5 [1]. These disturbances can reach the equipment either by conductive or radiative coupling pathways. When there is a physical pathway exists between the source of emission and the affected device, it is a conductive coupling. On the other hand, radiative coupling

Table 2.2: Categories and typical characteristics of power system EM phenomena [2]

Categories	Spectral Content	Duration	Voltage Magnitude
1. Transients			
(a) Impulsive			
i. Nanosecond	5-ns rise	$<$ 50 ns	
ii. Microsecond	1-μs rise	50 ns - 1 ms	
iii. Millisecond	0.1-ms rise	$>$ 1 ms	
(b) Oscillatory			
i. Low frequency	$<$ 5 kHz	0.3 – 50 ms	0 – 4 pu (per unit)
ii. Medium frequency	5 – 500 kHz	20 μs	0 – 8 pu
iii. High frequency	0.5 – 5 MHz	5 μs	0 – 4 pu
2. Short-duration RMS variations			
(a) Instantaneous			
i. Sag		0.5 – 30 cycles	0.1 – 0.9 pu
ii. Swell		0.5 – 30 cycles	1.1 – 1.8 pu
(b) Momentary			
i. Interruption		0.5 cycles – 3 s	$<$ 0.1 pu
ii. Sag		30 cycles – 3 s	0.1 – 0.9 pu
iii. Swell		30 cycles – 3 s	0.1 – 1.4 pu
(c) Temporary			
i. Interruption		$>$ 3 s – 1 min	$<$ 0.1 pu
ii. Sag		$>$ 3 s – 1 min	0.1 – 0.9 pu
iii. Swell		$>$ 3 s – 1 min	0.1 – 1.2 pu
3. Long duration RMS variations			
(a) Interruption, sustained		$>$ 1 min	0.0 pu
(b) Undervoltages		$>$ 1 min	0.8 – 0.9 pu
(c) Overvoltages		$>$ 1 min	1.1 – 1.2 pu
(d) Current overload		$>$ 1 min	
4. Imbalance			
(a) Voltage		steady state	0.5 – 2%
(b) Current		steady state	1.0 – 30%
5. Waveform distortion			
(a) DC offset		steady state	0 – 0.1 %
(b) Harmonics	0 – 9 kHz	steady state	0 – 20 %
(c) Interharmonics	0 – 9 kHz	steady state	0 – 2 %
(d) Notching		steady state	
(e) Noise	broadband	steady state	0 – 1 %
6. Voltage fluctuations	$<$ 25 Hz	intermittent	0.1 – 7 % (2.2 – 2 Pst)
7. Power frequency variations		$<$ 10 s	$\pm$ 0.10 Hz

occurs when there is no physical pathway but the emission propagates through electric and magnetic fields. Based on couplings and relative frequencies of the disturbances, IEC classifies the electromagnetic phenomena into six categories as shown in Table 2.1.

2.2.2 The IEEE Classification

The Institute of Electrical and Electronics Engineers (IEEE) put efforts to standardize power quality terminology to allow the parties involved in to have standard and consistent terms. The IEEE standard 1159-1995 [2] provides a classification of power quality events. The various power quality events are classified in seven general categories. The classification is based on event characteristics such as spectral content, duration, and magnitude as shown in Table 2.2.

2.3 Related Work

Power quality is a crucial component of power system reliability. Poor power quality may lead to service interruptions. To improve the reliability of power grid networks, power quality measurement devices are being deployed to closely monitor the power quality on underlying power links. As discussed, it is not feasible to monitor every segments of the network. Instead we propose to 1) intelligently place the monitoring devices on selected network segments; and 2) estimate the power quality on unmonitored links base on the known information from the monitored links.

We also address the relevant research problems such as 1) how many meters are required to achieve the desired level of network reliability; 2) based on reading from the monitoring devices, how to accurately identify a malfunctioning device that degrades the power quality in the power system; and 3) based on user requirements, environmental and physical constraints, what is the best choice for a monitoring device to be used. Note that, we need to use devices of different capabilities for different scenarios. This section covers the research work relevant to our proposed solutions addressing the above identified problems. We classify the existing research (and available techniques) related to this work in the following categories.

2.3.1 Classification of Power Quality Events

There are many approaches of classifying the power quality events. Typically, power quality is assigned a label which is based on magnitude and duration of the electromagnetic phenomena (e.g., voltage sag or swell). Electrical utilities typically report a System Average RMS Variation Frequency Index (SARFI) which is essentially a count of the number of times the magnitude and duration fall below (or above) a threshold. The IEEE and IEC also have their standards for classifying individual power quality events [1, 2]. These standards are detailed in Section 2.2. We use a discrete classification system in this work, similar to that described in the IEEE standard [2].

2.3.2 Power Reliability

The industry standard practices for electric power reliability in networks focus on measures such as Mean Time Between Failure (MTBF), reliability, and availability as defined by the IEEE Gold Book [10]. These measures are theoretical values, measured or calculated for components and networks operating under standardized conditions. They serve as methods for comparison but are not intended as predictive tools for networks that operate in realistic environments with varying temperature, humidity, load, and power quality.

Further, it is known that there exists a relationship between power quality and the lifetime and performance of components [9]. For an effective evaluation of power reliability, we need to accurately estimate power quality. [3], which motivates for the work we are proposing. The work proposed in [3] is relevant to our power quality estimation solution (see Chapter 4) where the authors propose an Expectation Maximization (EM) based algorithm to estimation the microgrid reliability. Although effective, the EM algorithm needs a long time to converge. We are thus motivated to find faster algorithms in power quality estimation.

2.3.3 Data Estimation Techniques

We use data estimation techniques to propose our power quality estimation solution (see Chapter 4). Here we give a short description of the EM and MaxEnt algorithms used in our work:

The Expectation Maximization (EM)

EM is a general approach to iterative computation of maximum-likelihood estimates when the observations can be viewed as incomplete data. Since each of the iteration of the algorithm consists of an expectation step followed by a maximization step, the algorithm is named as the EM algorithm. The successive iterations always increase the likelihood and the algorithm converges at a stationary point.

Maximum Entropy (MaxEnt) Estimation

MaxEnt solves convex optimization problems of the form,

$$\textbf{maximize } g(\vec{x}) = -\sum_{i=1}^{n} x_i \log x_i$$

$$\text{subject to } \mathbf{A}\vec{x} \leq \mathbf{c},\ \mathbf{B}\vec{x} = \mathbf{1},$$

where $\vec{x} \in \mathbb{R}^n$ is the optimization variable, $A \in \mathbb{R}^{m\times n}$, and $B \in \mathbb{R}^{m\times n}$ are problem parameters; and $\mathbf{1}$ is a vector with all 1's.

2.3.4 Sensor Deployment

There is a great body of work on the optimal sensor deployment problem [11]. The meaning of sensors is broad, including any measurement/monitoring devices. In the context of power networks, optimal deployment of phasor measurement units (PMU) has been studied [12]. Nevertheless, we have not seen any work on studying optimal meter deployment problem in the context of network-wide power quality estimation.

2.3.5 Bayesian Inference

We use Bayesian inference to identify high information locations for deploying smart meters (detailed in Chapter 5). The Bayesian inference methods are helpful in providing the new estimates of the PQ values on non-monitored links given evidences are obtained from the metered locations. Bayesian inference is a general and well-investigated discipline which has applications in a wide range of fields. Several algorithms are available to address specific problem in this domain. For the problem of meter placement, several message passing algorithms could be used to help us determine the optimal meter placement. We chose the belief propagation or sum-product algorithm [13] since it is well understood, has been shown to work for general topologies [14] including tree networks, and has several software libraries available.

Chapter 3

Our Analytical Framework

3.1 Motivation

The power network has many logical and physical similarities with data networks. We model the power network as data driven network which give us the opportunity to use the well-investigated network monitoring and data estimation algorithms to solve the network quality monitoring in power grids. We proposed model is described in next section.

3.2 The Model

We now model the power grid as a data driven network, *analogically*, where electrical components are represented as nodes, power links as data links, and power flow as data flow. Hence the power grid can be viewed as a data network where we have nodes connected via data links and the data links transmit numeric data (i.e., power quality values/events in our case).

In order to classify flow of current as data (integer values), we divide the time into small slices where in each slice we classify the flow of power on any link as integer values. For the sake of generality, we represent these classes from c_1 to c_n. The power meters measure power quality continuously and assign a power quality class to each time slice according to the power quality in the interval. So in every time slice, we know power quality values in terms of integers on links where the power meters are installed.

In order to simplify our model, we treat the power flow through each node as a

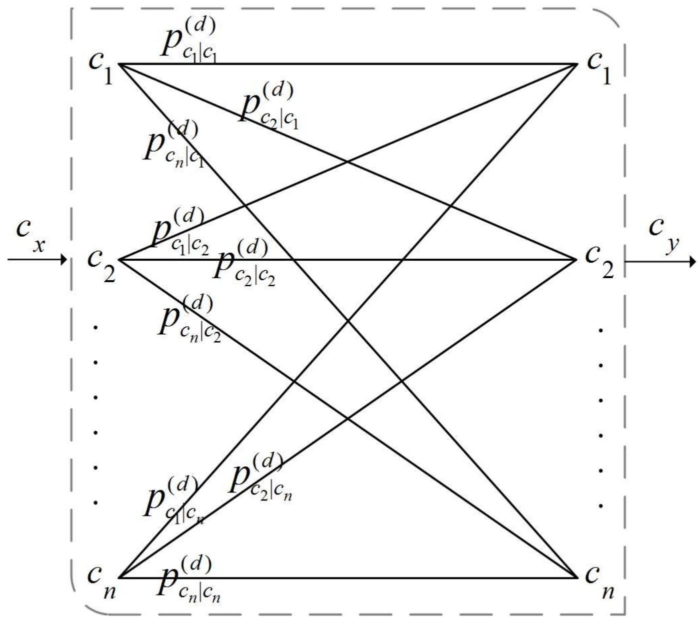


Figure 3.1: Power quality transition at each device d as a channel.

channel (shown in Figure 3.1). The input and output of this channel at each node comprises n power quality classes. The probability that a power quality c_x will be received as c_y at the output of the channel at each device d is represented by the symbol $p^{(d)}_{c_y|c_x}$. For each device d (or a subnet consisting of the concatenation of several devices), we call the $n \times n$ matrix consisting of the probability values $p^{(d)}_{c_y|c_x}$ the *power quality transition function*[1], or simply *transition function*. We represent the power quality transfer function $f(d)$ of a device d as a matrix as

$$f(d) = \begin{bmatrix} p^{(d)}_{c_1|c_1} & p^{(d)}_{c_2|c_1} & \cdots & p^{(d)}_{c_n|c_1} \\ p^{(d)}_{c_1|c_2} & p^{(d)}_{c_2|c_2} & \cdots & p^{(d)}_{c_n|c_2} \\ \vdots & \vdots & \ddots & \vdots \\ p^{(d)}_{c_1|c_n} & p^{(d)}_{c_2|c_n} & \cdots & p^{(d)}_{c_n|c_n} \end{bmatrix}, \tag{3.1}$$

where $p^{(d)}_{c_y|c_x}$ is the probability that the input quality c_x is received as c_y at the output of device d. Note that every row in the above matrix should sum to 1.

The above model significantly simplify the network complexity of the power grid. Using this analytical model, in the next few chapters, we propose various algorithms for power quality monitoring and demonstrate that this model significantly helps sim-

[1] For a device (or subnet) having multiple inputs/outputs, a power quality transition function is associated with each input/output pair.

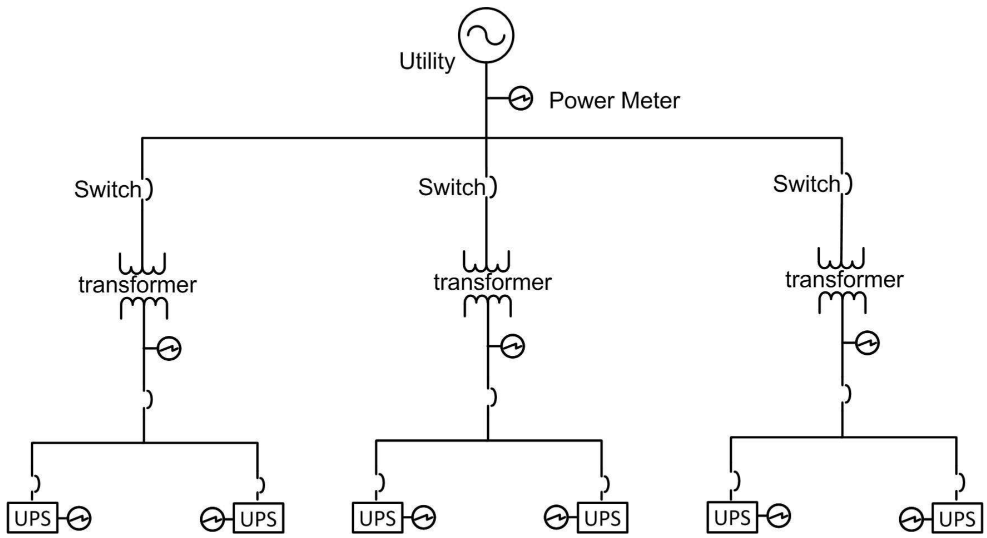


Figure 3.2: A simple view of power microgrid

plify things out there. A short summary of the proposing algorithms as applications of our analytical model is given in the next section.

3.3 Applications

We build various applications on top of the analytical framework we proposed in this Chapter. The applications are as follows.

3.3.1 Power Quality Estimation

Figure 3.2 shows a view of a power grid where there are different types of electrical devices connected to each other via power links. The smart meters are also installed on selected links. Moreover, every type of device has a power quality function which may be unknown. We want to estimate all the power quality functions based on the power quality values available on selected links where smart meters are installed.

In order to estimate the reliability of every device in the network, we need to estimate the power quality function $f(d_j)$ for each device d_j based on the quality function $f(s)$ of the subnet. It is clear that

$$f(s) = \prod_j f(d_j), \tag{3.2}$$

Our objective is to estimate $p^{(d_j)}_{c_y|c_x}$ (probability that power quality c_x will be mapped to power quality c_y at each device d_j). In order to solve the above research problem, we need to model the power network as data network and then we use data estimation techniques to solve Eq. (3.2).

3.3.2 Intelligent Meter Placement

For the meter placement problem, we propose an iterative approach for identifying network segments suitable for power meter placement. During each iteration of the algorithm we identify in a greedy manner the network segment that suffers from the most unpredictable power quality given the meters deployed so far. We then deploy the next power meter at that location.

We propose two algorithms 1) an entropy based algorithm; and 2) a Bayesian network or belief propagation based approach to solve the above problem. We take advantage of our analytic framework to calculate the uncertainty of the power quality values on various network segments. Part of the proposed work has accepted for publication and we plan to further investigate the issue and propose extensions of the current work.

We also investigate the problem of identifying the optimized number of meters required to achieve the desired level of reliability. We formulate the problem as an optimization problem where the objective is to reduce the number of meters while maintaining an acceptable level of reliability. In order to calculate the reliability (the uncertainty of power quality) on power links, we take advantage of our proposed analytical model where we represent the power network as a data network.

Chapter 4

Fast Estimation of Power Quality

Summary Power quality plays a critical role in the reliability of power networks. The monitoring of power quality, however, is a non-trivial task due to the high cost of measurement devices and the requirement on real-time responses. As a result, we need fast algorithms to estimate the power quality in various segments of a power network, using only a small number of measurement points. In this chapter, we propose a maximum-entropy (MaxEnt) based approach to estimating power quality in smart microgrid. Compared to other existing methods such as Monte Carlo Expectation Maximization (MCEM), the MaxEnt based approach is much faster.

Further, we identify a potential scalability limitation in the proposed solution and a possible extension of this work which will address the scalability issue is discussed at the end of this chapter. Some initial findings related to the newly proposing solution are detailed at the end of this chapter. Note that, the proposed work on our MaxEnt based solution have already completed as part of my PhD; these findings has already been published (reference available in Chapter 9). The extended MaxEnt based algorithm is also a key part of my PhD research which will be completed in near future. The time-line of the remaining research is shown in Chapter 8.

4.1 Introduction / Motivation

Power quality largely impacts the reliability and energy saving of power networks. Poor power quality such as voltage sags may lead to power outage and service interruptions. Service unavailability caused by power losses is a serious problem for many companies and organizations, e.g., it may result in a significant revenue loss for Internet service providers or even loss of lives in hospitals. To improve the reliability of power networks, organizations and large companies (e.g., Google data centers) adopt smart microgrid, and closely monitor the power quality in different segments of the microgrid.

Monitoring power quality, however, is not an easy task. Since the power measurement devices [6][7] (termed as smart meters in this proposal) are expensive, it is financially impractical to monitor every segment of a power network. The overhead of interconnecting these power meters and developing the power management system further increases the cost. In addition, in many cases direct monitoring of power quality is difficult, e.g., it is hard to install smart meters after power lines were sealed in hard-to-reach areas in a building. In general, we need to tackle the following challenge: based on a limited small number of monitored points in a power network, *how can we effectively estimate the power quality of other unmonitored segments of the network?*

We use our analytical framework proposed in Chapter 3 to represent the electric power network as data network. Using our proposed framework, we then model the power quality estimation problem as an optimization problem of missing data estimation in a data network.

We propose to use a Maximum-Entropy (MaxEnt) [8] approach to power quality estimation. The basic idea of MaxEnt is that out of all probability distributions consistent with a given set of constraints (i.e., the known measure values in our case), we should choose the one that has the maximum uncertainty to be the estimated power quality values. Intuitively, the principle of MaxEnt implies that we should make use of all the information that is given and avoid making (biased) assumptions about information that is not available. We model the problem of estimating power quality in such a way where we can effectively get the benefit of MaxEnt approach to correctly estimate the power quality values at links where we do not have any measuring device installed. We solve the formulated MaxEnt problem and validate its effectiveness and efficiency with a simulated microgrid system.

The proposed MaxEnt based approach may have a potential scalability issue. The proposed solution may not converge efficiently on subnet of larger sizes. In order to address this problem, we plan to extend the proposed MaxEnt algorithm. The possible extended MaxEnt approach is discussed in Section 4.7 of this chapter.

4.2 Related Work

According to the IEEE Gold Book [10], the industry practices for electric power quality in networks focus on measures such as reliability, availability, and Mean Time Between Failures (MTBF). While it is known [9] that lifetime and performance of electrical components are dependent on power quality, none of the measures defined in the IEEE Gold Book accounts for power quality. Moreover, these measures serve as theoretical values for comparisons and are not intended to work in real environment (with varying temperature, humidity, load, and power quality) as predictive tools for networks. Further, the ITI curve report illustrates the relationship between power quality and the likelihood of damage to electric components. While considering the importance of both the magnitude and duration of power quality events in isolation, it does not consider its cumulative effects over time.

The EM algorithm is one of the most widely-used algorithms for estimation and has been applied in a variety of research areas. In [3], the authors investigate the power of EM algorithm in the estimation of microgrid reliability. Although effective, the EM algorithm needs a long time to converge. We are thus motivated to find faster algorithms in power quality estimation for smart microgrid.

The measurement and monitoring of power quality are a vital part of today's smart grid. To classify power quality, a label is assigned to a power quality event, based on the feature of the event, e.g., the magnitude and duration of a voltage sage or swell. Typically, the power quality index, also known as System Average RMS Variation Frequency Index (SARFI), is reported as a count of the number of times the magnitude and duration fall below a threshold, standardized by the IEEE standard 1159-2009 [2].

4.3 Problem Formulation

Figure 4.1 shows a view of a power grid where there are different types of electrical devices connected to each other via power links. The smart meters are also installed on selected links. Moreover, every type of device has a power quality function which may be unknown.

We want to estimate all the power quality functions based on the power quality values available on selected links where smart meters are installed. We divide the power grid network into small subnets where in every subnet we have two smart

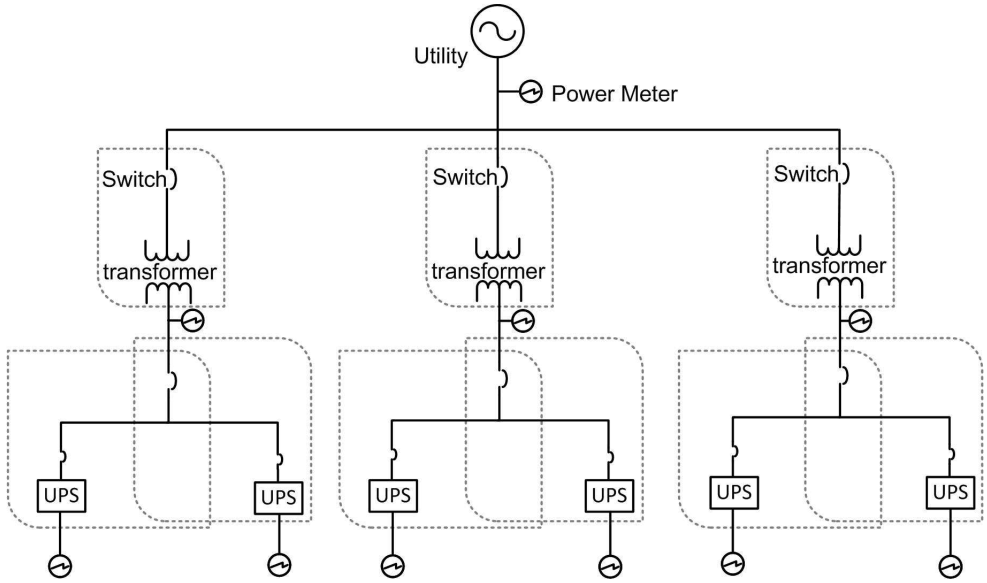
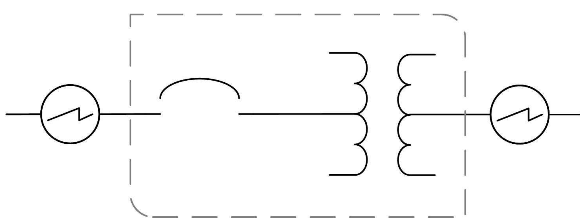
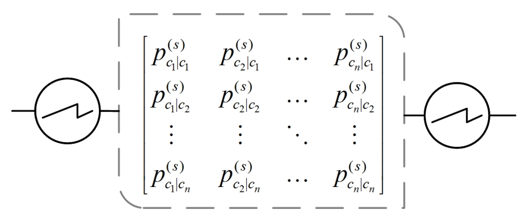


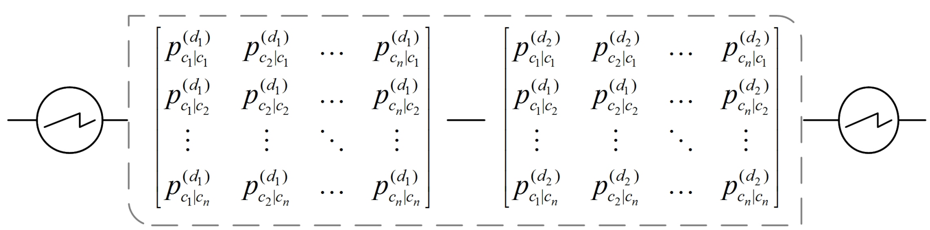
Figure 4.1: View of the power grid network under consideration. Subnets (within dotted lines) are formulated based on the positions of the power meters.



(a) A subnet containing 2 devices.



(b) Subnet as a single power transition matrix.



(c) Power transition matrix of each device d_j.

Figure 4.2: Subnet power transition matrix as a product of power transition matrices of individual devices.

meters, i.e., one at the input as the first node and one at the output as the last node of the subnet as shown in Figure 4.1.

Now, we consider every subnet as a single node which we call a black-box. Figure 4.2 shows the view of a subnet as a single node. For every black-box, we know the power quality values at the input as well as at the output. Based on this known power quality information, we calculate the power quality transition function by using some sample readings from the smart meters attached to both sides of every black-box. We represent the calculated power quality function $f(s)$ of subnet s as a matrix as follows:

$$f(s) = \begin{bmatrix} p^{(s)}_{c_1|c_1} & p^{(s)}_{c_2|c_1} & \cdots & p^{(s)}_{c_n|c_1} \\ p^{(s)}_{c_1|c_2} & p^{(s)}_{c_2|c_2} & \cdots & p^{(s)}_{c_n|c_2} \\ \vdots & \vdots & \ddots & \vdots \\ p^{(s)}_{c_1|c_n} & p^{(s)}_{c_2|c_n} & \cdots & p^{(s)}_{c_n|c_n} \end{bmatrix}, \tag{4.1}$$

where $p^{(s)}_{c_y|c_x}$ is the probability that the input quality c_x is received as c_y at the output of the subnet s. Moreover, the value of $p^{(s)}_{c_y|c_x}$ can be easily calculated by measuring power quality values at the input and output smart meters of the subnet. Note that every row in the above matrix must sum to 1.

Figure 4.2(a) shows a subnet containing two devices. The power quality transition function (as a matrix) of the subnet is shown inside the black-box in Figure 4.2(b). Our objective is to correctly estimate the transition functions of every device d_j in the subnet. These unknown functions are shown as matrices in Figure 4.2(c).

In order to estimate the reliability of every device in the network, we need to estimate the power quality function $f(d_j)$ for each device d_j based on the quality function $f(s)$ of the subnet. It is clear that

$$f(s) = \prod_j f(d_j), \tag{4.2}$$

which implies that

$$\begin{bmatrix} p^{(s)}_{c_1|c_1} & \cdots & p^{(s)}_{c_n|c_1} \\ \vdots & \ddots & \vdots \\ p^{(s)}_{c_1|c_n} & \cdots & p^{(s)}_{c_n|c_n} \end{bmatrix} = \prod_j \begin{bmatrix} p^{(d_j)}_{c_1|c_1} & \cdots & p^{(d_j)}_{c_n|c_1} \\ \vdots & \ddots & \vdots \\ p^{(d_j)}_{c_1|c_n} & \cdots & p^{(d_j)}_{c_n|c_n} \end{bmatrix} \tag{4.3}$$

Our objective is to estimate $p^{(d_j)}_{c_y|c_x}$ (probability that power quality c_x will be mapped to power quality c_y at each device d_j). We use the data estimation techniques to solve Eq. (4.3).

4.4 Power Quality Estimation using Entropy Maximization

Modeling the microgrids as data-driven networks helps us utilize the best available data estimation techniques to solve the power quality estimation problem. One of the most popular and widely-used data estimation techniques is EM algorithm. In a recent study [3], the authors successfully applied the EM algorithm to power quality estimation in microgrid. Although effective, the EM algorithm took a long time to converge. In this work, we propose to use a MaxEnt approach to estimating the power quality of unmonitored segments of the grid. Before we formulate the power quality estimation problem as a MaxEnt problem, first we give a short description of EM and MaxEnt algorithms:

- **The Expectation Maximization (EM):** EM is a general approach to iterative computation of maximum-likelihood estimates when the observations can be viewed as incomplete data. Since each of the iteration of the algorithm consists of an expectation step followed by a maximization step, the algorithm is named as the EM algorithm. The successive iterations always increase the likelihood and the algorithm converges at a stationary point.

- **MaxEnt:** MaxEnt solves convex optimization problems of the form,

$$\textbf{maximize } g(\vec{x}) = -\sum_{i=1}^{n} x_i \log x_i$$

$$\text{subject to } \mathbf{A}\vec{x} \leq \mathbf{c},\ \mathbf{B}\vec{x} = \mathbf{1},$$

  where $\vec{x} \in \mathbb{R}^n$ is the optimization variable, $A \in \mathbb{R}^{m \times n}$, and $B \in \mathbb{R}^{m \times n}$ are problem parameters; and $\mathbf{1}$ is a vector with all 1's.

Now, we model the power quality estimation problem as the MaxEnt problem to accurately estimate the power quality transition functions $f(d_j)$ with acceptable efficiency. Obviously, there are multiple possible power quality functions $f(d_j)$ which are consistent with Eq. (4.3). We consider only those solutions which not only satisfy Eq. (4.3) but are consistent with other design constraints, for instance: 1) every row in the matrix $f(d_j)$ must sum to 1 (or at least very close to 1); and 2) $p^{(d_j)}_{c_y|c_x}$ must not be negative. Other possible constraints are discussed later in this section.

The basic idea of using MaxEnt here is that out of all possible quality functions (probability distributions) consistent with the design constraints, we choose the one with maximum uncertainty. Intuitively, the principle of MaxEnt implies that we should make use of all the information (design constraints) that is available and avoid making (biased) assumptions about information that is not available. Our objective function becomes,

$$\textbf{maximize } g = -\sum_{j,\ x,\ y} p^{(d_j)}_{c_y|c_x} \log p^{(d_j)}_{c_y|c_x} \tag{4.4}$$

subject to following constraints:

1. All components of the estimated functions $f(d_j)$ must not be negative, that is,

$$p^{(d_j)}_{c_y|c_x} \geq 0 \tag{4.5}$$

2. Every row of $f(d_j)$ sum to 1. To allow negligible rounding errors, we introduce a small rounding error factor (ε_1) to be tolerated, i.e.,

$$\left| 1 - \sum_{y} p^{(d_j)}_{c_y|c_x} \right| \leq \varepsilon_1, \quad \forall x \tag{4.6}$$

3. The estimated functions $f(d_j)$ satisfy the condition $\prod_j f(d_j) = f(s)$. One may relax the condition by a small approximation error factor (ε_2) to adjust the rounding errors. This adjustment is necessary when we are interested in a close approximation of $f(s)$. This condition becomes,

$$\left| f(s) - \prod_{j} f(d_j) \right| \leq \varepsilon_2. \tag{4.7}$$

   Note that we slightly abuse the notation for simplicity. We use $-$ above to represent an element wise minus of two matrices and $|.|$ to change the values in the matrix to their absolute values. In addition, the symbol $\leq$ means all values in the left matrix is no larger than ε_2.

4. Every component of the estimated function $f(d_j)$ must not vary from its corresponding component of the "true" transition function $\acute{f}(d_j)$ by a factor ε_3,

i.e.,

$$\left| f(d_j) - \acute{f}(d_j) \right| \leq \varepsilon_3 \tag{4.8}$$

The meanings of the notations are the same as above.

Remark 1. *In practice, we do not know $\acute{f}(d_j)$. To avoid this problem, we can initially set $\acute{f}(d_j)$ as the transition function of the same type of device, which may be obtained via its specification or historical data of monitored devices of the same type. As time goes, this initial setting of $\acute{f}(d_j)$ should be updated with the optimal estimation function, i.e., $\acute{f}(d_j)$ is set to equal $f(d_j)$, and the updated $\acute{f}(d_j)$ is used for the next round of estimation. Such iterative updates capture the transition function of the (unmonitored) device, which may change over time.*

Remark 2. *Someone may argue that our solution may be biased toward the last constraint (i.e., Eq. 4.8). By ignoring the last constraint, we get many solutions consistent to the first three constraints and our objective function chooses the one having maximum uncertainty. Here, if we do not use constraint 4 (Eq. 4.8), we will be ignoring some known information about the transition functions of the unmonitored devices which may result in compromising the accuracy of the estimated transition functions. Further, in some rare cases, the last constraint may not be feasible when an obtained transition functions ($f(d_j)$) is different by an amount greater than ε_3 . In that case, we may ignore the last constraint or increase the value of ε_3.*

Remark 3. *It is worth noting that the objective function (4.4) is a non-Shannon measure, because $\sum_{j,\ x,\ y} p^{(d_j)}_{c_y|c_x} = \sum_j \sum_x \sum_y p^{(d_j)}_{c_y|c_x} > 1$. Nevertheless, by maximizing this non-Shannon measure, we obtain a good estimation of transition functions as demonstrated in our experimental evaluation. This is not by coincidence, since the objective function could be considered as the sum of several Shannon entropy functions (i.e., Given x and j, $\sum_y p^{(d_j)}_{c_y|c_x} \log p^{(d_j)}_{c_y|c_x}$ is a Shannon entropy measure). In our case, we treat each entropy function with the same weight. If we have more knowledge regarding the distribution of input power quality events, assigning different weights to different entropy functions may lead to better estimation. We leave this exploration as future work.*

Remark 4. *This work focuses on a centralized processing and as such we assume that there exists an underlying communication system to support data collection to a central point. The implementation of this communication system is beyond the scope*

Table 4.1: Transition Functions of Various Electrical Components [3]

		Output PQ				
		Class 1	Class 2	Class 3	Class 4	Class 5
Input PQ	Class 1	0.6	0.1	0.1	0.1	0.1
	Class 2	0.4	0.3	0.1	0.1	0.1
	Class 3	0.4	0.1	0.3	0.1	0.1
	Class 4	0.4	0.1	0.1	0.3	0.1
	Class 5	0.4	0.1	0.1	0.1	0.3

(a) Switch

		Output PQ				
		Class 1	Class 2	Class 3	Class 4	Class 5
Input PQ	Class 1	0.85	0	0	0	0.15
	Class 2	0.35	0.50	0.15	0	0
	Class 3	0.20	0.15	0.50	0.15	0
	Class 4	0.20	0	0.15	0.50	0.15
	Class 5	0.35	0	0	0.15	0.50

(b) Transformer

		Output PQ				
		Class 1	Class 2	Class 3	Class 4	Class 5
Input PQ	Class 1	1	0	0	0	0
	Class 2	0.1	0.9	0	0	0
	Class 3	0.1	0	0.9	0	0
	Class 4	0.1	0	0	0.9	0
	Class 5	0.1	0	0	0	0.9

(c) Bus

		Output PQ				
		Class 1	Class 2	Class 3	Class 4	Class 5
Input PQ	Class 1	1	0	0	0	0
	Class 2	0.8	0.2	0	0	0
	Class 3	0.8	0	0.2	0	0
	Class 4	0.8	0	0	0.2	0
	Class 5	0.8	0	0	0	0.2

(d) UPS

of this work. Further, the real-time issues of the monitoring and communication systems such as the data sampling and communication delay are ignored in the work.

Table 4.2: Convergence time (in seconds) comparison of MaxEnt vs EM algorithms.

		MaxEnt	EM		
			Iteration 5	Iteration 10	Iteration 15
Subnet size	2	2.16	40.3	117.7	402.6
	4	3.42	118.32	366.9	981.01

Table 4.3: Mean Squared Error comparison of MaxEnt vs EM algorithms.

		MaxEnt	EM		
			Iteration 5	Iteration 10	Iteration 15
Subnet size	2	0.00020	0.00017	0.00013	0.00010
	4	0.00030	0.00025	0.00019	0.00014

4.5 Performance Evaluation

We implement the proposed objective function and simulate a power microgrid using MATLAB. The view of the simulated network is shown in Figure 3.2 where only several network segments are monitored using smart meters. Our objective is to estimate the power quality values on network segment where no smart meter is installed. We use the same transition functions as in [3] as the ground truth. These power quality transition functions of various electrical components (switch, bus, ups, and transformer etc) in the smart grid are shown in Table 4.1.

We use non-linear constrained optimization algorithm named Sequential Quadratic Programming (SQP) to estimate the unknown power quality functions. Inputs to the algorithm are the known power quality functions for each subnet $f(s)$, error tolerance factors $\varepsilon_1 = \varepsilon_2 = 0.01$, and $\varepsilon_3 = 0.05$. The error tolerance is small enough for practical applications. The power quality matrix of each subnet is the product of the power transition functions (shown in Table 4.1) of the devices in that subnet. The simulated microgrid consists of subnets of two different sizes; one contain two devices (switch and a transformer) while the other containing four devices (switch, bus, switch, and UPS). Both of these subnets are shown in Figure 4.3. The power transition matrices of each subnet are calculated by multiplying the ground truth matrices of devices used in the corresponding subnet. Further, the simulation was performed on a desktop computer having Intel Dual-Core-i7 3.4 GHz processor with 4 GB physical memory.

Table 4.2 shows the convergence time comparison of both the EM and MaxEnt based solutions to power quality estimation. It can be seen that the convergence time

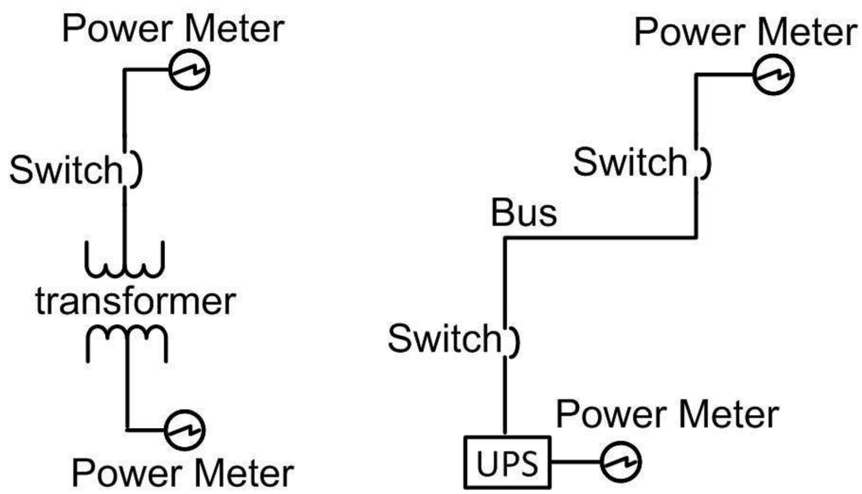


Figure 4.3: Two different kinds of subnets. The one at the left side containing two devices (switch, transformer) and the one shown at the right side containing four devices (switch, bus, switch, and UPS).

of MaxEnt is much faster as compared to that of EM algorithm. We measure the estimation accuracy using Mean Squared Error (MSE), which is a statistical measure quantifying the difference between values implied by an estimator and the true values of the quantity being estimated. The results are shown in Table 4.3. From the results, we can see that both the methods give very close estimations of the power quality transition functions, i.e., the difference between the estimated and corresponding ground truth functions is negligible.

4.6 Conclusions and Future Work

Reliability of power grid networks is critically important in today's life. Smart meters play an important role in estimating reliability of power networks but they are expensive devices and it is financially infeasible to install them on every link between devices in the power grid network. We propose a MaxEnt based model that accurately estimates power quality transition functions on unmonitored network segments. The experimental results show that 1) our MaxEnt based solution is much faster than the existing EM based solution to power quality estimation; and 2) the proposed solution accurately estimates the power transition functions.

Finally, the MaxEnt based model opens a new scope of methods to quantitatively measure and solve the reliability problems in smart grid. Like any other realistic solution, the MaxEnt based solution have a potential limitation. The proposed solution may not converge efficiently for sub-nets of larger sizes. We plan to address the issue and propose an extended version of our MaxEnt based solution. The possible extension is detailed in next section.

4.7 Possible Extension: PQ Estimation using Logical Integration

We plan to address the potential scalability limitation of our MaxEnt approach. The scalability problem arises as the number of unknown variables increases exponentially with increase in the number of components in a subnet. The idea for the extended work is to divide the larger subnets in logical components where each logical component will represent several physical components. We then estimate the transfer functions of the logical components instead of every physical component. Based on the logical transfer functions we then estimate the actual transfer functions of each physical device in a logical component. Note that this is a high level guideline which only sever as a good starting point toward the final solution. The final solution will be based on a comprehensive mathematical model and the proposed solution will be evaluated on various IEEE standard test simulated networks.

Chapter 5

Intelligent Meter Placement

Summary Power quality is a crucial component of power grid reliability. Due to the high cost of measurement devices, the monitoring of power quality is non-trivial. Our objective is to deploy measurement devices on suitable power links to reduce the uncertainty of power quality estimation on non-monitored power links. To realize our objective, we first model the power grid network as a data-driven network. Using entropy-based measurements and Bayesian network models, we propose different algorithms which identify the most suitable power links for power meter placement. Our Bayesian network based solution to meter placement in power grid is efficient, and has the potential to significantly reduce the uncertainty of power quality values on non-monitored power links.

Further, we identify a potential scalability limitation in the proposed solution and a possible extension of this work which will address the scalability issue is discussed at the end of this chapter. We plan to propose a conditional-entropy based algorithm which may overcome the scalability issue caused by our proposed solution. Some initial findings related to the newly proposing solution are detailed at the end of this chapter. Note that, the proposed work on our Bayesian network based solution have already completed as part of my PhD; these findings has already been published (reference available in Chapter 9). The extended conditional-entropy based algorithm is also a key part of my PhD research which will be completed in near future. The time-line of the remaining research is shown in Chapter 8.

Finally, another relevant problem of identifying the required number of power meters to achieve desired level of reliability is also detailed at the end of this chapter.

5.1 Introduction / Motivation

Electrical power networks are one of the critical infrastructures of our society. Due to our high dependence on electricity, the issue of reliability in electric networks has become a core research interest in the smart grid area [4]. Reliability evaluation of power grid, however, is challenging due to the existence of multiple electric utilities and the potential of cascading failures of power distribution systems [5]. One of the most influential factors impacting the reliability and energy saving of power networks is the power quality delivered to, and experienced by, critical electric equipment. Poor power quality, such as voltage sags, may lead to power outage and service interruptions. Hence, the monitoring of power quality is a crucial component of assessing and maintaining reliability in power grids.

To improve the reliability of power grid networks, power quality measurement devices are being deployed to closely monitor the power quality on underlying power links. Power meters are expensive devices [6, 7] and it is impractical to monitor every segment of the electric network. Instead, power quality in non-metered grid locations must be inferred given data obtained from the measured locations.

In general, we need to tackle the following question: given a fixed number of available power meters, which grid segments should be selected for monitoring such that power quality can be inferred as accurately as possible in the remaining non-monitored segments of the network.

We propose an iterative approach for identifying network segments suitable for power meter placement. During each iteration of the algorithm we identify in a greedy manner the network segment that suffers from the most unpredictable power quality given the meters deployed so far. We then deploy the next power meter at that location.

The approach builds on prior work by Gamroth *et al.* [3] in which a model was presented for predicting the propagation of power quality events through a power grid. The model assumes that time is slotted and power quality is discretized into a specific class. The power quality assigned at each time slot is characterized with its most extreme event. The work further introduced the concept of a device-specific transfer function that specifies how a power quality event experienced at the input of an electrical component will propagate through the component. In the current work, we use the same model of power quality event propagation as a basis for intelligent meter deployment.

Like every realistic solution, the proposed Bayesian network based approach may have a limitation. The proposed solution may not converge efficiently on larger networks. In order to address this issue, we are proposing to extend the current solution. The extended conditional-entropy based solution is detailed in Section 5.9 of this chapter. Further, we also address a relevant research problem of identifying the minimum number of required power meters to achieve a desired level of network reliability is elaborated in Section 5.10 of this document.

5.2 Related Work

This work is related to three categories of research and development: power quality classification, power reliability, and smart meter deployment.

On the first aspect, there are many approaches to the problem of classifying power quality events. Typically, quality is assigned a label based on the magnitude and duration of a voltage sag or swell. Electrical utilities typically report on indices such as System Average RMS Variation Frequency Index (SARFI) which is essentially a count of the number of times the magnitude and duration fall below a threshold. The IEEE also has a standard for classifying individual power quality events [2]. We use a discrete classification system in this work, similar to that described in the IEEE standard [2].

Regarding the second category, the industry standard practices for electric power reliability in networks focus on measures such as Mean Time Between Failure (MTBF), reliability, and availability as defined by the IEEE Gold Book [10]. The measures defined in [10] are theoretical values, measured or calculated for components and networks operating under standardized conditions. They serve as methods for comparison but are not intended as predictive tools for networks that operate in realistic environments with varying temperature, humidity, load, and power quality. It is known that there exists a relationship between power quality and the lifetime and performance of components [9]. For an effective evaluation of power reliability, we need to accurately estimate power quality [3], which motivates the meter placement problem studied in this work.

On the third aspect, there is a great body of work on the problem of optimal sensor deployment problem [11]. The meaning of sensors is broad, including any measurement/monitoring devices. In the context of power networks, optimal deployment of phasor measurement units (PMU) has been studied [12]. Nevertheless, we have not seen any work on studying optimal meter deployment problem in the context of network-wide power quality estimation.

5.3 Meter Placement Problem Formulation

Before we formally illustrate our proposed algorithms for the deployment of power meters in the electric power grid, we detail our assumptions about the structure and function of the power grid network as follows:

1. *The power grid network is a tree-structured network where the electric current flows from root node to the child nodes.* Note that this is a reasonable assumption at any particular instance in time. While enterprise level power grids used in places such as hospitals and data centers often have two utility feeds available as well as an independent emergency power source, only one power source is typically used at one time. See the IEEE Gold Book [10] for further information on recommended practices in the design of critical power systems.

2. *The probability mass function (*pmf*) of power quality values at the input link to the root node is known.* In other words, the distribution of power quality at the input to the network, usually the utility feed, is known. This is also a reasonable assumption, since electrical utilities typically report on indices such as System Average RMS Variation Frequency Index (SARFI) which is essentially a count of the number of times the magnitude and duration falls below a threshold. Furthermore, there are often independent bodies that gather statistics on power delivery service reliability that can also be incorporated into an estimate of power quality distribution [15].

3. *The power quality transfer function $f(d)$ is known for every device d.* A device-specific power quality transfer function could be estimated for specific models of electrical components through physical modeling or through the assessment of historical power monitoring data. Given a reasonable initial estimate, the transfer functions could be further refined through online learning techniques [3].

Given the assumptions listed above we can define a power meter placement algorithm as a process that takes as an input: the topology of the smart grid, an *a priori* estimate of the feed *pmf*, the power quality transfer function for each component, and

Algorithm 1: A Simple Entropy Based Algorithm

Input: distribution function of input link to device 1 i.e., $f_x^{(0)}$, transfer function $f(d)$, number of power meters M
Output: L (list of devices to be selected for meter placement)
begin
  foreach *(device d)* **do**
    $\hat{d} \leftarrow getParent(d)$;
    /* Note that device 1 (root of the tree) has no parent i.e., *getParent(1) = 0* */
    $f_x^{(d)} \leftarrow f_x^{(\hat{d})} \times f(d)$;
    $H(d) \leftarrow -\sum_{y=1}^{n} p_y^{(d)} \log p_y^{(d)}$;
    /* where $p_y^{(d)}$ is the y^{th} component of $f_x^{(d)}$ vector */
  end
  /* get N high entropy devices in vector H */
  $L \leftarrow getHighEntopyDevices(H, N)$
end

the total number of meters M. The output of the algorithm is a set of L locations for deploying power meters.

5.4 A Simple Entropy Based Approach

We propose that power meter may be deployed on network links where the power quality values are most uncertain. We measure the uncertainty of power quality on a link using Shannon's entropy measure. Therefore, the entropy formula to measure uncertainty at the output link of a device d becomes

$$H(d) = -\sum_{i=1}^{n} p_i^{(d)} \log p_i^{(d)},$$

where $p_i^{(d)}$ is the probability of getting power quality c_i at the output link of device d. We represent the output link of a device d as $l_o^{(d)}$ while the input link to the same device as $l_{in}^{(d)}$. Further, we represent the immediate parent of a node d as $\hat{d}$, the immediate child of a node d as $\check{d}$, and the the probability distribution of power quality values ($p_i^{(d)}$) at power link $l_o^{(d)}$ as $f_x(d)$ which is the product of $f_x(\hat{d})$ and the transfer function $f(d)$ of device d.

In order to calculate entropy of $l_o^{(d)}$, we need to know the power quality distribution function of that link. Starting from the root node of the tree-structured power network, we traverse nodes (devices) in level-order fashion to calculate the distribution function $f_x(d)$ as $f_x(d) = f_x(\hat{d}) \times f(d)$. After calculating the $f_x(d) = [p_1^{(d)}\ p_2^{(d)}\ \ldots\ p_n^{(d)}]$ where $p_y(d) = \sum_{x=1}^{n} p_x^{(d)} \times p_{c_y|c_x}^{(d)}\ \forall\ y = 1, 2, \ldots, n$, we use Shannon's entropy formula to calculate $H(d)$.

The details of our entropy based power meter algorithm are shown as Algorithm 1. The power meters are placed on links having maximum uncertainty. This simple algorithm is fast and useful when there is negligible impact of one link on any other link in the network. For instance, if some node always produces a power quality c_1 as output irrespective of the input quality (a stabilizer). Nevertheless, in most cases the network links are dependent on each other. Therefore, we need to consider the link dependency while calculating the uncertainty of a link, i.e., a meter reduces the entropy not only on the measured link, but also on other links. Further, based on our initial tests with the simple Algorithm 1, we conclude that it may create a poor allocation scheme for some cases. In the future, we will further improve this entropy based method to address the link dependency.

In the next section, we look into the possibility of dependency of parent links on their child links. With the help of a Bayesian network model, we calculate the conditional uncertainty of all links in the grid conditioned on data from deployed meters.

5.5 Bayesian Network Based Approach

This section describes another algorithm for selecting high information locations for deploying power meters in a power grid. The approach uses Monte Carlo sampling and probabilistic inference approaches to identify locations in the power grid which exhibit unpredictable power quality events. Unlike the simple entropy-based solution, this solution considers link dependency.

The problem is inherently challenging as the information received from a power meter flows not only the forward direction from the root nodes toward the leaf nodes, but also in reverse or upstream direction toward the root node (utility main) and back to all other nodes in the network.

To allow for this type of information flow, we cast the problem as a Bayesian network and model the power grid using a factor graph. Several message passing algorithms could be used to help us determine the optimal meter placement. We chose the belief propagation or sum-product algorithm [13] since it is well understood,

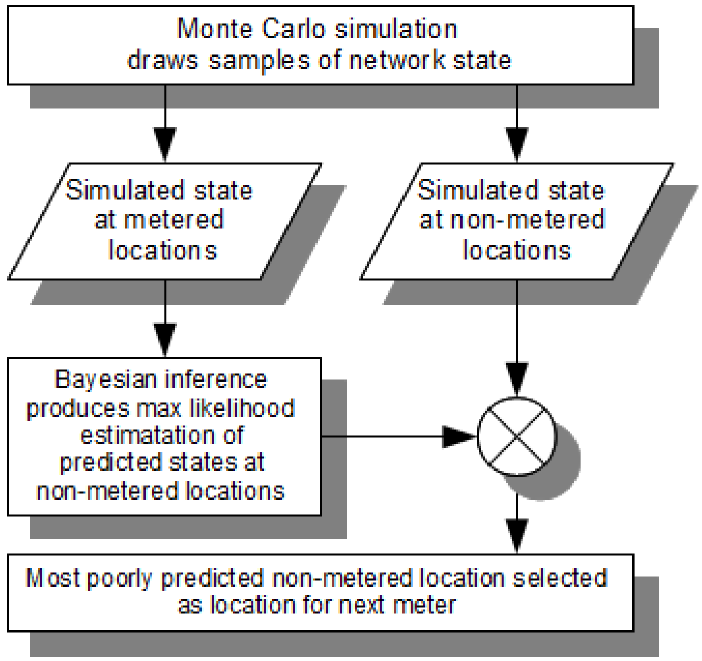


Figure 5.1: Data flow diagram of meter selection process during a single iteration of the greedy algorithm.

has been shown to work for general topologies [14] including tree networks, and has several software libraries available.

5.5.1 MC Event Sampling

Given the node transfer function $f(d)$ of device d, we use a Monte Carlo (MC) method to obtain a set of K samples at each node. At each time slot $i \in \{1 \ldots K\}$ we draw a sample c_1^i from the prior distribution of the utility feed. Then, for each node a *pmf* x_d^i is calculated given its node transfer function and the sample obtained from its parent node $\hat{d}$ using $x_d^i = F(d)x_{\hat{d}}^i$ and the sample c_d^i is drawn from x_d^i. We repeat this at each node of the tree starting from the root and ending at the leaves. The result is a set of K simulated samples $C_d^i = \{c_d^1, c_d^2, \ldots, c_d^N\}$ for each of the N links in the power network.

5.5.2 Event Inference using Belief Propagation

The samples obtained by the MC simulation of power quality propagation contain consistent sets of power quality values at both metered and non-metered locations.

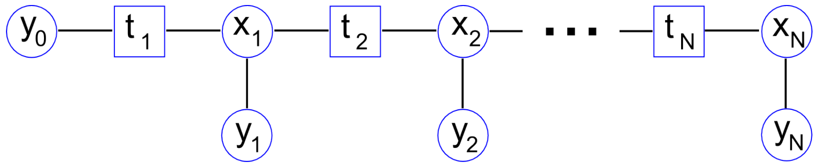


Figure 5.2: Power network modeled as a factor graph

We use Bayesian inference to infer the power quality at non-metered locations as a function of the simulated values observed at the metered locations and compare the resulting predictions to the simulated value seen at the non-metered locations. This process gives us a relative indication of our predictive strength on each link of the network. See Figure 5.1 for a system level description of this process.

To do the prediction, we first model the power network as a factor graph (Figure 5.2) and then use belief propagation to give us the inferred values of power quality at the output of each node using the (simulated) evidence obtained from the power meters. The factor graph has conditional probability nodes t, equality nodes x, and evidence nodes y. The t nodes represent actual electrical devices with a known transfer function. The x nodes represent wired connections on our network for which we have already obtained a set of samples using MC sampling. These nodes are constrained so that all edges connected to them are equal. The y nodes represent locations where a power meter could be placed. The non-metered nodes are initialized to a uniform *pmf* and the metered nodes are set to a trivial *pmf* with a probability of 1 at the true power quality event and 0 everywhere else.

For each time slot t_i we infer the maximum likelihood power quality event that would appear at each node given the current meter configuration. We then estimate the error rate for each node in the network. If the inferred event differs from the event given by the MC sample we add $1/K$ for that sample. At each round of the algorithm we greedily choose to place a meter at the node with the highest error rate. We terminate the algorithm when all meters have been placed. See Algorithm 2 and Figure 5.1 for further details.

Algorithm 2: Monte Carlo Predicted Error Algorithm

Input: The topology T of power grid; the pmf of the input feed to first device i.e., $f_x^{(0)}$; the set of transfer functions $F = \{f(d)\}, \forall d$; the number of power meters M to place; and the number of Monte Carlo samples to draw K

Output: L (list of devices to be selected for meter placement)

```
begin
    foreach (power meter m) do
        ε_l = 0, ∀ links l ∈ T;
        foreach (Monte Carlo Sample k) do
            c ← sample of instantaneous network state;
            w ← metered sub-set of c;
            z ← non-metered sub-set of c;
            ẑ ← predictPowerQuality(w, f_x^(0), F, T);
            foreach ( link l ∈ z) do
                if ẑ_l ≠ z_l then
                    /* Add to predicted error for this link */
                    ε_l ← ε_l + 1/K;
                end
            end
        end
        selectedLink ← max(ε);
        L.add(selectedLink);
    end
end

function predictPowerQuality(w, f_x^(0), F, T)
begin
    init pmf Ψ = {ψ_l}, ∀ links l ∈ T;
    Ψ′ ← BeliefPropogation given evidence w
    foreach ( link l ∈ T, l ∉ w) do
        z_l ← max probability power quality class inferred in ψ′_l;
    end
    return Z = {z_l}
end
```

5.6 Further Discussion: A Classification on Power Devices

We have observed that the probability of power quality values of a link $l_o^{(d)}$ is dependent on the uncertainty of 1) the transfer function $f(d)$, which lists conditional probabilities $p_{c_y|c_x}^{(d)}$; and 2) the distribution function $f_x(\hat{d})$. Based on various possible values of $f(d)$ and $f_x(\hat{d})$, different combinations arise. To facilitate later analysis on our experimental results, we group all possible cases into the following four different categories.

1. **Passive transfer function**: We call a transfer function $f(d)$ passive if it maps

Table 5.1: Networks used in our experiments

Network Configuration #	Topology	Device Configuration
1	Line	Uniform
2	Line	Varied
3	Tree	Uniform
4	Tree	Varied

the input power c_i to c_i with high probability. Such a transfer function results in a matrix with high probabilities on the diagonal i.e., $p^{(d)}_{c_y=i|c_x=i}$ is close to 1. In this case, $l^{(d)}_o$ has a much similar probability distribution as that of $l^{(d)}_{in}$ i.e., $f_x(d) \approx f_x(\hat{d})$. Now, if the input link is deterministic then the output link will also be deterministic and similarly if the input link has a uniform (uncertain) power quality distribution, we get the same uniform distribution at the output link. So, the $l^{(d)}_o$ is highly dependent on $l^{(d)}_{in}$.

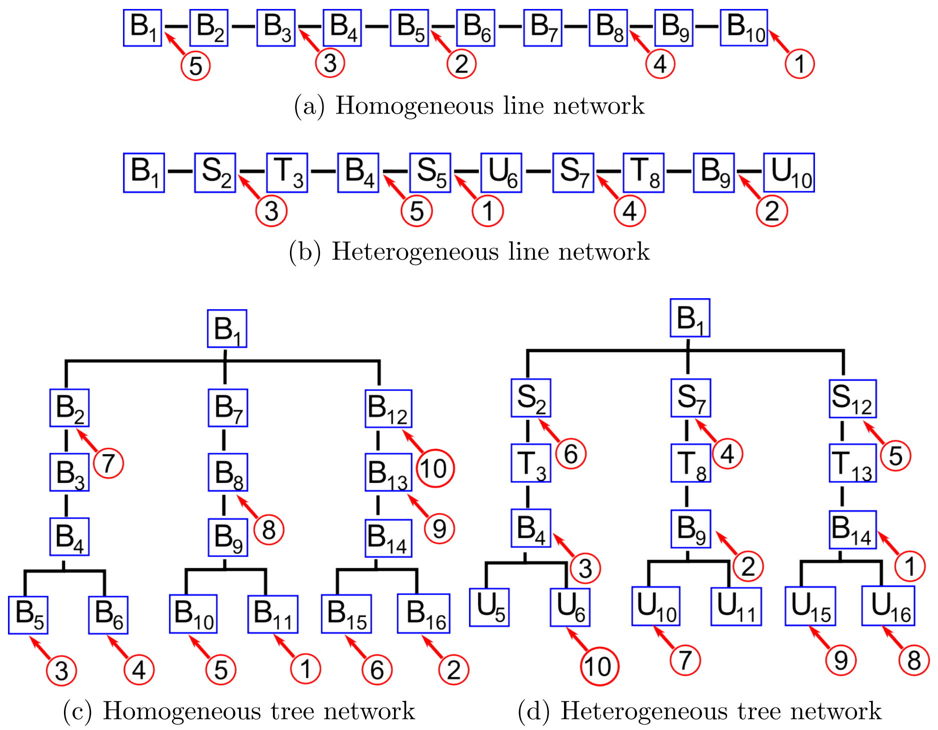
2. **Uniform transfer function**: $f(d)$ is uniform when every row of the matrix is uniformly distributed. In this case, for every input c_x, its mapping to any c_y is equally likely. We will always get a uniform output distribution $f_x(d)$ which is irrespective of whether the input distribution $f_x(\hat{d})$ is uniform or deterministic.

3. **Positively active transfer function**: We call a device positively active if it changes a power quality input c_x to a particular power quality (usually to a good quality) output with high probability. In this case, one column of the $f(d)$ matrix will have high probability values and the output distribution $f_x(d)$ will be deterministic irrespective of the input distribution.

4. **Negatively active transfer function**: In this case, a device d maps the input power c_x to some output c_y (where $c_x \neq c_y$) with high probability. Further, every input is mapped to a different output. Every row in $f(d)$ has a high probability value in a different column. In such a scenario, the output distribution is highly dependent on the input distribution.

5.7 Experiments

To test the meter placement algorithm, we used two network topologies. The first was a line network of ten devices. The second was a tree network with 16 devices.



(a) Homogeneous line network

(b) Heterogeneous line network

(c) Homogeneous tree network

(d) Heterogeneous tree network

Figure 5.3: Networks used in our experiments. B=bus, S=switch, T=transformer, U=UPS. Ordered circles correspond with the sequence of meters placed by our algorithm.

For each topology we choose two device configurations, one with all identical devices and one with a mixture of different devices. Each of the four networks used in our experiments is shown in Figure 5.3 and are enumerated in Table 5.1.

The devices considered are a bus, a switch, a transformer and a UPS. Power quality events are assigned a number from 1-5 in order of severity in accordance with [16] with 1 being a clean input. These event types are listed in Table 5.2 along with their descriptions. We used the transfer functions listed in Table 4.1 and assigned a prior on the utility feed of $\begin{bmatrix} 0.9947 & 0.0050 & 0.0002 & 0.00009 & 0.00001 \end{bmatrix}$.

For each network configuration we collected $K = 10000$ samples for each device using MC sampling. For the line network we placed $M = 5$ meters and for the tree network we placed $M = 10$ meters in order of importance. With these parameters, our algorithm took 90 minutes to run for the tree network and 40 minutes for the line network with a 2.3GHz i7 processor. At each iteration of the meter placement algorithm we report the three highest error rate values along with their corresponding nodes and the meter placement decision. These results are listed in Table 5.3.

Table 5.2: Event Types

Event #	Description
1	Good power quality / normal
2	Below 70% of nominal voltage for greater than 0.02 seconds or below 80% of nominal voltage for greater than 0.5 seconds
3	Below 70% of nominal voltage for more than 0.2 seconds
4	Interruption of at least 1 second
5	Interruption of at least 5 minutes

Table 5.3: Results for each network configuration

Round	Devices			Error Rates		
1	10	9	8	0.613	0.6088	0.5703
2	5	4	6	0.314	0.2908	0.2760
3	3	2	8	0.165	0.1650	0.1639
4	8	7	6	0.163	0.1613	0.0972
5	1	4	2	0.096	0.0953	0.0896

(a) Configuration 1

Round	Devices			Error Rates		
1	5	9	4	0.6470	0.5105	0.4921
2	9	8	7	0.5105	0.4608	0.3860
3	2	3	4	0.3585	0.3503	0.2847
4	7	4	3	0.1800	0.1702	0.1550
5	4	3	1	0.1702	0.1550	0.1044

(b) Configuration 2

Round	Devices			Error Rates		
1	11	5	16	0.413	0.412	0.412
2	16	6	5	0.406	0.403	0.402
3	5	6	4	0.385	0.382	0.317
4	6	10	15	0.180	0.179	0.179
5	10	15	8	0.179	0.179	0.165
6	15	13	12	0.179	0.160	0.110
7	2	8	12	0.100	0.099	0.097
8	8	13	12	0.099	0.093	0.093
9	13	12	3	0.093	0.092	0.089
10	12	3	7	0.092	0.089	0.085

(c) Configuration 3

Round	Devices			Error Rates		
1	14	9	4	0.503	0.502	0.496
2	9	4	8	0.502	0.496	0.445
3	4	3	2	0.496	0.439	0.366
4	7	12	2	0.204	0.203	0.203
5	12	2	10	0.190	0.188	0.104
6	2	10	16	0.179	0.104	0.103
7	10	16	15	0.104	0.103	0.103
8	16	15	6	0.103	0.103	0.099
9	15	6	11	0.103	0.099	0.099
10	6	11	5	0.099	0.099	0.098

(d) Configuration 4

5.7.1 Homogeneous line network

We consider first, the results obtained from a homogeneous line network (Figure 5.3a). For this configuration, the algorithm placed meters at the output of devices 10,5,3,8 and 1 in that order as shown in Table 5.3a and Figure 5.3a. Since all devices share the same transfer function and each one adds a small degree of uncertainty to the resulting *pmf*, we would expect the last device in the chain to have the highest degree of uncertainty; hence we would expect the first meter to be placed at the end of the chain. Once the first meter is placed the error rate for neighboring devices should be reduced, and this error reduction should be propagated toward the root. Prior to placing the second meter, we have knowledge at the beginning (from the prior *pmf*) and at end of the network and we know the least about the power quality at the midpoint, hence we would expect the second meter to be placed here. Subsequent placements should iteratively place meters at the nodes furthest from the metered locations, which is consistent with our results. This behavior is illustrated clearly in Figure 5.4.

5.7.2 Heterogeneous line network

Considering the heterogeneous line network of Figure 5.3b, it can be seen that the algorithm placed meters at device outputs 5,9,2,7,4 in that order. Meters were placed just before the two devices first, then after the remaining two. The fifth meter was placed before the second switch where the node distance from metered devices was greatest. Note that in Table 4.1 we see that buses and switches are both negatively active while transformers are both negatively and positively active; see Section 5.6. These can be placed in ascending order of expected entropy as bus, transformer, switch. The UPS is a positively active device, which means that for any given input event the probability of having a clean output event is high. However, in this case, the expected entropy is low only in the forward direction. If clean power is detected at the output of the UPS there is still a high degree of uncertainty regarding the input power quality. Therefore, placing meters at the inputs to the UPS devices is reasonable as initial meter placements.

5.7.3 Homogeneous tree network

Considering the results obtained from the homogeneous tree network (Figure 5.3c), we can see that meters one through six have been placed at the leaf nodes as expected and the subsequent meters have be placed along the main branches of the tree in midpoint locations.

5.7.4 Heterogeneous tree network

Finally, when considering the results obtained for the heterogeneous tree network shown in Figure 5.3d, it can be seen that the first three meters were placed at the Bus outputs just before the UPS branches and the next three meters were placed at the output of the switches as would be expected. The last four meters were placed

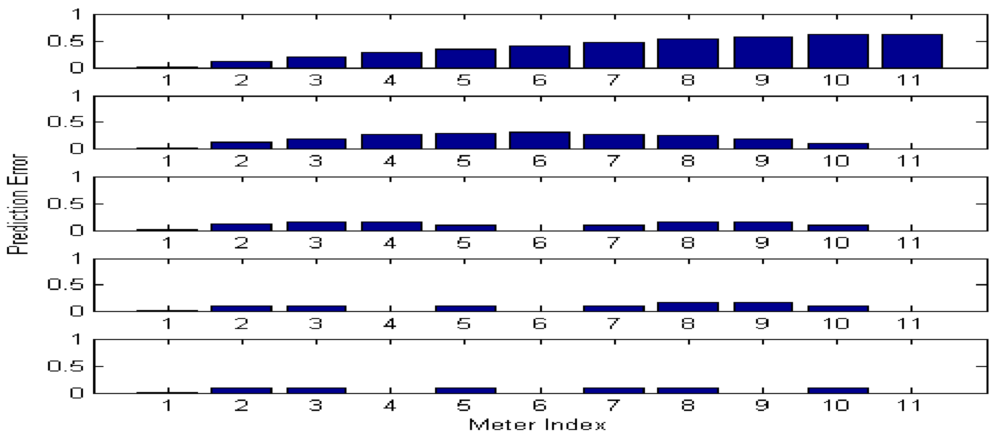


Figure 5.4: Prediction error at each round of meter placement (shown from top to bottom) for the uniform line network.

after the UPS outputs, suggesting that the error rate was low at the network segments feeding into the UPS devices.

5.8 Conclusions and Future Work

We formulate the problem of selecting suitable meter placements in power grids such that power quality can be best predicted. Two approaches were presented, one based on entropy and one considering prediction error. Experiments conducted using the last approach suggest that the algorithm produces meter placement recommendations that are consistent with expectations based on numerical analysis.

Future work will look at extending the scalability of the approaches. Currently we estimate the instantaneous maximum likelihood estimate of the power quality values at the non-metered locations conditioned on the specific values of the measurements obtained at the metered locations. It should be possible, however, to estimate the *pmf* of the power quality at the metered locations and then, in a single step, derived a message passing algorithm for computing the resulting conditional entropy (or expected prediction error) at all non-metered locations. This approach would considerably improve the running time of the algorithm.

In future, we also plan to consider larger networks, specifically the IEEE standard test networks. Moreover, we will also look into the possibility of extending our work to cover the networks containing loops to relax our tree network assumption made in this work. Another important and relevant research problem is to device a mechanism that calculate the optimal number of meters required to reduce the uncertainty of power quality in the smartgrid to an acceptable level.

5.9 Possible Extension I: A Conditional-Entropy Based Approach

We plan to address the scalability limitation of our proposed Bayesian network based solution for meter placement in smart grid. We propose a conditional-entropy based extension. We believe that the conditional-entropy based approach for calculating uncertainty of PQ values on segments in the power grid network is much faster than Bayesian network based approach. We also look into the possibility of proposing a hybrid approach using both our proposed Bayesian network and the prospective conditional-entropy based solution. The possible extension is discussed as follows.

5.9.1 Conditional-Entropy Based Approach

As discussed earlier in this chapter, the uncertainty of power quality values on a link is dependent on the uncertainty of power quality values on other links in the network. Secondly, from the concept of conditional entropy we know that entropy of a link given another link is always less than or equal to its original entropy i.e., $H(Y \mid X \leq H(Y))$. Since, every link $l_o^{(d)}$ if chosen for smart mater placement, influence the uncertainty of PQ values on other links i.e., it reduces the entropy of other links by a positive amount which is ≥ 0. Therefore, we consider the conditional entropy of all monitored links while deploying power meter at a link $l_o^{(d)}$.

Now, the conditional entropy of the output link $l_o^{(d_i)}$ of device d_i given that the smart meter is being installed on the output link $l_o^{(d_o)}$ of an observed device d_o is calculated using the formula

$$H(Y \mid X) = \sum_{x \in X} \left(p(x) \sum_{y \in Y} p(y \mid x) \log\left(\frac{1}{p(y \mid x)}\right) \right),$$

where X and Y are the distribution functions of the output links of d_o and d_i respectively. We write the above equation in terms of our power quality distribution vector

$f_x(d_o)$, device transition matrix $f^*(d_i)$ as under:

$$H(Y \mid X) = -\sum \left(f_x(d_o) \times \left(f^*(d_i) \otimes \log f(d_i) \right) \right),$$

where $\times$ represents the cross product, the symbol $\otimes$ represents the dot or componentwise product (also known as Hadamard product), and log is a componentwise log operation.

Further, the $\sum$ operation is the summation of components of the resulting vector after $\otimes$ and then $\times$ operations. Note that $f^*(d_i)$ is the combined transfer function of all the devices between links $l_o^{(d_o)}$ and $l_o^{(d_i)}$. Depending on the positions of d_o and d_i, the method of calculating $f^*(d_i)$ varies. Hence, the transfer function $f^*(d_i)$ is calculated in one of the three ways as under:

1. **Observed device d_o is a child of d_i:** Here we calculate the influence of a child device on a parent device. Note that the parent may not necessarily be the immediate parent. In order to calculate the entropy of parent given child using the general formula of conditional entropy, we need to first calculate the combined transfer function of devices between links $l_o^{(d_o)}$ and $l_o^{(d_i)}$.

   Here we use the concept of posterior probability (the Bayes theorem) to calculate $f^*(d_i)$. This function is simply the product of the reverse transfer functions of devices all the way from child to parent. The reverse transfer function $f'(d)$ (consist of $p(parent \mid child)$ or $p(X \mid Y)$) is calculated as $p(X \mid Y) = \frac{p(X)p(Y/X)}{p(Y)}$. In our case, the function $f'(d)$ of a device d which list $p(x \mid y)$ in the xth row and yth column is calculated as under:

$$f'(d) = \begin{bmatrix} f_x(\widehat{d}) \\ f_x(\widehat{d}) \\ \vdots \\ f_x(\widehat{d}) \end{bmatrix} \otimes \left[f(d)\right]^T \oslash \begin{bmatrix} f_x(d) \\ f_x(d) \\ \vdots \\ f_x(d) \end{bmatrix}^T,$$

   where $\otimes$ is the componentwise product, $\oslash$ is the componentwise division, and $\widehat{d}$ is the immediate parent of the device d .

   Finally:

$$f(d^*) = f(d_o) \times f(\widehat{d_o}) \times \ldots \times f(\widecheck{d_i}).$$

2. **Observed device d_o is a parent of d_i**: Here, the combined transfer function (i.e., $p(child \mid parent)$ or $p(Y \mid X)$) is simply the product of the normal transfer functions of devices between between links $l_o^{(d_o)}$ and $l_o^{(d_i)}$, i.e.,

$$f(d^*) = f(\breve{d}_o) \times \ldots \times f(d_i).$$

3. **Devices d_o, d_i belong to different sub-trees**: This is an interesting case where the devices d_o and d_i belong to two different sub-trees rooted by a dive d_r. In this case, the combined transfer function is calculated in two steps. First, we calculate the combined transfer function (say it is $f(d_1^*)$) of devices between links $l_o^{(d_o)}$ and $l_o^{(d_k)}$ using method 1. We then calculate the combined transfer function (say it is $f(d_2^*)$) of devices between links $l_o^{(d_k)}$ and $l_o^{(d_i)}$ using method 2. Finally: $f(d^*) = f(d_1^*) \times f(d_2^*)$.

5.9.2 The Algorithm

This section give a descriptive procedure of how to select a link for smart meter deployment. A comprehensive mathematical model and the actual algorithm will be investigated as part of this work. The idea here is to install each meter under consideration on a link i of the network which results in maximum reduction in overall network entropy. We consider all possible deployment points for every meter to be deployed and choose a link which reduce the network entropy at maximum. Note that a reduction in network entropy is the sum of entropy reduction on the underlying link i and all other links whose entropy is minimized/reduced in effect of placement on i.

This way, for every meter, we check all unmonitored links for a possible deployment. In order to calculate the overall network entropy for every possible link choice, we calculate the entropy of every link $l_o^{(j)}$ given that power meter is placed on $l_o^{(i)}$ as under. For device i, we recursively calculate the entropies of all of its neighboring devices and similarly if any neighboring device of i has neighbors (excluding device i), we recursively calculate the entropies of those neighbors given device i. In this fashion, we calculate the conditional entropies of all devices given device i and choose a device i which result in minimum network entropy. We repeat the same process until we deploy all smart meters. After every smart meter placement, we update the link entropies and for the next smart meter to be placed, we calculate a further possible reduction in the network entropy.

We calculate the conditional entropy of $l_o^{(j)}$ given $l_o^{(i)}$ by multiplying $f_x(i)$ with transition functions of all devices on the path between links $l_o^{(i)}$ and $l_o^{(j)}$ as discussed earlier in this section. We do not need to explicitly identify the path from $l_o^{(i)}$ to $l_o^{(j)}$ and we do not need to multiply the same transition functions again and again. The entropy calculation works in recursive fashion. Once we calculate the conditional entropy for a directly connecting neighbor of i, we then recursively calculate the entropies of neighboring devices of that neighbor. Here, it should be noted that 1) every device trigger the neighboring devices except the one who triggered the device itself. So no infinite recursion takes place and every link is accessed only once; 2) The product of transition functions calculated from device i to some device k will be used to calculate the next product; 3) if a device is invoking its parent device, we use reverse transition function of that device otherwise the normal transition function.

5.9.3 Conclusions

We propose a conditional-entropy based algorithm to meter placement in the power grid. Compared to our previous Bayesian-based algorithm, this solution seems to be much faster. The one time matrix multiplications in this approach are much faster than our previous requirement of re-sampling the network state after every possible meter deployment.

This work is still under progress where we cannot support our claims by experimental evaluations. Based on our experience with the previous and current solutions, we believe that this solution will be much faster. Further, we are also looking into the possibility of proposing a hybrid solution which will use both the Bayesian network, conditional-entropy based solutions.

5.10 Possible Extension II: Required Number of Power Meters

As discussed in earlier chapters, power quality plays a critical role in the reliability of power networks. The monitoring of power quality, however, is a non-trivial task due to the high cost of measurement devices and the requirement on real-time responses. As a result, we need to deploy less possible number of power meters to measure the power quality on various segments of the power grid network.

On the other hand, using small number of meters may compromise the purpose of network power quality monitoring. Ideally, power meters may be placed on every link of the power grid network to reduce the uncertainty of power quality values on every link to zero which will significantly help in improving the reliability of the grid.

We have to make trade-off between number of meters and network reliability. In order to maintain a balance between the two objectives, we need to device a mechanism that calculate the optimal number of meters required to reduce the uncertainty of power quality in the power grid to an acceptable level. We have to intelligently place less number of meters to reduce the cost to an acceptable level. The challenge here is to intelligently place the optimal number of meters to reduce the uncertainty and hence the overall reliability of the network to an optimal value. Formally, we tackle the problem of *how to device a mechanism that calculate the optimal number of meters required to reduce the uncertainty of power quality in the power grid to an acceptable level?*

5.10.1 Proposed Solution

We propose to model the identified issue of *number of power meters required* as an optimization problem. The objective is to reduce the number of meters while maintaining an acceptable level of reliability.

Our solution to this problem will be based on our solutions proposed earlier in this document, i.e., 1) Power Quality (PQ) estimation, 2) Intelligent Meter Placement, and 3) The Analytical Framework. The PQ estimation, and intelligent meter placement solutions help us reduce the number of meters in the network. Reusing these solutions significantly help in solving this problem. Detail of the reused components is as follows:

1. **PQ Estimation:** Since the meters are being placed on selected links, we use our proposed MaxEnt based algorithm to calculate the PQ values on unmonitored links of the network. We then calculate the reliability of the network in terms of PQ uncertainty on network segments. The total network reliability in terms of power quality is represented as R. The network reliability is sum of reliabilities of individual links which is represented as R_i where i is the i^{th} link in the network.

2. **Intelligent Meter Placement:** In order minimize the number of meters, we intelligently place the power meters on selected links using our proposed meter

placed algorithms (proposed in Chapter 5). After intelligent meter placement, we check if the desired reliability level is achieved. This way, the intelligent meter placement algorithm is used as part of solution to current problem (minimizing N while maintaining R).

3. **The Analytical Framework:** The above two solutions are proposed to be significant parts of the current solution. Both of the above methods are based on our analytical framework, solution to the current problem also becomes an application of the analytical framework.

5.10.2 The Model

Now we model the research problem of identifying the optimum number of meters as an optimization problem. Our objective function becomes:

$$\min_{n} R^{(N)} \geq R \tag{5.1}$$

where $R = \sum R_i$, $R^{(N)} = \sum R_i^{(N)}$, and $R^(N)$ represent the reliability of the network having N smart meters deployed. The objective is to minimize N while maintaining the reliability level R.

5.10.3 Our Algorithm

Based on our proposed model (Eq. 5.1) , we device Algorithm 3 that calculates the optimal number of meters required to achieve the desired reliability level R of the power network in terms of power quality.

Algorithm 3 shows a very abstract sketch of our proposing solution. We plan to further investigate the issue and give a detailed version of the algorithm.

5.10.4 Evaluation

We plan to evaluate the Algorithm 3 by simulating different kind of power grids using our analytic framework. The network types includes various tree and bus networks of different sizes. Further, we plan to evaluate our solution on both homogeneous and heterogeneous types of power networks.

Algorithm 3: An Optimum Number of Meters Calculating Algorithm

Input: reliability level R, the power network as adjacent matrix, and transfer function $f(d)$.
Output: number of meters N.

```
begin
    N ← 0
    while (R^(N) ≤ R) do
        N ← N + 1;
        deployNextMeter(); /* using Algorithm 2 of Chapter 5 */
        calculateNetworkPQ(); /* estimate power quality on unmonitored links using
        MaxEnt based estimation proposed in Chapter 4 */
        R^(N) = getNetworkReliability();
    end
end
```

5.10.5 Discussion

We formulate the research problem of identifying the optimum number of meters to be deployed in the power network to achieve the desired level of reliability. The problem is modeled as an optimization problem. Based on the objective function and reusing our relevant solutions, we propose a new algorithm that compute the minimum number of meters required. As part of this thesis, we plan to device a detailed version of the proposed algorithm and evaluate it on various types of power networks. We will take advantage of our proposed analytic framework to simulated the power grid networks.

Chapter 6

Detecting the Malfunctioning Devices

6.1 Introduction / Motivation

As discussed in Chapter 1, the main objective of this work is to increase the reliability of power networks in terms of power quality. In order to monitor the power quality, power quality measurement devices are being deployed. Since power quality meters are expensive devices, we propose to intelligently place the power meters on selected segments in the power network. We then estimate power quality on unmonitored links based on the known values from monitored links. Since the power quality readings (exact readings from monitored links, estimated reading from unmonitored links) are available now, we can use this information to estimate the state of the network and identify any potential malfunctioning device. Our research problem becomes: *how to detect a potential malfunctioning device in the power network based on available PQ readings*. Next section briefly elaborate the proposed idea of detecting the potential malfunctioning devices in the power network.

6.2 Proposal

Assume that one or more smart meters have continuously measured poor power quality. The power quality is indicated by some specific power quality index, for instance the System Average RMS Variation Frequency (SARFI) index . Based on the measured and estimated PQ values, we would like to know which device is most likely to be malfunctioning. Here, we assume that we know the transform function of each device if the device is working properly. We call these transfer functions the regular transform functions of the devices. Now, a malfunctioning device is the one whose estimated transform function deviates significantly from its regular transform function.

We plan to first give a comprehensive mathematical model of the problem. We then device a mechanism to calculate the deviation in transfer functions and finally we plan to propose an algorithm to efficiently identify any potential malfunctioning device in the power network. The proposed algorithm will be evaluated on various tree and bus structured network; specifically we will use the IEEE standard test networks for our simulations.

6.3 Conclusion

Power quality meters play an important role in the reliability of power networks. We plan to investigate the problem of identifying devices that degrade the power quality in the system. The proposed solution will be built on top of our already proposed work.

Chapter 7

Meter Selection Criteria

The rapid increase in power energy needs catalyzed the massive growth of electric networks. In order to meet the growing energy demand, electric industry seek to take advantage of novel approaches. Further, the need to merge the renewable distributed power generations with the legacy grids is driving the electric grid to a new grid paradigm – smart grid. According to a recent survey on smart grid, the research is focusing in the area is focusing on three systems in – the infrastructure system, the management system, and the protection system [17]. The smart grid infrastructure system consists of energy, information, and communication infrastructures where the smart metering is one of the key components.

Since the electricity grids consist of networks of varying physical characteristics, the capabilities of power quality meters varies accordingly. Second, there are many causes of power quality problems including voltage sags/swells, fast/sub-cycle impulses, harmonics, and high frequency noise etc, which will influence the choice of meters to be deployed. Another factor could be the frequency and potential effect of these causes as some of the causes occur frequently while the others occur rarely. Finally, depending on the users' requirements and financial budget, the capabilities of the power meters varies.

We plan to conduct a detailed research study to identify the required capabilities of a power meter based on: 1) user types; 2) financial budget; and 3) the environmental factors. Currently, many measurement devices use the level of voltage on electric lines as the measurement parameter to classify power quality. In additional to using the voltage level as a measure, we propose to consider physical power characteristics like level of current as well.

We plan to conduct a detailed study on the issue discussed above. Specifically we plan to: 1) study the causes and effects of PQ problems; 2) physical power characteristics on segments of different kind of networks; 3) the influence of environmental factors on power d; and 4) other driving factors like financial budget of the user etc. Finally, based on our findings, we will give our recommendations about what kind of power quality meter need to be deployed in different scenarios.

Chapter 8

Expected Contributions

The expected contributions and their corresponding milestones are listed in Table 8.1. The time line of the expected research is shown as a Gantt chart in Fig. 8.1.

Research Topic	Expected Contribution	Completion Date
Analytical Framework for Power Quality Monitoring	Literature Review	Finished
	Modeling of Power Network	Finished
	Porting Identified Problems on the Framework	Finished
Power Quality (PQ) Estimation	Literature Review on PQ	Finished
	MaxEnt based PQ Estimation	Algorithm Designed
	Experiments	Done
	Paper Publication	Published
	Extension of the work	November, 2014
Intelligent Meter Placement	Literature on Meter Placement	Finished
	Proposed Solutions: 1) Entropy Based 2) Bayesian Network Based	Algorithms Designed
	Experiments	Done
	Paper Publication	Published
	Extension of the work	April, 2014
Detecting Malfunctioning Devices	Literature Review	June, 2014
	Proposed Solution	July, 2014
	Paper Writing	August, 2014
Investigating the Meter Choices	Literature Review	January, 2015
	Proposed Solution	February, 2015
	Paper Writing	March, 2015
	Ph.D Dissertation	June, 2015

Table 8.1: Expected Contributions and their Expected Completion Dates.

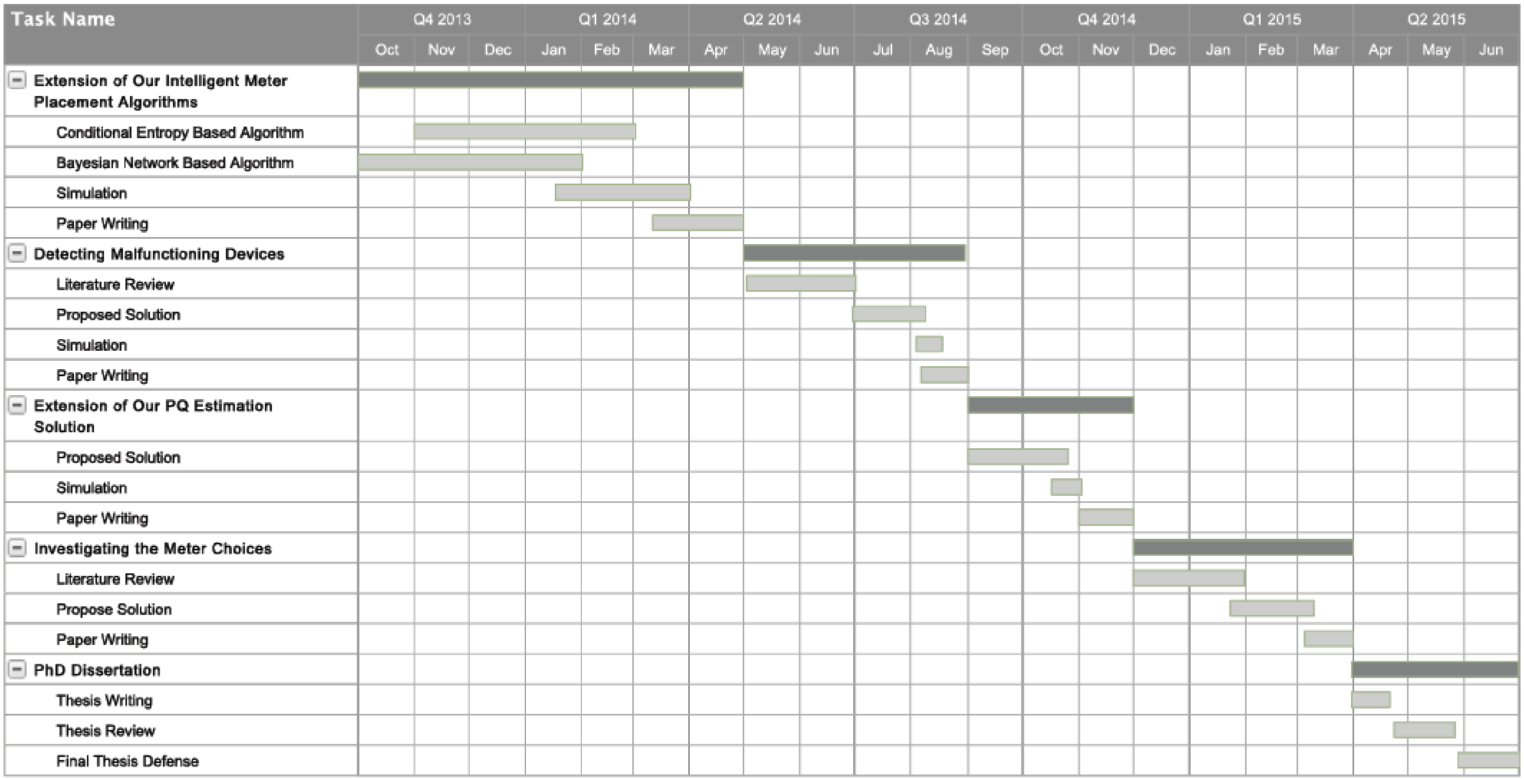


Figure 8.1: Gantt Chart of Expected Contributions.

Chapter 9

Publications

1. Sardar Ali, Kui Wu, and Dimitri Marinakis, "A maximum-Entropy Based Fast Estimation of Power Quality for Smart Microgrid," *IEEE SmartGridComm*, Vancouver, Canada, 2013.

2. Sardar Ali, Kyle Wetson, Dimitri Marinakis, and Kui Wu, "Intelligent Meter Placement for Power Quality Estimation in Smart Grid," *IEEE SmartGrid-Comm*, Vancouver, Canada, 2013.

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