Power Grid Fault Detection using an AMR Network

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***Abstract*—Smart grids have been introduced in many developed countries and facilitate more efficient and economical utilization of generated power. The components of such a grid are usually remotely monitored and selected components are controlled either manually or through advanced software programs. This is called an Advanced Metering Infrastructure (AMI) and the objective is to globally optimize available resources. In this paper we assume that an Automated Meter Reading (AMR) network is available. AMR is the precursor to an AMI system. AMR meters periodically report electrical energy consumption information to a centralized location and can also (since they contain batteries) transmit indications of power outage as well as power restoration. This information may also detect failed network components. The trade-offs considered are, the time taken to detect the failure, the accuracy of the fault decision and the amount of data required to perform these tasks.**

***Keywords*—AMI, AMR, Fault Detection, Internet of Things, Smart Grids**

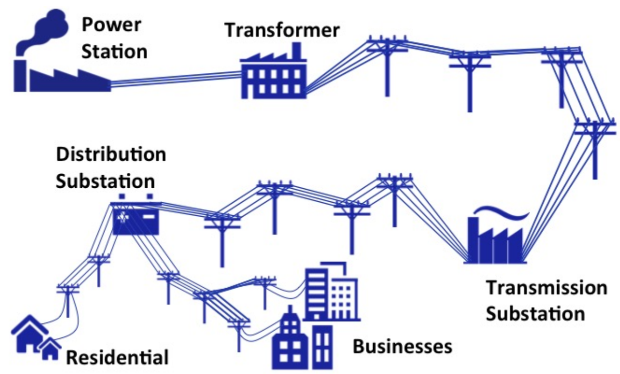

Fig. 1. Power Grid Architecture

I. Introduction

Smart grids (see Figure 1) use an Advanced Metering Infrastructure (AMI) to more efficiently support the transportation, distribution and consumption of electrical energy. It is an integrated system of smart meters, communications networks and data management systems that facilitate real-time two way communication between utilities and consumers [1]. Thus, AMI allows utilities to access an abundance of information. This information includes electrical consumption data, load profile data, demand, time-of-use, voltage profile data and power quality data [2]. AMI allows for more precise meter readings, earlier detection of meter failures, flexible billing cycles and reduced maintenance costs [3].

Smart meters can monitor and control all the devices and appliances in a customer's home as well as collect diagnostic information about the distribution grid [4]. These meters can display to customers in real-time their usage and, by extension, the cost that they are incurring. Smart meters can remotely switch off electricity to a customer and also remotely control the maximum electricity consumption [5]. This allows utilities to bill customers when they use energy from the grid but refrain when energy is used from the customer. With all the information that the customer receives, it allows them to make a more informed decision about their energy usage and thus can save money and reduce wastage of energy. Also, the utilities can enable dynamic pricing which is the process of either increasing or decreasing the price based on demand and this would help these companies have a more steady energy consumption throughout a day.

An AMI can also assist with outage management, allowing utilities to detect any faults (outages) and then determine the severity and location of the outage so that they can restore power quickly. Thus, fault detection and fault localization are very important. In contrast to AMI networks, Automatic Meter Reading (AMR) networks provide one way communication from the reader to the utility and is essentially used for reporting energy usage. These are less costly but have limited capability. In many developing countries AMR rather than AMI networks are available.

Previous work in this area typically assumes an AMI network and focus on use of readings within the network using Intelligent Electronic Devices (IED) to detect faults. Here is a summary of some of this work. The paper by Singh et. al. [6] presents a technique to detect and classify the different shunt faults on transmission lines for quick and reliable operation of protection schemes hence their focus was on transmission line faults. Similarly the paper by Silva et. al. [7] also focuses on transmission line faults. The papers [8] and [9] do investigate fault localization but this is achieved through information within the network. In [10] they investigate the optimal placement of sensors within the network for outage detection. In the paper by Kezunovic et. al.[11] the authors address the issue of improving the accuracy of fault location methods in smart grids using an abundance of Intelligent Electronic Device (IED) data. Here again the work is network-centric as access to information from devices within the network is assumed. In the work by Zhang et. al. [12] a wireless sensor network is deployed and used for fault detection in the power grid.

The research described in this paper varies from the published literature given the unique constraints. Firstly, this research is being performed for a utility company in a small island developing state. Secondly, although the distribution network has sensors that are used for fault detection, these are not optimally maintained and an alternative (supplemental) mechanism for detecting faults in the distribution network is required. Thirdly this mechanism should not require any additional equipment (i.e., no additional wireless sensor network, and no access to the internal sensor readings). Since the AMR network is well maintained, given it's paramount role in billing customers, the approach employed uses the AMR for fault detection. Although an AMR infrastructure is quite limited in functionality, we show that such a network may be used for detection of faults in the power system. In the next section the mathematical models used for the analysis is provided. This is followed by performance analysis results for some simple examples.

II. Mathematical Models

A. Wireless Meter Communication Network

In the power utility network being considered, each consumer is provided with a meter and this device periodically reports electrical consumption information to a centralized server (see Figure 2). On a periodic basis (e.g., every 15 minutes) each meter initiates transmission of its reading to a Cell Control Unit (CCU) using a Frequency Hopping Spread Spectrum Network. This is a shared network in which each meter uses an allocated frequency hopping pattern for its transmission. However, because of collisions, the initial attempt may not be successful and so additional attempts will be made until the transmission is successful. Failures are therefore due to either poor channel conditions or high interference. By properly choosing CCU sites one can ensure a sufficiently high reporting success rate. In this paper we will assume that each report succeeds with some probability but this probability will be aggregated with some other factors which we will discuss in later sections. Note that the initiation of a report takes place at periodic intervals but the correct receipt of a report may not be exactly periodic because of possible re-transmissions. However, within a 15 minute period we can assume that, if a report is received correctly then it occurs with equal probability throughout the period.

During an outage, each meter that is affected sends a Power Outage Notification (PON). When power is restored it also sends a Power Restore Notification (PRN). Note that since all affected meters will detect an outage at approximately the same time then they cannot all simultaneously send a PON as soon as the outage occurs since this will lead to high interference and low success rate. We therefore assume that PONs are transmitted using the same schedule as regular load reports.

Let p denote the residual success probability of a transmission of a PON. This is the success probability after all transmission attempts are made. Suppose that we start at some arbitrary time t_0 (e.g., the outage instant) and consider the period $[t_0, t_0{+}T]$ where T is the reporting period. We expect to receive, with probability p, at most one PON during this period and this can arrive at any time during the interval. Therefore the probability that a PON is received by time $t_0 + t$ is given by pt/T for $0 < t < T$. This is the transmission probability model we use for PONs from each affected meter. Note that in the Spread Spectrum network, a PON may be received by multiple CCUs. The same model can be used for such reports.

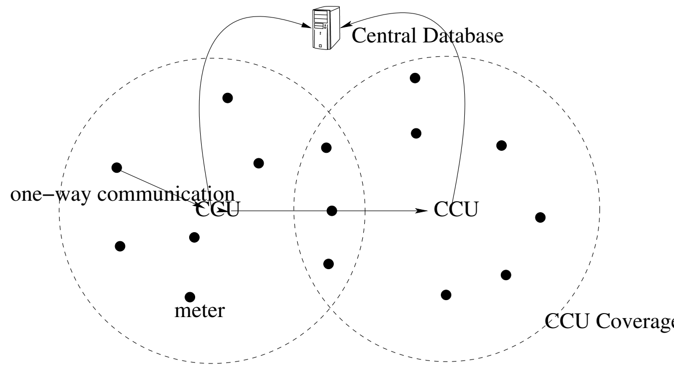

Fig. 2. Meter Communication Network

However, in this case the probability of correctly receiving the PON will be higher but for our analysis we do not consider this detail.

B. Power System Model

We model the transmission portion of the power grid as a mesh network and the distribution portion as a directed tree (see Figure 3) rooted at the distribution substation with the leaves being the smart meters. Our focus is failure of components in the distribution network (the distribution substation and transformers) and we ignore the transmission network which has significant redundancy due to its mesh layout. The children of the substations are transformers and the children of the transformers are smart meters. We use the following notation. We define the graph $G(V, E)$ where V denotes the set of vertexes and E denotes the edges where each edge $e = (i, j)$ connects two vertexes i and j. For each $i \in V$ we denote its set of children by C_i and its set of leaf descendants by D_i. For each leaf $j \in \{V\}$ we denote the set of ancestors of j by A_j. For any set S we use the notation $|S|$ to denote the number of elements in S. Finally $\{S - k\}$ will be used to denote the set S minus the element k

Failure of any node i results in all leaf descendants of i generating PONs. However given that each of these meters generated PONs we cannot conclude that node i had in fact failed. In fact all children of i may have failed leading to the same set of PON generating meters. However for our analysis we assume that the simultaneous failure of multiple nodes is unlikely and so our approach would be, given a set of PON generating meters, we determine the node that would have caused this event if it had failed.

Given a set of meters that generated PONs, we will determine the likely failed component. For this component we determine the probability that it failed. Since PON reports are not all immediately made, this probability will increase over time and after one report period will reach its highest value. So for example if we determine that we require the probability that the decision is correct is at least 0.95 then we can determine how long one must wait to achieve this probability. By varying various parameters we can determine the best trade-off to achieve the desired results.

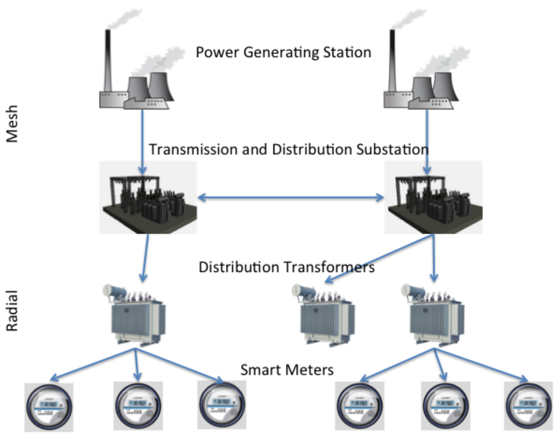

Fig. 3. Power Grid Tree Model

III. Performance Analysis

In this section we analyze the proposed power grid model described in the previous section. We follow this with some illustrative examples to show that the proposed approach, which does not require any new equipment, can provide satisfactory results especially if it is only being used as an additional tool for fault detection.

A. Instant PON Reporting

In practice there can be thousands of meters and so it may not be feasible to take into account all meter readings. Or it may be that in some cases a meter does not report an outage because the battery in the meter has drained. Therefore we will assume that each meter reports an outage with probability p. Note that this probability is being used to capture the probability that the meter is included in the algorithm (e.g., not all meters may be included in the inventory and this will capture the percentage that is included) and also the probability that a PON from a meter (that is chosen for the algorithm) arrives correctly at the CCU.

Note that, given the failure of a node i all leaf descendants of i will transmit a PON with probability p. However the inverse need not be true. For example, if we consider failure of a substation serving only two distribution transformers and all meters for one transformer reported their outage but none for the other transformer reports an outage then the conclusion would be that the transformer with the meters that did report correctly was faulty which is not the case. However, the latter case requires simultaneous failures of multiple components and we will ignore such events since they are unlikely.

Let us first demonstrate how we determine the potentially faulty component and then we will compute the probability that this determination is correct. Given the set of meters S, and assuming that a single fault occurred, the faulty component (node) is determined as follows. We find the closest common ancestor of all members of S that reported a PON. This can be easily computed using the pseudo-code provided in Figure 4.

```
S ← the set of meters
L ← 1                                          ▷ level counter
F ← 0                          ▷ denotes the faulty component
while F == 0 do  ▷ For each leaf k, A_k is ancestor list,
  if k ∈ S reports PON then x_k = 1 else x_k = 0
    for all k ∈ S do
        if x_k == 1 then
            if F == 0 then
                F ← A_k(L)
            else
                if F ≠ A_k(L) then
                    L ← L + 1
                    F ← 0
                    exit
                end if
            end if
        end if
    end for
end while
```

Fig. 4. Pseudo-code for determining faulty component

We next compute the probability of correctly determining the faulty component. In order to do this let us first determine the minimum amount of information required to make a correct determination. Note that if i is the faulty component (and we assume that it has more than 2 children) then at least two of its children must each contain at least one leaf descendant that reported the outage. If this was not the case and only one child of i had a leaf that generated a PON then the lowest common ancestor can get no further than this child. Also note that each of these children need only have one leaf descendant that reported the outage since that single leaf would cause the search for an ancestor along that sub-tree.

For any child k of node i let q_k denote the probability that one or more of the descendants of k reported a PON. This is given by

$$q_k = 1 - (1-p)^{|D_k|}. \tag{1}$$

Given these probabilities we can now compute the probability that i has two or more children with leaf descendants who reported a PON. This is simply given by

$$P_i = 1 - \left(\prod_{k \in C_i} (1-q_k)\right) - \left(\sum_{k \in C_i} q_k \prod_{j \in \{C_i - k\}} (1-q_j)\right). \tag{2}$$

Here we compute the probability that the decision was incorrect as the probability that no child had leaves that generated a PON plus the probability that exactly one child had a leaf that generated a PON (these are the two right hand terms). The probability that the decision is correct is then just one minus this quantity. We can now substitute to obtain

$$P_i = 1 - \left(\prod_{k \in C_i} (1-p)^{|D_k|}\right) - \sum_{k \in C_i} \left((1-(1-p)^{|D_k|}) \prod_{j \in \{C_i - k\}} (1-p)^{|D_j|} \right). \tag{3}$$

For example consider the case in which i has C children and each of them had M leaf descendants. In this case the above can be simplified to obtain

$$P_i = 1 - (1-p)^{MC} - C(1-(1-p)^M)(1-p)^{M(C-1)}. \quad (4)$$

B. Delayed PON reporting

In the above cases we assumed that the PON notifications were instant. However in practice this is not the case. When a failure occurs, if all meters simultaneously attempted to report a PON then the resulting interference would be very high and result in the failure of all or most notifications. We therefore assume that, on failure, the meter continues using the same reporting schedule that was used for load reports.

Let us assume that each meter makes a report every T seconds but that they independently choose their initial start time randomly between time 0 and time T. Again let p denote the probability of delivery of the PON when it is sent. However we now have a new factor. Suppose that the event occurs at time $t = t_0$. At time $t_0 + \tau$ the probability that a PON notification was attempted is τ/T and so the probability that at this time a PON for this meter was delivered is $p\tau/T$. At time $t_0 + T$ all meters that we previously considered as having reported a PON with probability p would have done so. We can now determine the probability of correct detection as a function of time as:

$$P_i = 1 - \left(\prod_{k \in C_i} (1 - p\tau/T)^{|D_k|}\right) - \sum_{k \in C_i} \left((1-(1-p\tau/T)^{|D_k|}) \prod_{j \in \{C_i - k\}} ((1-p\tau/T)^{|D_j|}) \right) \quad (5)$$

for $0 \leq \tau \leq T$.

Note that we have many different parameters, each with different trade-offs. p is determined by the actual number of meters that are used for the algorithm, how many of these are monitored for PONs (in most cases we can assume all) and the probability that a PON, when sent, arrives correctly. Note that the last factor is determined by the network design. For example if the network is only being used to collect load information for billing purposes then the network need not be very robust since only one or two readings per day will suffice for this purpose. In this case p will be low.

The parameter T determines how often a meter makes reports to the CCU. If this is small then the probability of successful delivery will decrease because of congestion or one may have to increase the number of CCUs. If this value is large then the PON notifications will be delayed longer on average and hence the detection time will increase. Also the operator may want to choose a large value and so have a single CCU manage a large number of meters. The other parameters such as number of meters per transformer, number of transformers per distribution substation etc. are determined by other requirements but these also affect how quickly one can correctly determine a fault by the proposed method.

C. Other Scenarios

Consider the case of a power line failure. This is equivalent to failure of an edge in the rooted tree. In this case if the proposed approach is used, the lower endpoint of the failed line will be determined as the failed node. Therefore the approach can still be used to isolate the failure. Of course the case in which the line from transformer to home is damaged is easily detected.

In our discussion above we focused on a single failure. However the approach can be expanded to include multiple failures as follows. Once a fault has been detected and identified then all leaf descendants of the faulty component can be removed from the tree and the algorithm can be continued to determine additional faults. Once the faulty component is repaired its leaf descendants can be re-added to the tree. In the case of simultaneous of near-simultaneous faults the following can be done. The algorithm may be able to capture one fault first in which case the tree can be updated and then the other one detected.

IV. An Illustrative Example

In our environment pole mounted 12kv/230V transformer explosions due to induced over-voltages from direct or nearby lightning strikes during tropical rainstorms are quite common and hence are our focus. Again note that this approach would typically be performed in addition to the more traditional approaches but may be useful when the traditional approach fails. Let us consider the following scenario (representative of a small island nation). Assume that each transformer is connected 20 meters apart and that each distribution substation connects to 200 distribution transformers. Hence a substation services 4000 customers. Suppose that a generator feeds power to 50 substations.

Let us first consider the case in which PON reports are delivered immediately. In Figure 5 we plot the probability of correct detection of the failed component as a function of the probability p that a meter that is affected generates a PON. We perform this for distribution transformers and substations. We see that, because of the large number of meters within the substation sub-tree, the probability of correct detection is quite high even for small p. In the case of the distribution transformers when p reaches around 0.1 (10%) we find that the probability of correct detection reaches around 90%.

Next we consider the more realistic case in which PON transmissions are not sent immediately when the outage occurs but is staggered in the same manner as load reports. In this case we assume $p = 0.5$ and $T = 15$ minutes with the same distribution of components as in the previous scenario. In Figure 6 we plot the probability of correct detection as a function of time. Here we find that it takes about 4 minutes before the probability of correctly determining the failed component reaches 0.95.

Next suppose that we wanted to decrease the fault detection time. Suppose that we assume that all meters are included in the algorithm and that the probability that an affected meter reports a PON within T time is 0.9. Therefore in this case we use $p = 0.9$. Furthermore we will assume $T = 10$ and so reports are made more frequently. In this case the probability

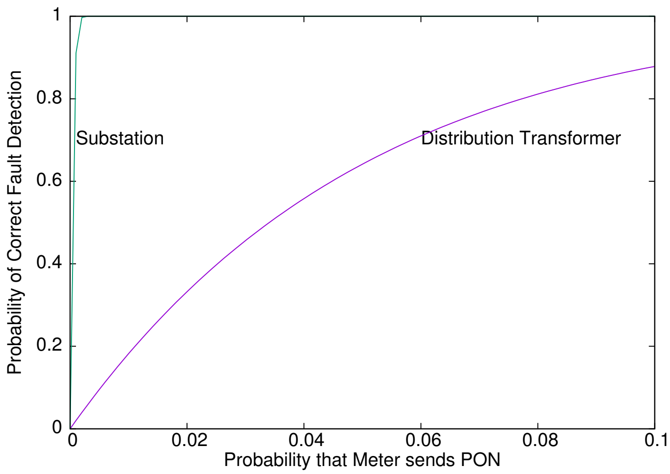

Fig. 5. Dependence of Accuracy on Number of Meters

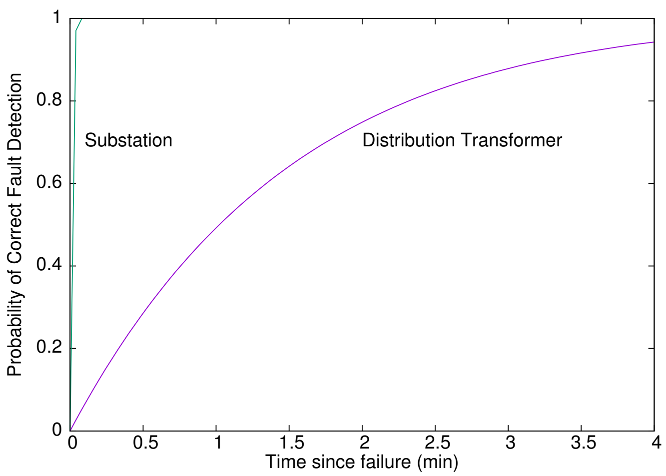

Fig. 6. Dependence of Accuracy on Time since Failure

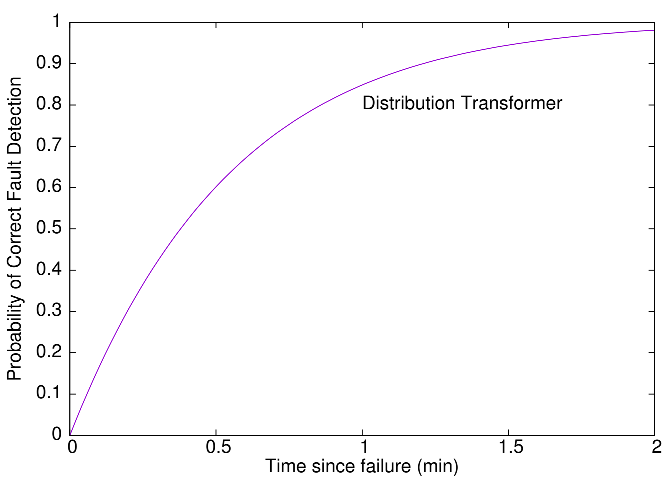

Fig. 7. Dependence of Accuracy on Time since Failure

of correct detection as a function of time is given in Figure 7 and we see the effect of these parameter changes on the detection time. Here the fault is detected within two minutes with a probability of about 0.99.

V. Conclusions and Future Work

We were tasked with using AMR meter readings (and nothing else) to detect faults in a power system of a small island state. In our scenario the distribution network is radial and the AMR network uses frequency hopping for transmissions. We developed a model that was used to determine the performance of the resulting approach. We showed that, although not instant, the approach can be used as a secondary scheme to determine failures and to locate the source of the failure. Such an alternative scheme is needed since in many cases the network component sensors or the reporting of these readings fail to work properly. The proposed scheme requires no additional equipment and can identify the fault in less time than it takes the crew to arrive. Based on this work we are developing an APP that can be used by the utility crews to pinpoint failures especially transformer failures. Since the GPS coordinates of all grid components are known the APP would use the previously described approach to determine the faulty component with sufficient accuracy and then indicate the location of the failed component on a map.

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