Graphical Model for Cyber-Physical Systems: The Case of State Estimation in Electric Power Systems

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Index Terms

Cyber-Physical Systems, Graphical Model, Distributed State Estimation, Robustness.

I. Background/Motivation

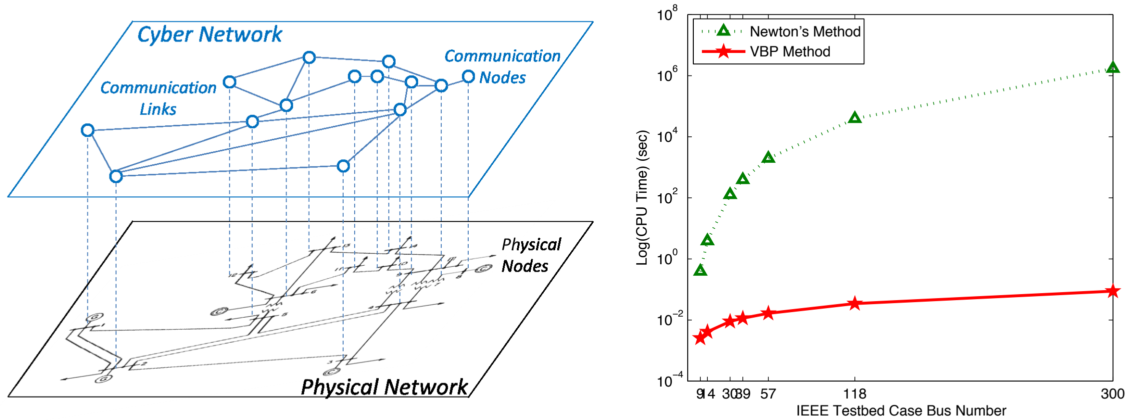
Recent advances in technology leads to the evolution in various intelligent system designs. Researches over Cyber-Physical Systems (CPS) aim at deepening the understanding about these intelligent systems and unifying their designs across domains. A fundamental question in CPS is how to integrate the cyber (i.e., computational and communication) intelligence and physical systems with increasing uncertainties in a proper way. An even harder question, for the next ear CPS, is how to build both layers into one single model and conduct efficient algorithm, key for many non-core engineering disciplines prevailed with complex physical laws. As an initial step, this work explores the answer over Electric Power System (EPS), and seeks to generalize the result to other class of utility networks (such as Water, Gas, Sewage networks, that virtually define modern life), leading to a distributed, secured, robust, and smart CPS-design.

For EPS, Energy Management Systems are currently an integral part of electric power utility operations. Their main function is to conduct state estimation (SE), based on redundant system-wide measurements using highly centralized Supervisory Control and Data Acquisition (SCADA), to assess critical outages, and generation scheduling for forecasted system demand. Unfortunately, significant gap exists in SE performance between the state-of-the-art methods and the desired informative data exploration, leading to fragile grid behaviors, such as blackouts. This problem may grow as new unconventional resources are being deployed within the electric power grids which were not designed for accommodating such resources in order to meet the social objectives of deploying clean resources and reduce the environmental footprint in the years to come. As such, proper modeling is in need to account for their uncertainties.

Beside, SE used by the industry today are hard to scale up and are computationally complex. To avoid excessive computational complexity, only Extra High Voltage (EHV), High Voltage (HV) and occasionally Medium Voltage (MV) representation of the complex multi-voltage level power grids are included. The low voltage (LV) distribution networks are not modeled nor supported by the on-line SE today. This, in turn, makes it difficult to estimate the status and states of many new diverse resources and users connected to the LV level distribution systems, such as small scale generations and loads including but not limited to renewable energy generators, i.e. wind and solar generators; responsive small electricity users; and electricity users which can offer storage to utility, such as electric cars. This need to estimate the on-line state in the entire electric power grid makes it even more difficult to manage all data in a centralized way than in the past. A multi-layer, distributed state estimation capable of accommodating interactive information exchange is likely to become the preferred approach between different layers within the very complex Cyber-Physical Systems for smart grid to integrate the objectives of various users.

II. Proposed Work

The above challenges are enormous as the industry paradigm shifts from the traditionally deterministic model based centralized monitoring architecture to probabilistic model based highly distributed interactive data and resource management. To manage huge uncertainties in a distributed way across energy providers, users and delivery providers, we consider a graph $G(V, E)$ representing the electrical power system as a graphical model, and model power grid states (bus voltages) as random variables on the graph vertices V; the edges E of the graph determine the interaction of state variables according to physical laws (i.e. Kirchoff laws). The graph of the physical network can be visualized as the physical layer in Fig.a.



(a) Physical Network and Cyber Network (14 Bus System).

(b) CPU time comparison.

The new probabilistic measurement model of AC power system SE is expressed as $z_i = h_i(\boldsymbol{v}) + u_i$, where the vector $\boldsymbol{v}$ represents the probabilistic power system states, instead of the conventionally used deterministic states. u_i is the i^{th} additive measurement noise. z_i is the i^{th} telemetered measurement, such as power flow and voltage magnitude. $h_i(\cdot)$ is a nonlinear function associated with the i^{th} measurement.

The probabilistic power system state estimator aims to find an estimate ($\hat{\boldsymbol{v}}$) of the true states ($\boldsymbol{v}$) that achieves the maximum a posteriori probability (MAP), given the measurement set $\boldsymbol{z}$ and the priori state information of $\boldsymbol{v}$ according to the measurement model. Such a process is achieved via the cyber network layer as in Fig.a. To obtain an efficient MAP estimate, we need to 1) obtain proper formulations for $p(\boldsymbol{v})$, $p(\boldsymbol{z}|\boldsymbol{v})$, and $p(\boldsymbol{z})$; and 2) employ efficient algorithms to conduct marginalization over $p(\boldsymbol{v}|\boldsymbol{z})$ with respect to $\boldsymbol{v}$. For $p(\boldsymbol{v})$ we can use uniform prior probability distribution to avoid bias or non-uniform one based on historical data. $p(\boldsymbol{z})$ is a constant. Since Variational Belief Propagation (VBP) discussed later is built on the exponential family, we use the additive Gaussian noise $\boldsymbol{u}$ to represent $p(\boldsymbol{z}|\boldsymbol{v}) \sim \exp\left\{-\sum_i (z_i - h_i(\boldsymbol{v}))^2/\right\}$.

For efficient algorithm, the VBP approach is used by randomly generating spanning trees of a meshed network. This is one way of organizing the "global" computation of state beliefs in terms of smaller local computations in graphical model enabled by distributed computation capability (such as a small embedded system) and communication capability (a wireless, telephony or Internet link) of components in the future smart grid (such as a small generator). Mathematically, the message-passing algorithm below is run until state convergence, $M^{n+1}_{t\to s}(v_s) = \alpha \max_{v_t}\left\{ \exp\left(\frac{\theta_{st}(v_s,v_t)}{\rho_{st}} + \theta_t(v_t)\right) \frac{\prod_{k\in\mathcal{N}(t)\backslash s}[M^n_{k\to t}(v_t)]^{\rho_{kt}}}{[M^n_{s\to t}(v_t)]^{(1-\rho_{ts})}} \right\}$, where θ_{st} and θ_t are the exponential parameters associated with the nodes (s,t) and the node t in the probability density function. ρ_{st} is the edge appearance probability. Preliminary simulation result over the IEEE standard test systems show reduced estimation error and $\log$-reduction in computational time (Fig.b).

III. Potential Impact to Cyber-Physical Systems

Such a result, if implemented successfully, will result in an improved understanding of distributed robustness monitoring in CPS, based on a solid probabilistic foundation, using the mathematical formalism of graphical models, thereby enabling substantial improvements in the reliability of Power Systems. Thanks to its simple reliance over measurement noise (with physical model) and local message passing (with cyber information, i.e., via communications and computations), the proposed single layer modeling method can be generalized to integrate CPS designs in different domains (including non-core engineering disciplines) under a unifying framework, key to the next next era of CPS designs. For instance, one can deploy cheap sensors across cyber-physical grids (i.e. Electric, Water, Gas, Sewage networks, that virtually define modern life), add our adaptive message passing algorithm, and create a automatic robust state estimation in various cyber-physical systems. Further, results from this research will expedite new graphical model analysis over cyber-physical systems, defining a new research direction for sustainable CPS designs.