Position Paper: Cyber Enabled Stochastic Management of Microgrids

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Microgrids are small-footprint power systems comprised of diverse power generation sources, energy storage devices, and loads. An appealing feature of microgrids is flexibility. Depending on ambient conditions, operational policies, and utility-power availability, they can operate in grid-connected, islanded, or hybrid modes. Like the bulk power system, microgrids are complex cyber physical systems (CPSs) with electrical, mechanical, economic, and communication, computing and control subsystems.

As a key part of the emerging distributed-generation paradigm, microgrids offer several system-level advantages. In addition to reducing transmission and distribution losses, these include increasing renewable integration, and ensuring a reliable and secure power supply to critical loads in residential, commercial, and industrial sectors. The importance of microgrids in sustaining critical infrastructure has come to light recently in the face of hurricane Sandy that struck large parts of the North-East U.S. As reported in `http://www.greentechmedia.com` on Nov. 20, 2012:

> *Amidst the blackouts ... a few islands of light and heat stood out. From the suburbs of Maryland and bucolic Princeton, N.J. to the hardest-hit sections of downtown Manhattan, microgrids—building or campus-wide backup power systems that can disconnect, or "island" from the grid—stood firm during the storm, proving their value in a disaster.*

Extenuating weather conditions due to global climate change may conceivably push microgrids to the forefront of disaster relief efforts. Global climate change notwithstanding, the benefits of distributed generation are now widely appreciated [1], and microgrids are key enablers of this paradigm shift.

Key Challenges

The critical issue in formulating effective approaches to *microgrid management* lies in the inherently stochastic environment within which microgrids operate. In order to increase deployment of microgrids it is necessary to develop modeling, estimation, and control tools that explicitly address:

i) **Uncertainty.** Renewable resources (such as photovoltaic systems) and uncontrollable loads (such as plug-in hybrid-electric vehicles) induce uncertainty and intermittency.

ii) **Reliability.** Lack of field data on failures and repairs in the constituent cyber-physical subsystems and employment of nascent technology make reliability a critical concern.

iii) **Security.** Uncertain and unpredictable cyber-layer attacks may have detrimental impacts on stability and quality of power in physical-layer subsystems.

Prior art

Theory and techniques for microgrid management that explicitly account for complex cyber-physical interactions within a stochastic operational environment have been lacking. With regard to microgrid reliability modeling, typical metrics derive from power distribution systems that focus primarily on system availability while discounting performance. To quantify *how well* the cyber-physical subsystems meet performance objectives (and not just *if* they are available), there is a need to characterize performability—a notion that captures a system's performance while acknowledging its reliability. Unlike robust performance which emphasizes worst-case scenarios, performability notions are better suited for quantifying performance within a probabilistic setting. Furthermore, classical methods for parameter identification and state estimation are difficult to implement in microgrids that contend with uncertainty and operate in multiple configurations. Likewise, current approaches to coping with cyber attacks typically assume linear time-invariant (LTI) models and ignore dynamics of e.g., power electronic interfaces, that are undeniably tied to system stability in small-footprint power systems. Additionally, it has been recognized that decentralized control is essential to ensuring data privacy and resilience to cyber attacks. However, optimal control of hybrid systems has largely focused on design of centralized controllers that require information from all spatially distributed subsystems. Obviously, this requirement is challenging to meet in microgrid management.

Proposed Framework

We contend that the range of uncertain phenomena that impact cyber-enabled microgrids can be captured using stochastic hybrid system (SHS) models. These models are well-suited for systems that operate in uncertain environments and have a discrete state (that takes values in a finite set) and a continuous state (that evolves according to a stochastic differential equation (SDE)). The different values that the discrete state may take can originate from uncertain generation/loads, failures in cyber/physical layers, and charging/discharging of energy-storage devices. The continuous state can account for electrical variables (e.g., network voltages, currents, and frequency), control/communication states, and economic indicators (e.g., expended repair cost, and incentives for participation in demand-response programs). While SDEs capture *small-signal* uncertainties introduced by thermal fluctuations, incident irradiation variation, and load uncertainty, jumps in discrete and continuous states are triggered by *large-signal* changes (e.g., a sudden drop in the power output of an inverter due to failure or sudden appearance of clouds).

The SHS framework encompasses a variety of commonly used stochastic modeling and analysis tools including: i) jump linear systems (linear flows and no jumps in the continuous state); ii) discrete-space continuous-time Markov chains (no continuous state and constant/time-varying transition rates for the discrete state); iii) Markov reward models (constant rate of growth in the continuous state); and iv) piecewise deterministic Markov processes (no diffusion terms in the SDEs). Given this generality, it is not surprising that SHS formalisms have been applied to study a host of other CPS including communication networks [2, 3], air-traffic management [4, 5], biochemical networks [6, 7], and bulk power systems [8, 9].

Example: Customer-Driven Microgrid

The state-transition diagram in Fig. 1 provides a graphical illustration of an SHS model for a customer-driven microgrid. This microgrid includes a neighborhood with high photovoltaic (PV) system penetration and a community-level charging station for plug-in hybrid-electric vehicles. In order to regulate active/reactive power for voltage/frequency control, and coordinate transitioning into/out of islanded modes, all power electronics interfaces are assumed capable of communicating among themselves and with a central utility-level controller.

Multiple operational modes may originate from uncertainty in ambient conditions, random failures, and cyber attacks. Markov models are commonly used to describe uncertainty in renewable resources. Regarding uncertain loads, Markovian assumptions are consistent with well-established power-system load models. Stochastic hybrid models have been also used to describe aggregate behavior of thermostatically controlled heating and cooling loads.

Perspectives & Concluding Remarks

The SHS-based framework to stochastic management of microgrids seeks tangible answers to the following questions: i) What are appropriate reliability metrics that quantify microgrid performance across different time scales using limited field data and affordable computations?; ii) What are the breakthroughs necessary to devise efficient strategies for microgrid state estimation and parameter identification in the face of unpredictable cyber-attacks?; and iii) What advancements are needed in optimal control methods to address microgrid operational uncertainty and multiple performance objectives, while respecting data privacy?

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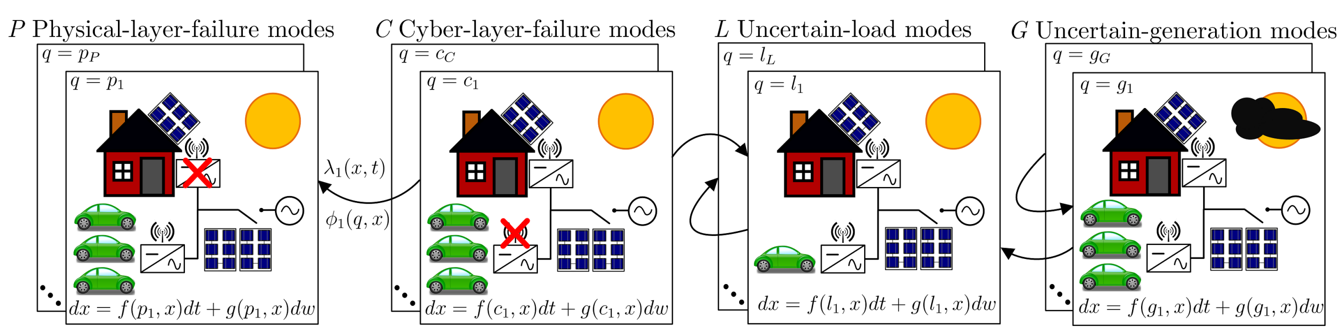

Figure 1: State-transition diagram with illustrative modes and corresponding transitions for CPS failures and uncertain generation/load. Details are hidden in the interest of clarity; e.g., $\{g_1, \ldots, g_G\}$ might correspond to G different irradiation levels (g_1 depicts one such irradiation level).