

Outage Detection for Distribution Networks Using Limited Number of Power Flow Measurements

Basel Alnajjab, Ananth Narayan Samudrala, Chen Chen, Rick S. Blum, Soumya Kar, and Emma M. Stewart

Abstract—Accurate topology estimation is crucial for effectively operating modern distribution networks. Line outages in a distribution network change the network topology by disconnecting some parts of the network from the main grid. In this paper, an outage detection (or topology estimation) algorithm for radial distribution networks is presented. The algorithm utilizes noisy power flow measurements collected from a subset of lines in the network, and statistical information characterizing errors in forecasting load demands. Additionally, a sensor placement scheme is presented. The sensor placement provides critical sensing for the outage detection algorithm so that any number of possible outages in the network can be detected. The performance of the proposed outage detection algorithm using the proposed sensor placement is demonstrated through several numerical results on the IEEE 123-node test feeder.

Index Terms—Outage detection, distribution networks, maximum likelihood (ML) detection, sensor placement.

I. INTRODUCTION

AS novel controls, applications, and services continue to be integrated into distribution networks, the demand for accurate and timely estimates of the network topology is becoming increasingly critical [1]. Maintaining the situational awareness in distribution networks is imperative for the effectiveness of many tasks in distribution networks. For example, the correct estimation of network topology is crucial for efficiently and reliably dispatching distributed energy resources [2], sectioning into microgrids [3], and providing de-

mand response [4] capabilities. Further, many techniques for distribution system state estimation (DSSE) [5] - [7] and many application functions of the distribution management system (DMS) require the knowledge of the correct network topology.

Outages change the topology of a distribution network. Line outages cause protective devices to automatically isolate some part of the network and form an island. The island formed due to the isolation might experience a loss of power supply due to the disconnection from the main grid. Alternatively, it is possible that the island remains energized by receiving power from a distributed generation (DG) unit [8], [9] or by a network re-configuration [10]. Whether the island is energized or not, the detection of outages that causes the isolation (outage detection) and the detection of the current topology of the network (topology estimation) are important tasks. Assuming that the topology of the outage free network is known, the detection of the outages that causes a topology change enables the construction of the current topology of the network. Hence, outage detection and topology estimation are equivalent tasks.

Due to several engineering and practical concerns, distribution networks are predominately operated as radial (tree) graphs in which power flows in one direction away from the root node of the tree. Typically, the substation of distribution network is considered as the root node of the tree. This radial nature of distribution networks has traditionally led them to have fewer installed sensors and monitoring devices compared to transmission networks. Transmission networks have mesh topologies and extensive monitoring. As a consequence of having fewer sensors, distribution networks have been historically less observable than transmission networks. Due to these differences, topology estimation and outage detection techniques devised for transmission networks [11]-[14] have limited applicability in distribution networks. Hence, there is a need for methods and techniques designed specifically for the distribution networks.

Traditionally, topology estimation in distribution networks have relied heavily on information obtained through phone calls from customers or expert systems [15] to identify and locate outages in the network. Knowledge-based methods utilizing different types of information from advanced metering infrastructure (AMI) and supervisory control and data acqui-

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sition (SCADA) systems have also been proposed [16]. However, these methods are limited in the number of simultaneous outages that they are able to detect.

Fortunately, recent advances in the development of measurement units and their increased adoption in distribution networks provide new data streams used for detecting multiple topology changes. In fact, some new phasor measurement units (PMUs) are being designed specifically for distribution networks with promising results [17], [18]. Also, some new topology estimation methods assuming the widespread adoption of these devices are being proposed. Using time series measurements from PMUs, a topology identification method is proposed in [19]. A topology detection method using optimal matching loop power is proposed in [20]. The network topology is identified using smart meter data in [21]. The mixed-integer quadratic programming is used for topology identification in [23]. A topology identification algorithm using voltage correlation data is proposed in [20]. The research in [24], [25] relying on a limited number of line flow sensors is more relevant to the work presented in this paper. In their work, the authors show that the outage detection problem over a full distribution network can be decoupled into smaller detection problems within the sub-trees of the same network. They also propose a mathematical framework which provides analytical metrics that describe the performance of their outage detection scheme.

In this paper, a novel outage detection (or topology estimation) algorithm and a novel sensor placement algorithm are presented for radial distribution networks. The sensor placement scheme provides critical sensing for the outage detection scheme. Reference [25] presents that power flow measurements are superior to voltage measurements when using only a small number of measurements for detecting outages in a distribution network. This is because voltage differences between nodes are small in a distribution network, and the deviations in power flows caused by outages are larger than those of voltages. Hence, in this work, sensors measuring power flows are considered. We assume that a sensor at a node measures the power flow (both the real power flow and the reactive power flow) along every line connecting to that node. Using noisy power flow measurements from these sensors and nodal load forecasts, a novel outage detection algorithm is proposed. Additionally, a sensor placement algorithm based on a deterministic treatment of the load forecasts is proposed. Numerical results are presented to demonstrate the performance of the outage detection algorithm for the IEEE 123-node test feeder with the proposed sensor placement.

The remainder of this paper is organized as follows. In Section II, the system model is presented followed by the notations. In Section III, the outage detection problem is described. Section IV presents the novel sensor placement algorithm. In Section V, the novel outage detection approach is proposed. Section VI presents numerical results. The numerical results employ the proposed sensor placement scheme along with the proposed outage detection scheme to detect randomly generated outages in the IEEE 123-node test feeder. Finally, conclusions are drawn in Section VII.

II. SYSTEM DESCRIPTION AND NOTATION

A. Topology of a Distribution Network

A distribution network with a radial (tree) structure is considered, where the power is supplied to the feeder at the root node of the tree. The nominal (outage free) distribution network with $N+1$ nodes is modeled as a radial tree graph $\mathcal{T}_{full}=(V, E)$. $V=\{0, 1, \dots, N\}$ represents the set of nodes in the network. The set $E=\{e_1, e_2, \dots, e_N\}$ consists of all the edges in the network, where $e_n \triangleq (m, n)$ represents the edge connecting node n to its parent node m . Without loss of generality (WLOG), node 0 is considered as the point of common coupling (PCC), i.e., the substation or the point where the distribution network under analysis is connected to the main grid. Hence, node 0 is the root node of the tree \mathcal{T}_{full} . Regarding the root node, the following assumptions are made.

1) Assumption 1: the root node 0 is the only power source in the distribution network.

2) Assumption 2: the line connecting the root node to the main grid is directly monitored by the operator since it carries the power supply required for the entire distribution network. Hence, in this work, sensor placement for this line is not considered.

Figure 1 illustrates a simple tree with the above discussed notations.

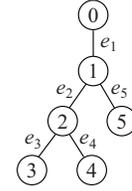


Fig. 1. An example tree.

B. Load and Power Flow Models

Each node (except the root node) in the distribution network has a power consumption demand (load) that must be supplied to it through an outage-free path connecting it to the root node. However, there are some nodes that have no power consumption demand, i.e., zero-injection nodes. Set zero-injection nodes be Z . The real and reactive power consumption loads at a node $i \in \mathcal{V} \setminus Z$ (nonzero-injection nodes) are represented as \tilde{d}_i^p and \tilde{d}_i^q , respectively. We apply the linearized DistFlow equations for the power flow model [26]. In linearized DistFlow equations, the current on a line of the distribution network is approximate to zero since it is small in practice. Under this approximation, the real and reactive power losses on a line can be regarded as zero. The root node is the sole power supply in the network (Assumption 1). Using the linearized DistFlow equations, the real and reactive power flows on a line can be represented as:

$$\tilde{d}^p(e_n) = \sum_{i \in D(n; \mathcal{T}_{tree})} \tilde{d}_i^p \quad (1)$$

$$\tilde{d}^q(e_n) = \sum_{i \in D(n; \mathcal{T}_{tree})} \tilde{d}_i^q \quad (2)$$

where $\tilde{d}^p(e_n)$ and $\tilde{d}^q(e_n)$ are the real and reactive power

flows on line e_n , respectively; \mathcal{T}_{true} is the unknown true (actual) network topology; and $D(n; \mathcal{T}_{true})$ is a function returning a set of all nonzero-injection nodes $i \in \mathcal{VZ}$ that are downstream from node n in \mathcal{T}_{true} . The objective of the topology estimation is to estimate \mathcal{T}_{true} . In an outage free scenario, \mathcal{T}_{true} is equal to \mathcal{T}_{full} .

The forecasts (or expected values) for real and reactive loads for node i are represented by d_i^p and d_i^q with forecast errors $c_i^p = \tilde{d}_i^p - d_i^p$ and $c_i^q = \tilde{d}_i^q - d_i^q$, respectively. Regarding the forecast errors, we make the following assumption.

Assumption 3: forecast errors are mutually independent normal random variables, i.e., $c_i^p \sim N(0, \sigma^2)$ and $c_i^q \sim N(0, \sigma^2)$, where σ^2 is the forecast error variance [24], [25].

Under Assumption 3, the true real and reactive loads at node i can be modeled as random variables distributed as $\tilde{d}_i^p \sim N(d_i^p, \sigma^2)$ and $\tilde{d}_i^q \sim N(d_i^q, \sigma^2)$, respectively.

Note that for simplicity in this paper, it is assumed that the real and reactive load forecasts for every node have the same error variance σ^2 . However, even if the error variances are different for real and reactive loads at various nodes, the proposed sensor placement and outage detection algorithms shall remain valid and will still work.

C. Measurement Model

In this work, sensors are placed at a subset of nodes in a distribution network. We consider that a sensor at a node measures both the real and reactive power flows along all lines connecting to that node. Examples of such sensors are micro-PMUs [17] and linewatch L sensors [27]. Sensor placement is represented as a set of nodes \mathcal{P} where $\mathcal{P} \subset \mathcal{V}$. Also, $E(\mathcal{P})$ denotes the set of lines whose real and reactive power flows are measured under placement \mathcal{P} .

$$E(\mathcal{P}) = \{e | e \subset E\} \quad (3)$$

where e is the incident on some $v \in \mathcal{P}$.

The real and reactive power flow measurements made by the sensors are modeled as measurements that are free of sensor noise. This is because sensors communicate their measurements in real time, whose errors (sensor noise) are negligible compared to the errors of load forecasts (c_i^p and c_i^q) that are based on non-real-time information [25].

In this work, outage detection is analyzed in two different cases. In the first case (Case 1), only real power flow measurements are used for outage detection. In the second case (Case 2), the real and reactive power flow measurements are summed up and the sums are used for outage detection. Considering both real and reactive power flow measurements for outage detection (Case 2) results in better performance than only considering real power flow measurements (Case 1). The algorithms and discussions generalized in this paper can be applied to both the cases. Hence, the following notations are adopted. The load and the load forecast (or expected load) at a node i are represented as \tilde{d}_i and d_i , respectively. In Case 1, since only real power flow measurements are used, we have $\tilde{d}_i = \tilde{d}_i^p$ and $d_i = d_i^p$. In Case 2, since both real and reactive power flow measurements are used by summing them up, we have $\tilde{d}_i = \tilde{d}_i^p + \tilde{d}_i^q$ and $d_i = d_i^p + d_i^q$. Hence, we

can simply represent the loads at all nodes $i \in \mathcal{VZ}$ in the network by the vector $\tilde{\mathbf{d}}$ and the load forecasts by the vector \mathbf{d} . Since the load forecast errors are mutually independent normal random variables (Assumption 3), we can write $\tilde{\mathbf{d}} \sim N(\mathbf{d}, \Sigma)$ with $\Sigma = \sigma^2 \mathbf{I}$ in Case 1 and $\Sigma = 2\sigma^2 \mathbf{I}$ in Case 2, where \mathbf{I} is an identity matrix with dimensions $N-1$. Thus, the measured power flow through line $e_n \in E$ is given by:

$$y_{\mathcal{T}_{true}}(e_n) = \sum_{i \in D(n; \mathcal{T}_{true})} \tilde{d}_i \quad (4)$$

Based on Assumption 3 for the noise in the load forecasts, a nonzero $y_{\mathcal{T}_{true}}(e_n)$ will be normally distributed with a mean value $\bar{y}_{\mathcal{T}_{true}}(e_n)$ (expected power flow) given by the right-hand side of (4) with each nonzero \tilde{d}_i replaced by d_i , and a variance that equals the number of downstream nodes with nonzero forecast times σ^2 in Case 1, and $2\sigma^2$ in Case 2.

D. Outage Model

Outages are modeled as any number of disconnected lines in the network. The set of all edges in outage is represented by F , where $F \subset E$. Each outage breaks the network into two parts. Hence, outages result in a forest $\mathcal{F}_{outage} = (\mathcal{V}, E_f)$, where $E_f \triangleq E \setminus F$ is the set of lines excluding outage lines. Because of \mathcal{T}_{full} , the error-free network is a single connected tree, and every line outage will increase the number of trees in the forest by one. For example, if $|F|=k$ outages occur, the graph describing the network with outages \mathcal{F}_{outage} is a forest composed of $k+1$ components, i.e., trees $\mathcal{T}_0, \mathcal{T}_1, \dots, \mathcal{T}_k$.

Since the power is drawn solely from the root node, only one of the trees in \mathcal{F}_{outage} will be energized and it will be the tree which contains the root node. WLOG, the energized tree is denoted by \mathcal{T}_0 since the numbering is arbitrary. \mathcal{T}_0 may be described as $\mathcal{T}_0 = (\mathcal{V}_0, E_0)$, where $\mathcal{V}_0 \subset \mathcal{V}$ and $E_0 \subset E_f$ are the set of nodes and the set of lines that remain energized by the substation after the occurrence of all outages, respectively. As a result, all the lines not included in E_0 will have zero power flowing through them. All sensor measurements collected under any possible placement on these lines will be equal to zero. Therefore, an outage on a line e_m that is the downstream of another outage line e_n will have no effect on the measurements collected in E_0 , since it is going to be disconnected from the energized tree irrespective of whether it is in outage or not. Therefore, we exclude the detection of such downstream outages in our analysis. The following definition highlights these type of outages and the reason for excluding them.

Definition 1 (topologically undetectable outages): an outage affecting a line $e_j \triangleq (i, j) \in E$ will have no effect on any possible measurement under any possible sensor placement, otherwise it will still be excluded from the grid-connected part of the network. Such an outage carries no practical significance on the topology estimation problem. The measurement data obtained from sensors will be unable to distinguish such outages, irrespective of the sensor placement. Hence, these outages are called topologically undetectable outages, and such outages are not considered in this work.

III. OUTAGE DETECTION PROBLEM

In this section, the outage detection problem and the challenges it poses are discussed. An optimal outage detector must determine both the number of line outages and the lines in outages. We consider outage detection using the knowledge of \mathcal{T}_{full} (the outage-free network topology), nodal load forecasts, and the sensor measurements $\mathbf{Y} = [y(e_{n_1}), y(e_{n_2}), \dots, y(e_{n_p})]$. A possible detection method is to employ a maximum likelihood (ML) detector that may be expressed as:

$$\hat{F} \in \arg \max_{F \in S_s(E)} \Pr(\mathbf{Y}|d, F) \quad (5)$$

where $S_s(E)$ is the superset of E ; and \hat{F} is chosen after enumerating all elements of $S_s(E)$. The size of $S_s(E)$ is exponential in $|E|$ (the number of links in the network), which makes it infeasible enumerating all the possible outage scenarios for most distribution networks. Even after excluding all topologically undetectable outages, it is shown in [25] that the number of outage scenarios grows exponentially in $|E|$ for a worst-case distribution network. However, [25] presents that the ML detection problem (5) for the entire network may be decoupled and solved over smaller disjoint subtrees in the network as long as each sub-tree is rooted at a node whose parent edge, i. e., the edge that connects the node to its parent node is monitored by a sensor. As a result, only a few sensors measuring power flows along several lines in the network can help solve (5) efficiently by decoupling the full distribution network into smaller and more manageable problems.

In addition to the exponential size of $S_s(E)$, another problem affecting the performance of outage detection is the ambiguity that might occur in the ML detector (5). Ambiguity in ML detection occurs when the sensor locations are such that multiple outage scenarios result in the same expected flow along the measured lines. In most cases, careful placement of sensors in a network will enable us to make sufficient number of measurements that can help differentiate the different outages causing ambiguities. One way is to place a sensor closer to the line whose failure causes the ambiguity of the detector. A simple illustrative example showing the effect of sensor placement on the ability to identify and differentiate detectable outages is demonstrated in Fig. 2. The blue nodes in Fig. 2 represent a node endowed with a sensor. The number next to each node in Fig. 2 represents the load or demand of the node.

With the sensor at node 0 in Fig. 2(a), we are able to observe the power flow only on line e_1 . Since line e_1 must carry the entire power supply required for loads at nodes v_1 , v_2 and v_3 , we expect the measured flow on line e_1 (assuming noise free sensor measurements) to be 50. However, line outages change the measured flow. Depending on the outage scenario of the network, the measured flow could be any member of the set $C(e_1) = \{0, 10, 30, 50\}$. Since the demands for nodes 2 and 3 are both 20, the outage of either line results in a measured flow of 30 on e_1 makes the distinction between line outages of e_2 and e_3 impossible. However, placing a sensor at node 1, as shown in Fig. 2(b), enables us to

distinguish the line outages of e_2 and e_3 since the sensor at node 1 measures the power flows along e_1 , e_2 , and e_3 . If e_2 is in outage, then the sensor measures zero flow on e_2 and a flow of 20 on e_3 . If e_3 is in outage, the measurements are exactly opposite, thus providing us with enough measurements to distinguish and detect. This is the fundamental logic that we shall use in proposing the sensor placement technique.

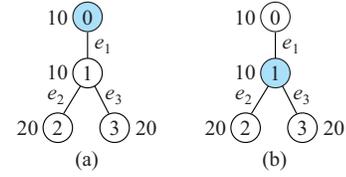


Fig. 2. Effect of sensor placement on the ability to distinguish outages. (a) Outages in e_2 and e_3 are indistinguishable. (b) Outages in e_2 and e_3 are distinguishable.

Unfortunately, there are still some outage scenarios that result in the ambiguity of the ML detector (5), which cannot be resolved under any possible sensor placement. These outage scenarios involve zero-injection nodes. Consider the tree and sensor placement of Fig. 2(b) for example, and suppose that node 1 is a zero-injection node with zero demand instead of 10. In this case, we will be unable to distinguish the scenario where e_1 is in outage and the scenario where both e_2 and e_3 are in outage, even though the sensor measures the flow along every line in the network. These types of outages are referred to as “numerically indistinguishable”, because it is not possible to distinguish them by any detector under any sensor placement due to the numerical value of the demand of the node. A group of such outages associated with the same expected flow measurements is referred to as a set of numerically indistinguishable outages. Throughout this paper, we consider the occurrence of a outage from a set of numerically indistinguishable outages as occurrences of all outages in that set. Hence, we consider the detection of an outage that is numerically indistinguishable as detections of all outages from the set. We adopt this procedure because we are unable to identify the exact outage from a set of indistinguishable outages. In the next section, a novel sensor placement scheme is proposed, in which the sensor locations are chosen such that numerically indistinguishable outages are the only indistinguishable outages in the network.

IV. SENSOR PLACEMENT

It is shown in [25] that the outage detection problem for the complete distribution network tree can be decoupled into local detection over disjoint sub-trees that are rooted at nodes which have the power flow on their parent edge measured by a sensor. Hence, the decoupling of the detection depends on the sensor placement since each disjoint sub-tree is rooted at a node with a sensor. However, due to the decoupling, the performance of the outage detection for the complete distribution network now depends on the performance of local detection in each disjoint sub-tree. Hence, the sensor placement in each disjoint sub-tree must guarantee that all topologically detectable outages can be identified. To this end,

a novel sensor placement scheme is proposed. The following definition formalizes the concept of identifiability.

Definition 2 (identifiable outages): an outage in line e_n is identifiable under a given placement and noise-free nodal load forecasts if the expected power flow along e_m is unique with all topologically detectable outages involving line e_n and any or none of the lines that are downstream from node m along e_m . e_m is the first line endowed with a sensor along the (directed) path from node n to the root node 0. The uniqueness of the expected flow along e_m is allowed to be violated only when numerically indistinguishable outages are considered.

In our sensor placement scheme, sensors are placed at a minimal set of nodes \mathcal{P} such that the power flow measurements on the lines monitored by the sensors ($E(\mathcal{P})$) are sufficient to distinguish every outage scenario, and thereby making every outage scenario identifiable. Representing the topology of a distribution network by \mathcal{T} , the proposed recursive sensor placement scheme is given in Algorithm 1 as the recursive function $Placement(\cdot)$, which calls the following functions.

1) $Child(n, \mathcal{T})$: this function returns a set containing all child nodes of node n in the network \mathcal{T} .

2) $UpFlow(n, \mathbf{d}, \mathcal{T})$: this function outputs a vector comprised of all possible power flows along line e_n . We may calculate the elements of the vector using (4).

3) $UpdateTopology(n, \mathcal{T})$: this function returns the network \mathcal{T} after removing the line e_n and the entire sub-tree rooted at node n from \mathcal{T} .

4) $Size(\cdot)$: this function returns the size (or length) of the set or vector provided to it as an input.

5) $IsEmpty(\mathbf{x})$: this function returns a logical true (1) if the vector \mathbf{x} is empty; otherwise, it returns a logical false (0).

6) $Unique(\mathbf{x})$: this function returns a logical true if all elements of the vector \mathbf{x} are unique; otherwise, it returns a logical false otherwise.

7) $CombineVects(\mathbf{x}_1, \mathbf{x}_2)$: this function returns a vector constructed from combining the vectors \mathbf{x}_1 and \mathbf{x}_2 as described by the following Subroutine 1.

The sensor placement is obtained by calling the function $Placement(\cdot)$ with the inputs set as the root node ($n=0$), \mathcal{P} chosen as an empty set, \mathcal{T} chosen as \mathcal{T}_{full} , and the vector $\mathbf{d} = [d_1, d_2, \dots, d_N]^T$ constructed such that d_i is the expected load for node $i \in \mathcal{V} \setminus \{0\}$ with $d_i = 0$ when node i is a zero-injection node. The function $Placement(\cdot)$ starts at the root node and traverses the tree in a depth-first search manner. At each depth, the algorithm constructs arrays of expected power flows for the visited lines or edges. The full array of expected power flows $flow_array$ for a line e_n is constructed only after visiting all child nodes of node n . Since every node in a network except the leaf nodes has child nodes, the arrays of expected power flows are constructed starting from the leaf nodes of the tree. The constructed arrays continue to grow as the algorithm backtracks from leaf nodes towards the root node. The arrays consist of the complete set of all possible expected flows on each line.

Algorithm 1: $Placement(n, \mathcal{P}, \mathbf{d}, \mathcal{T})$

```

1: Input: node  $n$ , current placement  $\mathcal{P}$ , load forecasts  $\mathbf{d}$ , and topology  $\mathcal{T}$ 
2: Output:  $flow\_array$ , updated  $\mathcal{P}$ , updated  $\mathcal{T}$ 
3: Begin
4:  $S = Child(n, \mathcal{T})$ 
5:  $s = Size(S)$ 
6: if  $s = 0$  &  $n \neq 0$  // No children
7:    $flow\_array = UpFlow(n, \mathbf{d}, \mathcal{T})$ 
8:   return
9: else if  $s = 1$  &  $n \neq 0$  // One child and non-root node
10:   $[f\_array, \mathcal{P}, \mathcal{T}] = Placement(S, \mathcal{P}, \mathbf{d}, \mathcal{T})$ 
11:   $flow\_array = [UpFlow(n, \mathbf{d}, \mathcal{T}), flow\_array + UpFlow(n, \mathbf{d}, \mathcal{T})]$ 
12:  return
13: else
14:   $indx = []$ 
15:   $f\_array = []$ 
16:  for  $i = 1$  to  $s$  do
17:     $[f\_array[i], \mathcal{P}, \mathcal{T}] = Placement(S[i], \mathcal{P}, \mathbf{d}, \mathcal{T})$ 
18:    if  $IsEmpty(f\_array[i]) = 0$  then
19:       $indx.append(i)$ 
20:    end if
21:  end for
22:  if  $d_n \neq 0$  and  $Size(indx) = 1$  then
23:     $flow\_array = [UpFlow(n, \mathbf{d}, \mathcal{T}), f\_array[1] + UpFlow(n, \mathbf{d}, \mathcal{T})]^T$ 
24:  else if  $d_n = 0$  and  $Size(indx) = 1$  then
25:     $flow\_array = f\_array[1]$ 
26:  else
27:     $flow\_array = []$ 
28:  for  $j = 1$  to  $Size(indx)$  do
29:     $flow\_array = CombineVects(flow\_array, f\_array[j])$ 
30:  end for
31:   $flow\_array = [UpFlow(n, \mathbf{d}, \mathcal{T}), flow\_array + UpFlow(n, \mathbf{d}, \mathcal{T})]^T$ 
32:  end if
33:  //Check if all values are unique
34:  if  $Unique(flow\_array) = 1$  then
35:    return
36:  else
37:    //Place sensor at node  $n$ 
38:     $\mathcal{P} = \mathcal{P} \cup n$ 
39:     $flow\_array = []$ 
40:    //Update expected flow above sensor
41:     $[\mathcal{T}] = UpdateTopology(n, \mathcal{T})$ 
42:  return
43: end if
44: end if

```

If any line e_n has repeated values of expected flows in its array, then it means that two different outage scenarios in the sub-tree rooted at node n result in the same flow measurement on line e_n . The only way to differentiate the similar outage scenarios is to measure the power flow on line e_n .

and the lines connecting node n to its child nodes. This is achieved by placing a sensor at node n as illustrated in Fig. 2(b) in which a sensor is placed at node 1.

Subroutine 1: *CombineVects*(x_1, x_2)

```

1: Input: vectors  $x_1$  and  $x_2$ 
2: Result: vector  $x$ 
3: Begin
4:  $n_1 = \text{Size}(x_1)$ 
5:  $n_2 = \text{Size}(x_2)$ 
6: if  $n_1 = 0$  then
7:    $x = x_2$ 
8: return
9: else if  $n_2 = 0$  then
10:   $x = x_1$ 
11: return
12: end if
13:  $x = [x_1, x_2]^T$ 
14: for  $i = 1$  to  $n_1$  do
15:   for  $j = 1$  to  $n_2$  do
16:     $x.append(x_1[i] + x_2[j])$  // Append summation to the vector  $x$ 
17:   end for
18: end for
19: return

```

The lines connecting leaf nodes to their parent nodes always have a unique set of expected power flows because there is only a single node contributing to the power flow on that line. Hence, no sensors are placed at leaf nodes. Also, no sensors are placed at nodes with a single child node, since if a node n has a single child node, the expected power flows for the line e_n will always be unique, providing the node does not have a zero demand. If a node n has zero demand, then the repeated value in the expected array of flows for line e_n is discarded since it is associated with a numerically indistinguishable outage. Hence, a sensor is placed at a node m with more than one child node if and only if the expected power flows in the flow array *flow_array* for the line e_m are not all unique.

Placement of a sensor at a node n distinguishes all outage scenarios in the sub-tree rooted at node n and thereby enables their unique detection. This creates one of the disjoint sub-trees discussed previously. Due to this, the sub-tree rooted at node n can be ignored when continuing to traverse the remainder of the distribution network, thus decoupling the ML outage detection. Therefore, when the algorithm backtracks from a node with a sensor (Lines 37-39 in Algorithm 1), it returns to the parent node an empty array of expected flow values, and also deletes the sub-tree rooted at node n (Line 41 in Algorithm 1). However, if the elements in the array of expected flows *flow_array* of a line e_n are all unique and no sensor is required at node n , the array of flows is grown until another sensor is placed or the remainder of the tree is traversed completely.

It is important to note that the repeated values in the array of expected flows for a line e_n indicates that some outages

in the downstream of the node n will be unidentifiable if a sensor is not placed at node n . This can be easily understood by comparing the sensor placements of Fig. 2(a) and Fig. 2(b). Hence, it is by construction that the proposed scheme ensures that all the detectable outages in the network will be identifiable. Further, the obtained placement is guaranteed to have the minimum number of sensors required to achieve identifiability. This can be intuitively explained. Suppose that a sensor is removed from the obtained placement. By construction, removing any sensor from the obtained placement is guaranteed to result in some unidentifiable outages. We could attempt to recover identifiability in the network by changing the locations of some of the other sensors in the network. However, this is not possible since moving any of the other sensors would result in some other unidentifiable outages. Thus, no other placement scheme can guarantee the identifiability of all outages in the network with a fewer number of sensors than the proposed placement scheme.

It is important to note that in the proposed sensor placement the nodal load forecasts are assumed to be noise-free, i.e., the true load is equal to the expected load and the true power flow is equal to the expected power flow, and the expected loads are used to perform the sensor placement. However, the true loads and the true power flows are noisy distributions of the expected loads and flows. This might raise some issues. Therefore, the following definition discusses the effect of having noisy nodal load forecasts on the detectability of identifiable outages.

Definition 3: it is important to note that a sensor placement in which all detectable outages satisfy Definition 2 under noise-free conditions, does not guarantee the perfect detection under noisy conditions. For example, consider the case where the distribution network and sensor placement are given in Fig. 2(a) and suppose that the nodal load forecasts for v_2 and v_3 are 19.9 and 20.1, respectively. In this case, all outages in the network are identifiable, but if the variance of the noise affecting the load forecasts is sufficiently large, the performance of an outage detector relying on power flow measurements along line e_1 is likely to be unfavorable, unless a sufficiently large number of measurements are made so that a more accurate estimate of the flow on e_1 can be obtained. On the other hand, a placement where some outages fail to satisfy Definition 2 cannot ensure any detection method to differentiate those outages with any number of collected measurements even in the absence of noise. The reason is that the mapping between the expected flow measurements and possible outage scenarios are not unique in this scenario.

The complexity of the proposed sensor placement algorithm is polynomial, i.e., $O(N+1)$, where $N+1$ is the number of nodes in the network. For each line in the network, an array of flows is constructed using the flow arrays of the downstream lines. The algorithm starts at the parent edges of the leaf nodes. For the parent edges of the leaf nodes the flow arrays consist of only two elements, i.e., zero when the line is in outage and the expected flow when the line is not in outage. Then, these flow arrays are used to construct the flow arrays of the edges above and this recursive process

continues with the root node. If a sensor is placed at a node, the algorithm returns an empty flow array vector; otherwise, it returns the computed flow array vector. Since each node is visited exactly once in this recursive process and the flow arrays are constructed using the available downstream flow arrays, the complexity of the placement is $O(N+1)$.

V. OUTAGE DETECTION

This section presents the novel outage detection algorithm. The objective of the algorithm is to identify all the topologically detectable outage lines as the set F , and then construct the current topology of the energized tree \mathcal{T}_0 . Since the proposed sensor placement ensures the identifiability under noise free conditions, the outage detection approach will detect all the topologically detectable outages with absolute certainty in the absence of noise. In practice, nodal load forecasts are noisy and therefore the performance of outage detection will depend on the noise statistics.

The outage detection algorithm is started by initializing the set of line outages F as an empty set and the topology of the energized tree \mathcal{T}_0 as the nominal outage free topology \mathcal{T}_{full} . A line outage will result in the loss of all loads downstream of the outage. Due to this, the power flow on the line in outage and all the lines downstream of the outage will be zero. Also, the power flows on some of the lines remaining in \mathcal{T}_0 will be reduced due to the disconnection. Hence, the first step is to identify all the lines in $E(\mathcal{P})$ that have a zero flow measurement. Let this set be E_Z . Some of the lines in E_Z might be the lines in outage while some of the lines might have zero flow due to an upstream line outage. Hence, the next step is to identify the lines in E_Z that are actually in outage. If a sensor installed at a node n measures zero flow along a line drawing power from n but measures a positive flow on the line e_n , we can identify with absolute certainty that an outage occurs on the line with zero flow. Using this approach, we can identify the lines in E_Z that are actually in outage and include them in the set F . Such line outages are called directly identifiable line outages, and are represented by the set F_D . Alternatively, it is also possible that a zero flow is measured on all lines connected to a node n (with a sensor), including the line e_n . In this case, it is possible that e_n is in outage. However, we cannot conclude with the certainty that e_n is in outage unless we are sure that there is no line outage upstream of e_n . Hence, we shall return to the remaining lines in E_Z , i.e., $E_Z \setminus F_D$, once we identify any upstream line outage.

After identifying the lines in $E(\mathcal{P})$ with zero flow, the next step is to adjust the expected flows of the remaining lines in $E(\mathcal{P})$ that have non-zero measured flows, i.e., $E(\mathcal{P}) \setminus E_Z$. This is performed by subtracting the expected flows of the lines in E_Z from the expected flows of the lines in $E(\mathcal{P}) \setminus E_Z$ that are in the upstream of the directly identifiable outages, i.e., according to the graph structure \mathcal{T}_0 . The reason behind this is intuitive. Since the lines in E_Z have zero flow, we can conclude that the loads downstream of those lines are disconnected from \mathcal{T}_0 with certainty, irrespective of whether the lines themselves are in outage or not. Due to this, for some

of the lines in $E(\mathcal{P}) \setminus E_Z$ that are in the upstream of the lines in E_Z , we cannot expect the power flows to be the same as in an outage-free scenario. The power flows would be reduced due to the loss of loads. Hence, we perform the subtraction. After this step, we update \mathcal{T}_0 by removing the lines E_Z and all the lines downstream of E_Z .

Next, for all the lines in $E(\mathcal{P}) \setminus E_Z$, in order of decreasing depth, a hypothesis test is performed to detect whether the measured (non-zero) flow matches with the updated expected flows or is less. This is performed by the following simple binary hypothesis test.

$$H_0: y_{\mathcal{T}_{true}}(e_n) = \bar{y}_{\mathcal{T}_{updated}}(e_n) \quad (6)$$

$$H_1: y_{\mathcal{T}_{true}}(e_n) < \bar{y}_{\mathcal{T}_{updated}}(e_n) \quad (7)$$

where $\bar{y}_{\mathcal{T}_{updated}}(e_n)$ is the updated expected value for $y_{\mathcal{T}_{true}}(e_n)$ (the measured flow on line $e_n \in E(\mathcal{P}) \setminus E_Z$), which is obtained by using (4) after replacing \tilde{d}_i with d_i . Based on Assumption 3, the decision between the two hypotheses is done using (8), which is compared to a threshold value chosen to ensure a desired false alarm probability according to the popular Neyman-Pearson lemma [28].

$$z_n = \frac{(y_{\mathcal{T}_{true}}(e_n) - \bar{y}_{\mathcal{T}_{updated}}(e_n))^2}{\sigma^2} \quad (8)$$

For a line $e_n \in E(\mathcal{P}) \setminus E_Z$, if hypothesis H_1 is chosen, the line is included in a set A . For each line in A , the value $\Delta y(e_n) = y_{\mathcal{T}_{true}}(e_n) - \bar{y}_{\mathcal{T}_{updated}}(e_n)$ is computed. The value $\Delta y(e_n)$ is the difference between the measured flow on e_n and our updated expected value for it. We also define an isolated subtree $S(e_n)$ for each line $e_n \in A$ composed of all lines and nodes downstream of node n . Further, we associate each subtree $S(e_n)$ with the corresponding value of $\Delta y(e_n)$. Next, for each sub-tree $S(e_n)$, we generate an array of expected flows on line $e_n \in E(\mathcal{P}) \setminus E_Z$ with all topologically detectable outages that may occur in $S(e_n)$. However, generating the array of expected flows with all possible outages is computationally expensive. To simplify this, we check if there are any single line outages in $S(e_n)$ that would result in a $\Delta y(e_n)$ which is significantly larger than the one we obtained. If yes, we exclude all such single line outages from the process of generating the array of expected power flows for the sub-tree. This is intuitive because if the outage of a single line results in a larger $\Delta y(e_n)$ than the one we obtained, it is impossible for the line to be in outage. This motivates the simple binary hypothesis test.

$$H_0: \Delta y(e_n) \leq y_{\mathcal{T}_{true}}(e_n) - \dot{y}_{S(e_n)e_m}(e_n) \quad (9)$$

$$H_1: \Delta y(e_n) > y_{\mathcal{T}_{true}}(e_n) - \dot{y}_{S(e_n)e_m}(e_n) \quad (10)$$

where $\dot{y}_{S(e_n)e_m}(e_n)$ is the expected power flow on line e_n in the single outage scenario where line e_m is in outage. If H_1 is accepted in (10), all outages involving e_m can be ignored when constructing the array of expected power flows for the subtree $S(e_n)$.

To generate the array of expected power flows for the subtree $S(e_n)$ with $e_n \in E(\mathcal{P}) \setminus E_Z$, we traverse $S(e_n)$ using a depth-

first search method as long as we continue to accept H_1 in (10). Then, if we find a line where H_1 in (10) is rejected, we generate a vector of expected power flows associated with the outages involving that line and all the lines below it. Then we backtrack and continue to traverse the sub-tree using a depth-first search as long as we accept H_1 . Once all the vectors of expected power flows are generated over the different regions of $S(e_n)$ where we accept H_1 , they can be concatenated to create the array of expected flows by using the function *CombineVects*. For each sub-tree $S(e_n)$, we employ a modified version of the ML detector given in (5) to identify the outages in $S(e_n)$. We modify the ML detector given in (5) by replacing $S_s(E)$ with the set of outages that map to the values in the array of expected flows for $S(e_n)$, and by replacing Y with the power flow measurement for line e_n . It is in this step that we identify the majority of outages in the network. We update the set F with the detected line outages. Also, we remove the detected line outages and the line downstream of those outages from \mathcal{T}_0 , thereby updating the current topology. We repeat this for each sub-tree.

Now, we return to the line $e_n \in E_Z \setminus F_D$, i.e., the line which has a measured flow zero and where node n is endowed with a sensor. For every such line, if none of the identified outages in F are on the upstream path from the node n to the root node (or the next node endowed with a sensor), we can conclude with the certainty that the line e_n is in outage. Then, we update F with all the lines in $E_Z \setminus F_D$ that we conclude to be in outage. Also, we remove the detected line outages and the lines downstream of those outages from \mathcal{T}_0 , thereby updating the current topology. Finally, the values of F and \mathcal{T}_0 correspond to the detected line outages and the current topology of the distribution network, respectively. Note that unlike the sensor placement algorithm, the complexity of the outage detection algorithm depends on several specific factors of the network such as the nominal topology, the nodal load statistics, the sensor placement and the outages in the network. The sensor placement in turn depends on the nodal load statistics and the nominal topology. Since the nodal load statistics and the outages are operation characteristics of the network, which are time-dependent and user-dependent, we do not provide a complexity analysis of the outage detection algorithm.

VI. NUMERICAL RESULTS

This section presents numerical results which illustrate the performance of the outage detection algorithm. This algorithm apply power flow measurements obtained from the sensors according to the proposed sensor placement algorithm. In the numerical results, a modified version of the IEEE 123-node test feeder is considered, in which all lines are assumed to be single phase and the load demand at each node to be the sum of spot loads over all three phases. As explained in Definition 2, noise-free sensor measurements are considered. However, nodal forecasts are considered to be noisy. As mentioned above, we analyze our outage detection algorithm in two different cases. Note that for Case 2, we assume that the nodal forecast noise in the real and reactive

flow measurements are independent and identically distributed normal random variables.

Firstly, we find the sensor placement for the IEEE 123-node test feeder by applying our sensor placement algorithm. This results in a sensor placement with 20 sensors located at nodes:

$$\mathcal{P}^* = \{1, 3, 8, 13, 18, 23, 26, 36, 40, 44, 57, 67, 76, 78, 81, 89, 93, 97, 105, 110\} \quad (11)$$

The node numbers in (11) follow those given in the documentation of the test feeder. Figure 3 shows the IEEE 123-node test feeder with the sensor locations under \mathcal{P}^* indicated by red circles.

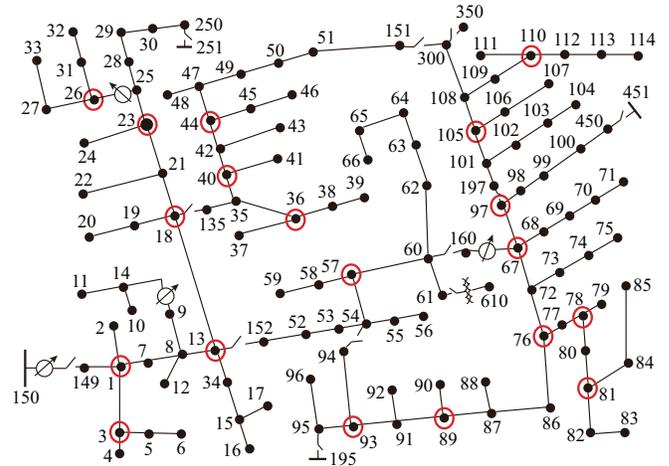


Fig. 3. IEEE 123-node test feeder with sensor locations obtained by using proposed algorithm.

At first, we simulate the probability of detection of the proposed algorithm against the standard deviation of the error in nodal forecast σ . We run the detection algorithm for 1000 different runs. In each run, we choose a random number of topologically detectable line outages from a uniform distribution over the number of lines in the feeder. By recording the number of runs in which the outages are correctly identified and dividing it by the number of runs (1000), the probability of detection is estimated. Figure 4 illustrates the results. Note that the smallest nodal demand in the IEEE 123-node test feeder is 20, so a standard deviation of 2 is quite significant. From Fig. 4, it can be clearly observed that employing both real and reactive power flow measurements significantly increases the probability of detection, especially for higher values of σ . This should be expected as the number of measurements for detection is doubled by including reactive power flow measurements.

The results illustrated in Fig. 4 are obtained by choosing a random number of topologically detectable outages. A large number of generated outage scenarios involve the scenarios where a significant number of outages are very close to the root node. Due to the outages close to the root node, the deviations in the measured flows are large and this may improve the detection performance. We obtain additional results by restricting the number of outages N_1 to be uniformly distributed between 1 and 20, so that the majority of the gen-

erated outages would be farther from the root node. Figure 5 illustrates these results and shows that the probability of detection has decreased for both Case 1 and Case 2 in comparison with the results of Fig. 4.

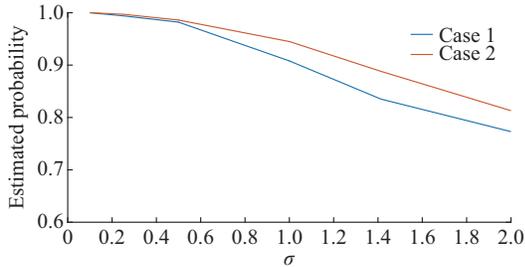


Fig. 4. Estimated probability of detection versus σ with no restriction on the number of outages.

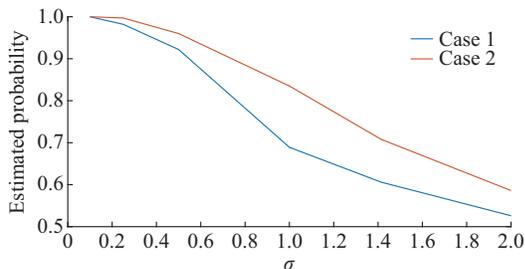


Fig. 5. Estimated probability of detection versus σ with maximum number of outages as 20.

Finally, Fig. 6 illustrates the effect of increasing the number of measurement samples per sensor T used for detection. The results for Fig. 6 are obtained in Case 1 with load forecast $\sigma = 2$.

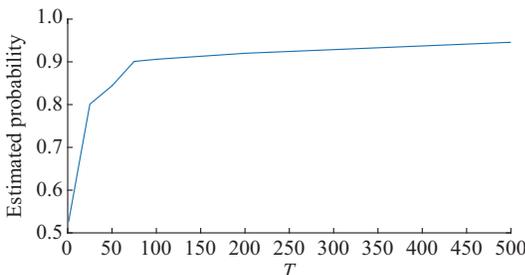


Fig. 6. Estimated probability of detection versus T .

The results of Fig. 6 show that only a small number of measurement samples are needed in order to achieve significant increases by the probability of detection. Further increase in the number of samples does not significantly improve the probability of detection.

VII. CONCLUSION

This paper focuses on topology estimation and outage detection in radial distribution networks. Noisy nodal load forecasts and power flow measurements of a subset of the lines in the network are used for outage detection. The power flow measurements are obtained by the sensors installed on a subset of nodes. For the sensor placement, a recursive sen-

sor placement algorithm is proposed that provides the minimum number and locations of sensors so that all topologically detectable outages in the network are identifiable. Using the measurements obtained from the proposed sensor placement, a novel algorithm of outage detection and topology estimation is proposed. The algorithm takes advantage of the decoupling nature of the ML detector over sub-trees in the network. Finally, numerical results for the IEEE 123-node test feeder are presented. The results illustrate the performance of the outage detection algorithm and the proposed sensor placement algorithm. In the following study, we will work on extending our algorithms to networks with distributed generators and microgrids since these networks pose critical challenges [29] that are not considered in the current formulation.

REFERENCES

- [1] A. J. Wood and B. F. Wollenberg, *Power Generation, Operation, and Control*. Hoboken: John Wiley & Sons, 2012.
- [2] A. Von Meier and G. D. Rodriguez, "Monitoring for impacts of distributed resources: initial planning considerations," in *Proceeding of 2013 IEEE PES General Meeting*, Vancouver, Canada, Jul. 2013, pp. 1-5.
- [3] Z. Wang and J. Wang, "Self-healing resilient distribution systems based on sectionalization into microgrids," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 3139-3149, Nov. 2015.
- [4] J. Medina, N. Muller, and I. Roytelman, "Demand response and distribution grid operations: opportunities and challenges," *IEEE Transactions on Smart Grid*, vol. 1, no. 2, pp. 193-198, Sept. 2010.
- [5] C. N. Lu, J. H. Teng, and W. H. E. Liu, "Distribution system state estimation," *IEEE Transactions on Power Systems*, vol. 10, no. 1, pp. 229-240, Feb. 1995.
- [6] R. Singh, B. C. Pal, and R. A. Jabr, "Choice of estimator for distribution system state estimation," *IET Generation, Transmission & Distribution*, vol. 3, no. 7, pp. 666-678, Jul. 2009.
- [7] M. Baran and T. E. McDermott, "Distribution system state estimation using ami data," in *Proceeding of 2009 IEEE/PES Power Systems Conference and Exposition*, Seattle, USA, Mar. 2009, pp. 1-3.
- [8] F. Katiraei, M. R. Irvani, and P. W. Lehn, "Micro-grid autonomous operation during and subsequent to islanding process," *IEEE Transactions on Power Delivery*, vol. 20, no. 1, pp. 248-257, Jan. 2005.
- [9] J. E. Tate and T. J. Overbye, "Line outage detection using phasor angle measurements," *IEEE Transactions on Power Systems*, vol. 23, no. 4, pp. 1644-1652, Nov. 2008.
- [10] J. E. Tate and T. J. Overbye, "Double line outage detection using phasor angle measurements," in *Proceeding of 2009 IEEE PES General Meeting*, Calgary, Canada, Jul. 2009, pp. 1-5.
- [11] H. Zhu and G. B. Giannakis, "Sparse overcomplete representations for efficient identification of power line outages," *IEEE Transactions on Power Systems*, vol. 27, no. 4, pp. 2215-2224, Nov. 2012.
- [12] Y. C. Chen, T. Banerjee, A. D. Dominguez-Garcia *et al.*, "Quickest line outage detection and identification," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 749-758, Jan. 2016.
- [13] C. Fukui and J. Kawakami, "An expert system for fault section estimation using information from protective relays and circuit breakers," *IEEE Transactions on Power Delivery*, vol. 1, no. 4, pp. 83-90, Oct. 1986.
- [14] Y. Liu and N. N. Schulz, "Knowledge-based system for distribution system outage locating using comprehensive information," *IEEE Transactions on Power Systems*, vol. 17, no. 2, pp. 451-456, May 2002.
- [15] A. von Meier, D. Culler, A. McEachern *et al.*, "Micro-synchphasors for distribution systems," in *Proceeding of 2014 IEEE PES Innovative Smart Grid Technologies*, Washington, USA, Feb. 2014, pp. 1-5.
- [16] G. Cavraro, R. Arghandeh, G. Barchi *et al.*, "Distribution network topology detection with time-series measurements," in *Proceeding of 2015 IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*, Washington, USA, Feb. 2015, pp. 1-5.
- [17] Y. Gao, Z. Zhang, W. Wu *et al.*, "A method for the topology identification of distribution system," in *Proceeding of 2013 IEEE PES General Meeting*, Vancouver, Canada, Jul. 2013, pp. 1-5.

- [18] J. D. Watson, J. Welch, and N. R. Watson, "Use of smart-meter data to determine distribution system topology," *The Journal of Engineering*, vol. 2016, no. 5, pp. 94-101, Mar. 2016.
- [19] Z. Tian, W. Wu, and B. Zhang, "A mixed integer quadratic programming model for topology identification in distribution network," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 823-824, Jan. 2016.
- [20] D. Deka, M. Chertkov, and S. Backhaus, "Structure learning in power distribution networks," *IEEE Transactions on Control of Network Systems*, vol. 5, no. 3, pp. 1061-1074, Sept. 2018.
- [21] Y. Zhao, R. Sevlian, R. Rajagopal *et al.*, "Outage detection in power distribution networks with optimally-deployed power flow sensors," in *Proceeding of 2013 IEEE PES General Meeting*, Vancouver, Canada, Jul. 2013, pp. 1-5.
- [22] R. Sevlian, Y. Zhao, A. Goldsmith *et al.*, "Outage detection using load and line flow measurements in power distribution systems," *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 2053-2069, Mar. 2018.
- [23] R. Dobbe, D. Arnold, S. Liu *et al.*, "Realtime distribution grid state estimation with limited sensors and load forecasting," in *Proceeding of 2016 ACM/IEEE 7th International Conference on Cyber-Physical Systems (ICCPS)*, Vienna, Austria, Apr. 2016, pp. 1-10.
- [24] QineitQ North America. (2018, Oct.). Linewatch low voltage utility sensors. [Online]. Available: <https://www.qineitqna.com/linewatch-sensors/linewatch/linewatch-low-voltage-utility-sensors/>
- [25] S. M. Kay, *Fundamentals of Statistical Signal Processing: Detection Theory*. New York, USA: Prentice Hall, 1998.
- [26] V. Telukunta, J. Pradhan, A. Agrawal *et al.*, "Protection challenges under bulk penetration of renewable energyresources in power systems: a review," *CSEE Journal of Power and Energy Systems*, vol. 3, no. 4, pp. 365-379, Dec. 2017.
- [27] X. Chen, M. B. Mcelroy, Q. Wu *et al.*, "Transition towards higher penetration of renewables: an overview of interlinked technical, environmental and socio-economic challenges," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 1, pp. 1-8, Jan. 2019.
- [28] M. U. Usman and M. O. Faruque, "Applications of synchrophasor technologies in power systems," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 2, pp. 211-226, Mar. 2019.
- [29] A. Landeros, S. Kozziel, and M. F. Abdel-Fattah, "Distribution network reconfiguration using feasibility-preserving evolutionary optimization," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 3, pp. 589-598, May 2019.

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