Intelligent Meter Placement for Power Quality Estimation in Smart Grid

Sardar Ali, Kyle Weston, Dimitri Marinakis, and Kui Wu
Dept. of Computer Science, University of Victoria, BC, Canada
sali@csc.uvic.ca, kweston@kinsolresearch.com, dmarinak@kinsolresearch.com, wkui@ieee.org

***Abstract*—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 proposed solution is efficient, and has the potential to significantly reduce the uncertainty of power quality values on non-monitored power links.**

I. INTRODUCTION

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 [1]. 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 [2]. 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 (termed as power meters in this paper) are being deployed to closely monitor the power quality on underlying power links. Power meters are expensive devices [3] 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.

In this paper, 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.* [4] 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.

The rest of the paper is organized as follows. We briefly introduce related work in Section II. To facilitate understanding and problem illustration, we model the electric power grid as a data-driven network and formalize our problem definition in Section III. In Sections IV and V, we present algorithms for meter placement in the power grid network. To ease the understanding of our experimental results, we classify electric devices in different categories in Section VI. We present results from an experimental study in Section VII and conclude the paper in Section VIII.

II. 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 [5]. We use a discrete classification system in this work, similar to that described in the IEEE standard [5].

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 [6]. The measures defined in [6] 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 [7]. For an effective evaluation of power reliability, we need to accurately estimate power quality [4], which motivates the meter placement problem studied in this paper.

On the third aspect, there is a great body of work on the problem of optimal sensor deployment problem [8]. 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 [9].

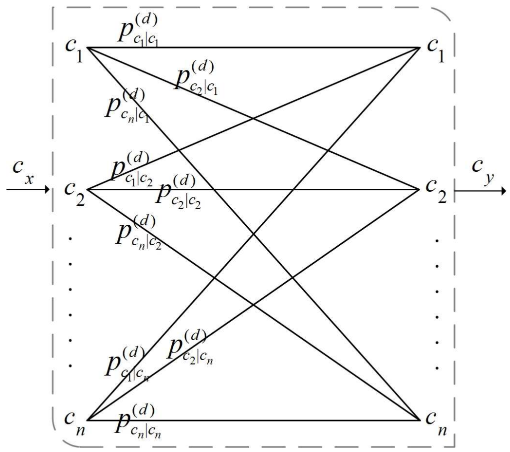


Fig. 1. Power quality transfer at each device d as a channel.

Nevertheless, we have not seen any work on studying optimal meter deployment problem in the context of network-wide power quality estimation.

III. Problem Formulation

A. Power Grid as a Data Driven Network

We model the power grid network as a data-driven network, in analogy, where we represent the electrical components as network nodes, power links as data links, and the flow of power as data flow on the links. We assign the power quality on a link at an instance in time as a discrete class (from c_1 to c_n). The power quality class c_1 represents the best power quality while c_n represents the worst quality. Since power meters measure power quality continuously, we assign a power quality class c_i to the power quality on a link as the worst power quality event measured on that link in the time interval. In every time slot, we record a power quality class of each link where a smart meter is installed.

Moreover, in order to simplify our model, we treat the power flow through each node as a channel (shown in Figure 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, we call the $n \times n$ matrix consisting of the probability values $p^{(d)}_{c_y|c_x}$ the *power quality transfer function*[1], or simply *transfer function*. We represent the power quality transfer function $f(d)$ of a device d as a matrix as

$$f(d) = \begin{bmatrix} p^{(d)}_{c_1|c_1} & p^{(d)}_{c_2|c_1} & \cdots & p^{(d)}_{c_n|c_1} \\ p^{(d)}_{c_1|c_2} & p^{(d)}_{c_2|c_2} & \cdots & p^{(d)}_{c_n|c_2} \\ \vdots & \vdots & \ddots & \vdots \\ p^{(d)}_{c_1|c_n} & p^{(d)}_{c_2|c_n} & \cdots & p^{(d)}_{c_n|c_n} \end{bmatrix}, \qquad (1)$$

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. A similar model for power quality propagation has been used before by Gamroth *et al.* [4].

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

B. The Problem: Power Meter Placement

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 centres 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 [6] 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 [10].
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 modelling 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 [4].

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

IV. 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

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

$f_x(d)$ 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.

V. 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.

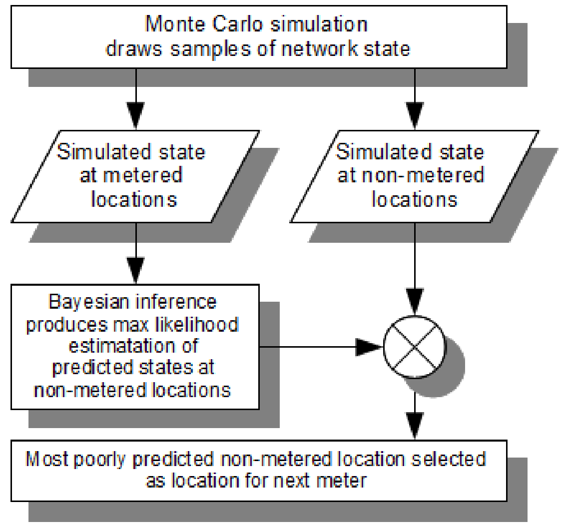


Fig. 2. Data flow diagram of meter selection process during a single iteration of the greedy algorithm.

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 [11] since it is well understood, has been shown to work for general topologies [12] including tree networks, and has several software libraries available.

A. Methodology

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.

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. 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 2 for a system level description of this process.

To do the prediction, we first model the power network as a factor graph (Figure 3) 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

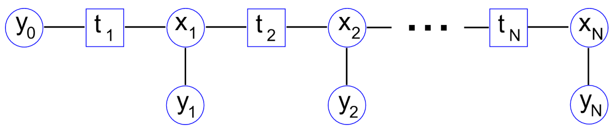


Fig. 3. Power network modeled as a factor graph

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**
        $\epsilon_l = 0, \forall$ links $l \in T$;
        foreach *(Monte Carlo Sample k)* **do**
            $c \leftarrow$ sample of instantaneous network state;
            $w \leftarrow$ metered sub-set of c;
            $z \leftarrow$ non-metered sub-set of c;
            $\hat{z} \leftarrow$ predictPowerQuality$(w, f_x^{(0)}, F, T)$;
            foreach *(link $l \in z$)* **do**
                if $\hat{z}_l \neq z_l$ **then**
                    /* Add to predicted error for this link */
                    $\epsilon_l \leftarrow \epsilon_l + 1/K$;
                end
            end
        end
        selectedLink $\leftarrow \max(\epsilon)$;
        $L.add(selectedLink)$;
    end
end

function predictPowerQuality$(w, f_x^{(0)}, F, T)$
begin
    init pmf $\Psi = \{\psi_l\}, \forall$ links $l \in T$;
    $\Psi' \leftarrow$ BeliefPropogation given evidence w
    foreach *(link $l \in T, l \notin w$)* **do**
        $z_l \leftarrow$ max probability power quality class inferred in ψ_l';
    end
    return $Z = \{z_l\}$
end

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 2 for further details.

TABLE I
NETWORKS USED IN OUR EXPERIMENTS

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

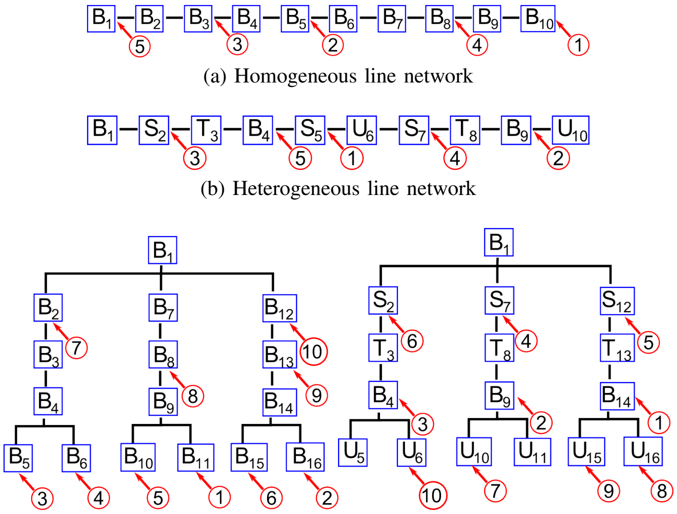
VI. Further Discussion: A Classification on Power Devices

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 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., $p_{c_y=i|c_x=i}^{(d)}$ is close to 1. In this case, $l_o^{(d)}$ has a much similar probability distribution as that of $l_{in}^{(d)}$ 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 $l_o^{(d)}$ is highly dependent on $l_{in}^{(d)}$.
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.

VII. 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. 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 4 and are enumerated in Table I.



(a) Homogeneous line network

(b) Heterogeneous line network

(c) Homogeneous tree network

(d) Heterogeneous tree network

Fig. 4. 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.

TABLE II
DEVICE TRANSFER FUNCTIONS

x\y	1	2	3	4	5
1	.9	.1	0	0	0
2	0	.9	.1	0	0
3	0	0	.9	.1	0
4	0	0	0	.9	.1
5	0	0	0	0	1

(a) Bus

x\y	1	2	3	4	5
1	.7	.1	.1	.05	.05
2	0	.7	.1	.1	.1
3	0	0	.7	.2	.1
4	0	0	0	.7	.3
5	0	0	0	0	1

(b) Switch

x\y	1	2	3	4	5
1	.85	.15	0	0	0
2	.15	.7	.15	0	0
3	0	.15	.7	.15	0
4	0	0	.15	.7	.15
5	0	0	0	0	1

(c) Transformer

x\y	1	2	3	4	5
1	1	0	0	0	0
2	.8	.2	0	0	0
3	.8	0	.2	0	0
4	.8	0	0	.2	0
5	.8	0	0	0	.2

(d) UPS

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 [13] with 1 being a clean input. These event types are listed in Table III along with their descriptions. We used the transfer functions listed in Table II and assigned a prior on the utility feed of $[\ 0.9947 \quad 0.0050 \quad 0.0002 \quad 0.00009 \quad 0.00001\ ]$.

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 IV.

A. Homogeneous line network

We consider first, the results obtained from a homogeneous line network (Figure 4a). 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 IVa and Figure 4a. 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

TABLE III
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 IV
RESULTS FOR EACH NETWORK CONFIGURATION

Round	Sorted Devices			Sorted Error Rates		
1	10	9	8	0.6132	0.6088	0.5703
2	5	4	6	0.3141	0.2908	0.2760
3	3	2	8	0.1653	0.1650	0.1639
4	8	7	6	0.1639	0.1613	0.0972
5	1	4	2	0.0967	0.0953	0.0896

(a) Configuration 1

Round	Sorted Devices			Sorted 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	Sorted Devices			Sorted Error Rates		
1	11	5	16	0.4126	0.4124	0.4123
2	16	6	5	0.4061	0.4036	0.4029
3	5	6	4	0.3850	0.3827	0.3177
4	6	10	15	0.1802	0.1799	0.1793
5	10	15	8	0.1798	0.1793	0.1652
6	15	13	12	0.1793	0.1605	0.1100
7	2	8	12	0.1000	0.0996	0.0976
8	8	13	12	0.0994	0.0932	0.0931
9	13	12	3	0.0931	0.0929	0.0897
10	12	3	7	0.0920	0.0897	0.0857

(c) Configuration 3

Round	Sorted Devices			Sorted Error Rates		
1	14	9	4	0.5032	0.5027	0.4968
2	9	4	8	0.5027	0.4968	0.4457
3	4	3	2	0.4968	0.4391	0.3661
4	7	12	2	0.2041	0.2036	0.2032
5	12	2	10	0.1907	0.1888	0.1042
6	2	10	16	0.1795	0.1042	0.1038
7	10	16	15	0.1042	0.1038	0.1031
8	16	15	6	0.1038	0.1031	0.0997
9	15	6	11	0.1031	0.0997	0.0995
10	6	11	5	0.0997	0.0995	0.0981

(d) Configuration 4

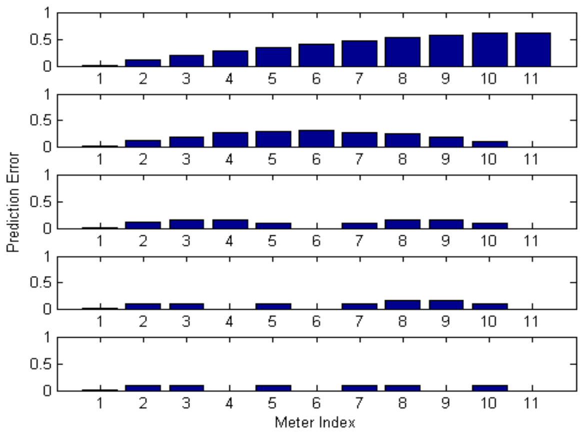


Fig. 5. Prediction error at each round of meter placement (shown from top to bottom) for the uniform line network.

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.

B. Heterogeneous line network

Considering the heterogeneous line network of Figure 4b, 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 II we see that buses and switches are both negatively active while transformers are both negatively and positively active; see Section VI. 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.

C. Homogeneous tree network

Considering the results obtained from the homogeneous tree network (Figure 4c), 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.

D. Heterogeneous tree network

Finally, when considering the results obtained for the heterogeneous tree network shown in Figure 4d, 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 after the UPS outputs, suggesting that the error rate was low at the network segments feeding into the UPS devices.

VIII. Conclusion and Future Work

In this paper 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.

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