STOCHASTIC QUEUING MODELS FOR DISTRIBUTED PV ENERGY

Anthony Kuh

University of Hawaii Department Electrical Engineering Honolulu, HI 96822 kuh@hawaii.edu

Index Terms: distributed solar modeling, stochastic models

ABSTRACT

In the past few years there have been a tremendous growth in distributed PV generation on commercial and residential buildings. Increasing distributed PV generation has raised concerns about the stability of the distribution grid due to the intermittency of solar PV energy. Before smart grid optimization and control algorithms can be formulated we must obtain a better understanding of the behavior of the distributed PV energy contributions to the electrical grid. This paper develops stochastic models to model each distributed energy source using both spatial and temporal processing. A goal is to develop simple stochastic models that accurately model the distributed energy produced from the PV sources with possible storage so that key events (e.g. ramp downs due to cloud cover can be characterized). The production of energy from PV panels is modeled as a queue with inputs being the nonstationary solar irradiation, the energy produced modeled by a deterministic function, and a queue modeled by storage which can be sold to the grid or used by local loads. A second queue models solar irradiation with inputs being weather conditions (sunny, partly cloudy, cloudy).

1. INTRODUCTION

In recent years there has been a substantial interest in developing smart microgrids that combine distributed renewable energy generation with adoption of energy efficient principles such as demand response (DR) to promote more intelligent energy management practices. By *microgrids* we mean small scale versions of the current centralized electrical grid [1]. By *smart microgrids* these grids will have local goals such as *reliability, carbon emission reduction, diversification of energy sources, and cost reduction* [1] established by the community. To achieve these goals we need to understand the behavior of the distributed renewable energy generation (DREG) by developing appropriate sensor Chuanyi Ji and Yun Wei

Georgia Institute of Technology Department Electrical and Computer Engineering Atlanta, GA 30332-250 jichuanyi, yunwei@gatech.edu

and monitoring networks to collect data from the environment and outputs of the DREG and to then develop effective stochastic models where we can analyze the DREG. Distributed solar photovoltaic (PV) systems are already playing a large role in DREG implementation. This paper develops stochastic spatial and temporal models for distributed solar (PV) and discusses both sensing and monitoring as well as modeling and analysis efforts at the University of Hawai'i at Manoa (UHM) and the Georgia Institute of Technology (GIT).

Increasingly at Universities and testbed locations both in the United States and internationally conversions are being made to smart microgrids. Some examples include the Illinois Institute of Technology with their Perfect Power program [2], University of California at San Diego where they generate about 85% of their energy on campus [3], and the University of Texas at Austin where they collaborate with their industry partners on the Pecan Street initiative [4]. The University of Vermont is working with Sandia National Laboratories to build a smart grid in Vermont [5]. Internationally, South Korea is building a smart grid testbed on Jeju island [6]. Each program combines academic, industry, and government partners, however each microgrid location has its own unique energy profile and set of challenges. Efforts are underway to construct a smart microgrid at UHM with the first steps being sensing and monitoring of data followed by developing models and analysis tools.

The emergence of a large number of smart microgrids is expected to change fundamentally how our energy grid operates in the future (see [7][8] and references therein). Currently, centralized control dominates generation and distribution of energy [9]. In contrast, DREG such as rooftop solar panels and solar farms generate energy locally at microgrids. DREG can thus be utilized, shared, and traded locally, which moves microgrids towards more energy self sufficiency. The state of Hawai'i currently relies on oil as the dominant source of energy for electricity generation with more than 90% produced from fossil fuels. The Hawaii Clean Energy Initiative is a memorandum of understanding between the state of Hawaii and the Department of Energy that sets targets of 70% of energy (40% from renewable sources and 30% of energy savings to come from energy efficient practices) by 2030 [10]. The University of Hawai'i at Manoa which pays some of the highest electricity rates in the country is working on developing a smart campus microgrid at UHM to reduce energy costs by having more DREG (through solar PV) and energy efficient practices.

Decentralized energy generation and consumption at microgrids raise significant technical challenges for modeling and sensing. Renewable energy sources such as solar draw power from nature. The energy generated is thus intermittent, i.e., varying randomly and dynamically, depending on weather conditions[11]. For example, solar energy from Photovoltaic (PV) can go from peak production to zero energy in a few minutes with cloud coverage. This results in the so-called ramping state [11], where energy outputs exhibit non-stationary (random and dynamic) behaviors. Such non-stationary behavior plus dynamic loads challenge modeling, optimization and control of a large number of microgrids [9].



Figure 1: A microgrid with renewable solar source.

The goal of this work is to develop analytical models for microgrids as a foundation of optimization and control. We first develop a dynamic queuing model, i.e., $GI(t)/G(t)/\infty$ queue [12], that characterizes renewable sources, storage and loads. Such a model quantifies intermittent renewable energy as a non-stationary random process. The Transient Littles Theorem is then applied to relate generated and dispatched renewable energy in a simple fashion. We then extend the model to a virtual queue that characterizes impacts of weather on renewable energy generation. Transient Little's Theorem then quantifies ramping states resulting from exogenous weather. We use pertinent quantities from the queuing model to motivate learning from sensory data. Real-data is being collected at University of Hawaii on renewable sources, and will be used to learn model parameters. This contributes to novel models for the microgrid as well as weather impacts, relating dynamic network queues with learning from data.

Section 2 discusses parameters of the microgrid illustrating the relationships between DREG (solar PV), battery storage, the electrical grid, and loads. Section 3 presents a model of solar energy with storage as a dynamic queueing model. Section 4 incorporates the effects of weather on the solar energy. Section 5 discusses how we can learn parameters from data and Section 6 discusses getting solar data and energy readings and further directions for this research in modeling multiple distributed solar sources. Section 7 summarizes results of this paper.

2. MICROGRID

At a macroscopic level, a microgrid consists of a (physical) network and exogenous weather as shown in Figure 1. A necessary first step for modeling is to identify heterogeneous variables relating to the network and exogenous weather. A physical network consists of the following components and variables:

- (a) A renewable source¹, e.g., solar for this work, that generates energy X(t) locally. X(t) enters a storage device, where parts of the energy can be distributed to the load or sold to the grid, equivalent to the special case of zero storage time.
- (b) A storage device has renewable energy X(t) as its input. The storage device then dispatches a portion of the energy $X_1(t)$ to load and $X_2(t)$ to be sold back to the grid.
- (c) Load that consumes energy from either the renewable or external sources.

Exogenous weather include the following variables:

- (a) solar radiation R(t) at a solar panel;
- (b) other weather variables W(t) such as cloud formation, temperature, wind speed and direction. These variables impact solar radiation R(t).

¹A microgrid can have multiple renewable sources but can be aggregated into one for simplicity of formulation.



Figure 2: Network: A $GI(t)/G(t)/\infty$ queue.

3. DYNAMIC NETWORK MODEL

3.1. Transient Queue

We model the physical network of a microgrid as a dynamic queue that includes a renewable source, storage, and load as shown in Figure 1. Here, renewable energy X(t) is considered as a deterministic function f() of solar radiation, i.e., X(t) = f[R(t)], where a solar panel converts solar radiation R(t) to energy X(t). As solar radiation R(t) varies randomly and dynamically with weather, X(t), the energy generated is considered as a random process with an arbitrary arrival time distribution GI(t).

Consider an increment of energy $\Delta X(t) = X(t + \delta t) - \delta t$ X(t) is stored for S(t) time-duration before being dispatched. Assume that X(t) is an independent increment process, i.e., the increments at disjoint time intervals are independent. Assume that storage duration S(t) has a general probability density function q(v|t), where q(v|t) means that the probability density function of storage duration can be non-stationary, i.e., varies with respect to time t of its generation. For example, if the peak generation and the peak demand do not coincide in time, storage duration can be longer at the peak generation for high penetration of the renewables. Hence q(v|t) characterizes and determines the control, e.g., dispatch aspect of a microgrid. Different dispatches schemes, e.g., on how to satisfy demands and how to trade with the grid, result in different g(v|t). Hence, g(v|t) represents aggregated effects of dispatching. The probability for the storage duration to exceed time t_0 is

$$\Pr(S(t) > t_0) = \int_{t_0}^{\infty} g(v|t) dv, \qquad (1)$$

where $Pr(S(t) > t_0)$ varies with time t.

Given the above quantifies, the physical network can be modeled as a transient $GI(t)/G(t)/\infty$ queue as shown in Figure 2. The arrival process to the queue is renewable energy X(t). Here renewable energy X(t) is considered as a non-stationary random process [13][12]. The departure process corresponds to dispatch $X_1(t) + X_2(t)$. Both arrivals and departures exhibit general and time-varying distributions. ∞ means that dispatching energy can experience delays ranging from zero to infinity; and there is no loss in energy storage.

 $GI(t)/G(t)/\infty$ queue was analyzed by Bertsimas et. al. in [12]; and recently applied to model large-scale outages of power distribution by Wei. et.al. [14]. A recent work applies a queuing model to study the effect of limited energy storage by Walid et.al. [15].

3.2. Transient Little's Theorem for Network

A transient queue with general arrival and departure processes does not allow simple solutions [12]. However, if the first moment is considered, $GI(t)/G(t)/\infty$ queue provides an analytically tractable approach in form of the Transient Little's Theorem [12].

To apply the transient Littles Theorem to the physical network, we consider the rate of energy generated $\lambda(t)$ at time t. $\lambda(t)$ characterizes the expected increment of generated energy in a unit time, i.e.,

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{E[\Delta X(t)]}{\Delta t}.$$
 (2)

Let N(t) be the amount of energy in storage at time t. The Transient Littles Theorem characterizes the expected value of N(t) through the rate of energy generation and the probability of storage time, where

$$E[N(t)] = \int_{0}^{t} \lambda(u) \operatorname{Pr}(S(u) > t - u) du.$$
(3)

Here, intuitively, $\lambda(u)du$ is energy generated at duration du at time u, and $\Pr(S(u) > t-u)$ is the probability that the generated energy is stored for at least t-u duration. Hence, $\int_0^t \lambda(u) \Pr\{S(u) > t-u\} dv$ is the total average amount of energy that is in storage until time t. The mathematical proof of the theorem can be found in [12]. Therefore, two quantities, rate function $\lambda(t)$ and probability of storage time $\Pr(S(t) > t_0)$, completely determine the expected energy in storage. These two quantities can be estimated from measurements.

4. WEATHER AND RENEWABLE SOURCE

We now focus on the renewable solar source and weather. Weather variables W(t) impact solar radiation R(t) and thus solar energy generated X(t). As weather is not completely predictable, solar radiation R(t) assumes to relate to weather randomly. For example, given weather forecasts or measurements $\hat{W}(t)$, $W(t) = \hat{W}(t) + Z(t)$, where Z(t) is a random forecast- or measurement-error.

Weather conditions determine states of renewable sources, and thus the rate $\lambda(t)$. For example, a renewable solar source can be viewed as in three states: (1) Low (l) generation corresponding to cloudy weather, where the rate $\lambda(t) = \lambda_l$ is a small constant $\lambda_l \ge 0$; (2) high (h) generation corresponding to sunny conditions where rate $\lambda(t) = \lambda_h$ is a large constant $\lambda_h > \lambda_l$; (3) ramp up/down (r) generation resulting from clouds that move in and out, where rate $\lambda(t)$ varies between λ_l to λ_h . For simplicity, we only focus on a ramping state, and assume that occurs at interval [0, t] for t > 0. In the ramping state when clouds move in and out, a source generates energy at a variable rate $\lambda_r(w), w \in [0, t]$.

Now consider exogenous weather variables W(t) as a random process with an arbitrary time-varying distribution. When and how long a renewable source is in ramping is random and impacted by weather. Let $X_r(t)$ be the amount of energy in ramping at time t. Let $\Pr(S_r(u) > t - u)$ be the probability for a solar source to stay in ramping in interval (u, t). The transient Littles Theorem can be used once more, where the expected value of $X_r(t)$ is

$$E[X_r(t)] = \int_0^t \lambda_r(u) \Pr(S_r(u) > t - u) du, \quad (4)$$

where $\lambda_r(u)du$ is the average amount of energy generated in a ramping state in duration du at time u. $\Pr(S_r(u) > t-u)$ is the probability for the solar source to stay in ramping in interval (u, t). Note that these two quantities are both function of weather variables. In other words, weather variables need to be characterized in theory to completely determine average rate $\lambda_r(u)$ of the energy generated and the probability $\Pr(S_r(u) > t - u)$ in a ramping state.

In summary, two $GI(t)/G(t)/\infty$ queues model both the (physical) network and the ramping states of renewable energy generation. The first queue models usage and dispatch of the generated solar energy in a microgrid. The second queue models the impact of weather to the renewable solar-energy generation. Weather can be random and dynamic, i.e., non-stationary. So is the solar energy generated and dispatched. Thus the arrival and departure processes of these questions are non-stationary in general.

5. LEARNING FROM DATA

The above models motivate learning from data. In particular, we focus on weather and renewable energy generation for learning because weather is not controllable but possibly learnable.

Two quantities emerge as pertinent to characterize nonstationary behaviors of ramping,

- rate function $\lambda_r(t)$,
- probability $\Pr(S_r(u) > t u)$ of ramping duration.

The probability of staying in ramping, $Pr(S_r(u) > t - u)$, is determined by weather measurements. Given such measurements, the problem becomes density estimation, i.e., learning a probability distribution from data [16]. Many learning algorithms can be applied (see [16] and references

therein). Empirical rate function can be learned using increments of energy generated also. Weather measurements are important for providing the knowledge of when and how long a ramping state is going to be.

When weather measurements are not available, such a probability of staying in ramping as well as the rate function can be learned using sensor measurements, i.e., solar irradiation. An advantage for using such measurements is simplicity, where low cost sensors can be used for data collection at solar panels instead of costly equipment for weather data. A disadvantage is that solar radiation then depends on symptoms of ramping rather than root causes that are weather variables. Therefore, it is not clear whether data on solar radiation can enable prediction on when and how long a source shall be in a ramping state.

Learning characteristics of solar sources from weather measurements has been conducted in the prior work (see[17] [18][7] and references therein). This work differs from the prior work in combining analytical models with learning: We identify intrinsic randomness and dynamic resulting from exogenous weather, and the corresponding quantities to learn from the queuing models. This avoids learning "symptoms". Combined modeling and learning also reduces complexity in learning so that physical characteristics of system components such as solar energy conversion can be treated by design rather than learning.

6. DISCUSSION

This Section consists of two parts. We first discuss methods extension of the single DREG model to multiple sources and models of the microgrid. We then discuss methods that we are using to get solar irradiation and energy data using sensing and monitoring at UHM.

6.1. Multiple sources and models of the microgrid

Extension can be made to multiple distributed renewable energy generation (DREG) by having a queue for each distributed PV energy source. For source k, the arrival rate $\lambda_k(t)$ again depends on weather variables W(t), but also depends spatially on other arrival rates $\lambda_j(t)$ where $j \neq k$. The aggregate arrival rate given by $\Lambda(t) = [\lambda_1(t), \ldots, \lambda_m(t)]^T$ where m is the number of distributed sources is a vector random process. The process can be characterized by parameters of assumed models (e.g. a vector markov process).

The state of the microgrid can then be modeled as a queueing network with generation from substations, DREG, and loads. This can be modeled as a bi-directional graph with sources (DREG and generation from substations) and destinations (loads). This is a subject of current research involving not only models for generation, but also for loads. Analysis and verification of models is through simulations and getting access to data.

6.2. Sensing and monitoring deployment

At the University of Hawaii sensors and monitors are being deployed on rooftops of buildings around campus to monitor environmental resources such as solar irradiation, temperature, humidity, and wind speed and direction. This will allow for modeling of $\Lambda(t)$ from data and the use of weather models. Once distributed PV is deployed on rooftops of buildings energy produced by the PV will be monitored and the parameters of the queueing model discussed here for the University of Hawaii site can be determined. We are also reading meters of energy consumption on buildings and more monitors will be deployed on the campus microgrid such as advanced metering infrastructure (AMI) to more accurately model the electrical grid. Then a queueing network model can be formulated to model the energy generation and usage on the University of Hawaii campus microgrid. The Georgia Institute of Technology also has deployed solar PV and data will be gathered from the environment and energy produced so that parameters of the queueing model for the Georgia Institute of Technology site can also be determined.

7. SUMMARY

This paper discusses using queueing models to model energy produced by solar PV with inputs being parameters such as solar irradiation and outputs being energy produced by the PV. The solar irradiation can be modeled by a second process with inputs being weather conditions and other parameters such as solar irradiation from other sources distributed spatially. We envision that these models will be ultimately useful in forming stochastic models for energy generation and usage on a microgrid. This will be helpful in the formulation of optimization and control algorithms for developing demand side management algorithms to more efficiently use energy, reduce costs, and stabilize the grid. The models will be confirmed by using the University of Hawaii and the Georgia Institute of Technology as testbeds.

8. REFERENCES

- [1] "What are smart microgrids," Galvin Electricity Initiative, http://www.galvinpower.org/microgrids/, Website Report.
- [2] "Perfect power," Illinois Institute of Technology, http://www.iit.edu/perfect_power/, Website Report.
- [3] "Sustainability 2.0 a living laboratory," University of California San Diego,

http://sustainability.ucsd.edu/initiatives/energyproduction.html, Website Report.

- [4] "Sustainability 2.0 a living laboratory," University of Texas, Austin, http://www.pecanstreet.org/, Website Report.
- [5] "Vermont-sandia partnership," University of Vermont, http://www.uvm.edu/ vtsandia/?Page=smartgrid.php, Website Report.
- [6] "Jeju island smart grid test-bed," Jeju Special Self-Governing Province Smart Grid Division, http://smartgrid.jeju.go.kr/eng/, Website Report.
- [7] S. Ranchurn, P. Vytelingum, A. Rogers, and N. Jennings, "Putting the "smarts" into the smart grid: A grand challenge for artificial intelligence," *Communications of The ACM*, vol. 55, no. 4, pp. 83–97, 2012.
- [8] W. Saad, Z. Han, F. Poor, H.V., and T. Basar, "Game theoretical methods for the smart grid," *CoRR*, vol. abs/1202.0452, 2012.
- [9] N. Masoud and M. Illic, "Technical challenge in modernizing distribution electric power systems with large number of distributed generator," in *IEEE Power & Energy Society*, June 2009.
- [10] "Hawaii clean energy initiative," Department of Business Economic Development & Tourism, http://www.hawaiicleanenergyinitiative.org/, Website Report.
- [11] S. M. and K. J., "Pv ramping in a distributed generation environment: A study using solar measurements," National Renewable Energy Laboratory, http://www.nrel.gov/docs/fy12osti/54141.pdf, Technical Report, 2012.
- [12] D. Bertsimas and G. Mourtzinou, "Transient laws of non-stationary queueing systems and their applications," *Queueing Syst. Theory Appl.*, vol. 25, no. 1/4, pp. 115–155, Jan 1997.
- [13] S. M. Ross, *Introduction to Probability Models*, 10th ed. Academic Press, 2010.
- [14] Y. Wei, C. Ji, F. Galvan, S. Couvillon, G. Orellana, and J. Momoh, "Non-stationary random process for large-scale failure and recovery of power distributions," *CoRR*, vol. abs/1202.4720, 2012.
- [15] K. Yang and A. Walid, "Outage-storage tradeoff in smart grid networks with renewable energy sources," in *International conference on Computing, Networking & Communications, ICNC*, 2012.

- [16] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, 2nd ed. Wiley, November 2000.
- [17] A. Kalogirou, "Artificial neural networks in renewable energy systems applications: a review," *Elsevier*, vol. 5, no. 4, pp. 373–401, 2001.
- [18] W. Glassley, C. Van Dam, H. Shiu, J. Huang, G. Braum, and R. Holland, "California renewable energy forecasting, resource and mapping," California Institute for Energy and Environment, http://ucciee.org/downloads/renewableenergyforecasting.pdf, Technical Report, 2010.