# Structure Learning in Power Distribution Networks

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***Abstract*—Traditional power distribution networks suffer from a lack of real-time observability. This complicates development and implementation of new smart-grid technologies, such as those related to demand response, outage detection and management, and improved load monitoring. In this paper, inspired by proliferation of metering technology, we discuss topology estimation problems in structurally loopy but operationally radial distribution grids from measurements, for example, voltage data, which are either already available or can be made available with a relatively minor investment. The primary objective of this paper is to learn the operational layout of the grid. Further, the structure learning algorithm is extended to cases with missing data, where available observations are limited to a fraction of the grid nodes. The algorithms are computationally efficient—polynomial in time—which is proven theoretically and illustrated in numerical experiments on a number of test cases. The techniques developed can be applied to detect line failures in real time as well as to understand the scope of possible adversarial attacks on the grid.**

***Index Terms*—Missing data, power distribution networks, power flows (PFs), structure/graph learning, voltage measurements.**

## I. Introduction

THE POWER grid is composed of a network of transmission and distribution lines that enable the transfer of electrical power from generators to loads. The design, operation, and control of these networks are typically hierarchical with a major division between the transmission network of high-voltage lines connecting substations and power plants, and the distribution network of medium- and low-voltage lines that connect the distribution substations to the end-users. Here, we focus on distribution networks.

The design of distribution networks may appear to be loopy or meshed, however, for practical engineering concerns, the vast majority of distribution grids are operated as "radial" networks, that is, as a set of nonoverlapping trees. Switches in the network are used to achieve one radial configuration out of many possibilities. Each tree in the network has a substation at the root and customers positioned at the other nodes. Switching from one tree-like operational configuration to another is typically caused by system upsets, for example, faults and outages, and may occur few times a day or even an hour.

The radial configuration distinguishes distribution networks from transmission networks that generally have multiple loops energized all the time to guarantee continuous delivery of power to every node, even in the case of occasional line faults and outages. Radial configurations have led to lesser monitoring, observability, and state estimation in distribution as compared to meshed transmission networks [1]. The recent proliferation of smart grid technology, including smart meters that measure electricity consumption at the node level, has created new opportunities to extract information important to distribution grid operators and planners. Such efforts are also getting additional attention in view of mounting concerns over data security and protection of user privacy [2].

In this paper, we seek to *develop low-complexity algorithms to learn the current operational structure in "radial" distribution networks using only nodal measurements*. Nodal measurements may include voltage magnitudes, voltage phases (potentially), and power injections that are typically available at smart meters, pole-mount or pad-mount transformers, and distribution phasor measurement units. This is consistent with the recent expansion of smart grid monitoring devices that generally provide nodal voltages and power injections at fine spatial resolution, that is, at the individual customer level, but do not provide any edge flow data. Additional instrumentation is emerging for pole-mount or pad-mount transformers [3], however, these new devices still only provide nodal voltages and aggregated customer power injections.[1] Furthermore, we analyze learning the operational grid structure with missing data, where observations from a subset of nodes are not available. Accurate structural estimation impacts many important applications, including failure identification [4], [5], outage management, and recovery following major and minor disruptions (for example, hurricanes to individual lightning strikes), grid reconfiguration [6] for power flow (PF) optimization and generation scheduling [1], [7], and quantification of the need for additional meter placement. From an adversarial viewpoint, our work can be viewed as low-intrusion learning by a rogue agent interested in estimating the grid structure for a data attack [8]–[11].

### A. Related Work

Our work falls in the broad category of "graph learning" problems that have been approached from different directions. For general graphs and graphical models [12], maximum-likelihood

[1] We use the term "power injection," "power consumption," and "load" interchangeably to denote the power profile at each interior (nonsubstation) node of the distribution system.

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