Modeling Smart Microgrids for the Developing World with Probabilistic Supply and Demand Inputs

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Abstract

Developing world microgrids often balance insufficient supply with growing, unpredictable demand. Deterministic and probabilistic simulators exist to model these microgrids, and each focuses on different technical aspects. With the addition of smart meters into microgrids, monitoring and control is now available at high granularity, which enriches microgrid planning and operation. This research is designing a new simulator to model smart microgrids with discrete probability distributions as supply and demand inputs. In our model, smart meters allow real-time power clipping for demand side management, effectively smoothing the system load curve as needed. To compare clipping schemes for grid operation and generation mixes for planning, we aggregate inputs by convolution then compute expected energy sold and probability of avoiding power cuts. The simulator plots these values for different combinations of power clipping threshold and number of customers clipped.

1 Introduction

Microgrids consist of significantly different architectures and equipment mixes depending on a region's infrastructure and development level. Microgrids in the developing world constitute a special case, where customer demand is unpredictable and often grows rapidly when electricity becomes available for the first time. Another challenge in first-access microgrids comes when generation has limited capacity [1] and is increasingly supplied by intermittent renewable sources.

Smart meters offer the monitoring and control needed to meet unpredictable loads with different mixes of supply resources. Smart meters on the market today have wired and wireless two-way communication and the ability to limit individual loads dynamically with power or current limits set remotely. Therefore smart grids need not rely on traditional hard-coded, binary control from simple current limiters. Smart meters allow automatic collection of data that is more frequent and more reliable, so by instrumenting each load and generator with a meter, a smart microgrid can empirically develop probabilistic models of each supply and demand node [2].

While tools exist for grid planning and some specifically for microgrid planning, many focus on topology and losses in the distribution grid (e.g., GridLAB-D) or on economic returns from the system (e.g., HOMER and the tool from [3]). Tools that are predominantly deterministic like HOMER have limited effectiveness for selecting and sizing generation technologies, since they take deterministic supply inputs that are fixed at each time step. For effectively planning a microgrid, probabilistic methods are needed to account for variation and uncertainty. Adding smart meters into a microgrid increases complexity by allowing loads to be individually monitored and controlled. Controllable demands present new variables to consider for planning and operation.

For modeling smart microgrids in the developing world, a new toolbox is needed for both planning and operation. The new simulator should account for supply intermittency and demand variation. It should allow for high growth in demand over time and load clipping when demand exceeds the available generation. To model this varying generator and consumer behavior, the simulator should treat each individually controlled node stochastically and allow for the demand at consumer nodes to be attenuated. This research is developing the features described above in the Load Attenuating Stochastic Simulator (LASS) [2].

LASS takes inputs for each supply and demand node, with each node modeled as a probability mass function (PMF) at each time step. Using 1D convolution, it aggregates individual loads into one system load and similarly aggregates individual supplies into one system supply. A power capacity threshold is defined for each customer that agrees to their demand being clipped at times of low generation. With this threshold value, LASS defines a clipped demand PMF for each of these customers, and by 2D convolution the aggregate clipped demand PMFs are calculated to account for the effect of demand before clipping on the clipped result, i.e. the conditional probability is calculated given unclipped demand values. The resulting aggregate PMFs are then used to calculate expected energy sold and the probability of serving all customers without power cuts.

Section II describes some complexities of microgrids and simulation tools that currently exist to address those difficulties. Section III explains the new functionalities that smart grids offer in a microgrid context. Section IV gives a fuller overview of LASS with an example of its capabilities from a case study based on a rural village microgrid in Rwanda.

2 Microgrids and Simulation Tools

Simulation tools for microgrids have grown with the grid technologies themselves. Since the early 1900's, graph tools like minimum spanning trees have helped lower the cost of distribution systems [4] A more difficult problem arises when limited generation capacity is likely to be surpassed by system load, as occurs in rural microgrids of developing countries [1]. These problem scenarios become more likely for installations where reliable, fossil-burning generators are replaced by intermittent renewable energy options like wind and solar. Current tools to address this problem are either deterministic, probabilistic, or a combination of the two.

Deterministic tools that are currently available look at systems of renewable distributed generation at least primarily with precise computations of generation and supply for each time step. The simulator in [3] calculates each generator's efficiency and power capacity depending on the given generation technology and external inputs. For each power and efficiency calculation, this tool makes assumptions about the physics of the given technology. For PV this simulator assumes one-dimensional thermal heat conduction to estimate the efficiency of a PV panel given the external temperature at each time step. Similarly, for wind turbines this simulator estimates the output power capacity with linear interpolation of the power curve data provided from the turbine manufacturer. For micro-hydro, the simulator uses Gordon's model to calculate the system flow rate. These and other generation technologies are integrated into a single microgrid system with a control algorithm implemented in the Excel/VBA environment. But without a probabilistic accounting for input variations in these generation models, even a perfect control strategy will suffer when the assumptions for each input prove imprecise. Errors in the assumptions for each technology can compound when all the generation technologies are looked at in aggregate as a system's instantaneous generation mix.

The simulator in [3] uses its energy calculations to evaluate energy production and decide a control strategy. After these stages, the simulator predicts hourly energy flows and performs economic analysis by calculating cost per unit of electricity for each generator. Only after these stages does it perform a stochastic optimization stage before recommending a final system configuration. The probabilistic results do not inform grid operation, though, so a different probabilistic simulator is needed for adaptive control.

Several probabilistic tools available today rely on nonsequential Monte Carlo methods. While this approach can represent one or multiple contingencies across distributed generators [5], it generally cannot distinguish between probabilistic variations in behavior at the granularity of individually controlled loads. For this granularity, an analytical method with a PMF representing each load and supply provides benefits for accurately and precisely predicting system load and supply variations.

To plan for uncertainty and granularity, LASS is being developed as a stochastic simulator that does not rely on Monte Carlo methods. LASS accounts for variation by precisely calculating probability from PMF inputs. Each load and generator having their own PMF's – independent, discretized distributions – provides the granularity to accurately model independent agents in a microgrid system. To monitor and control the power consumption of these agents in real time, additional hardware must be added into the system beyond traditional load limiting devices [1]. Smart meters provide this functionality and are therefore a key part of microgrids modeled by LASS.

3 Smart Meters for Microgrids

Smart meters enable monitoring of individual load consumption and generator production to high precision. Sampling rates can be set by the meter manufacturer or grid operator, and data collected can be stored locally and to the cloud. With these capabilities, smart meters introduce the granularity needed to do stochastic simulation – to precisely account for the randomness inherent to a given system. As demonstrated in [1], smart meters are currently deployed in developing world microgrids as well as developed world grids. We view the microgrid as a network of nodes equipped with meters – each generator a supply node and each consumer a demand node. Though distribution lines are in place for power flow, data about power generation and consumption are transmitted wirelessly between the nodes and a central gateway processor (two-way communication). Demand nodes sample current and power consumed at frequencies of multiple KHz then communicate these readings wirelessly to the gateway. Supply nodes each have a 3-phase meter rather than a standard smart meter, and the 3-phase meter senses instantaneous generated capacity but offers no control of the generators. The gateway collects and stores information from each node locally then routinely stores the information from all nodes in the cloud.

Depending on the total supply capacity available, the gateway manages each demand node and commands power or current limits that can depend on a specific customer's classification (high priority load vs. dispensable load, etc.). The demand nodes each receive their command (whether to clip and to what capacity) then carry out this command by allowing, limiting, or entirely cutting their load's instantaneous consumption. In this way the gateway actively manages the demand loads with low latency. The gateway stores consumption data from all demand nodes and bills the customers accordingly from their pre-paid accounts. Customers can be charged different electricity prices, e.g., a tier of customers that agrees to have their load clipped to a low threshold at the grid manager's discretion would pay less per kWh than the tiers with higher thresholds or no threshold.

Initial tests of the smart microgrid implementation in [1] show highly consistent frequency (85% of samples within 0.5 Hz of the mean). The voltage values are bimodal, since the meter in their example serves one of two dedicated phases from the 3-phase generator. Regarding voltage values, 90% are within 2V of the average for their specific phase. These results attest that smart meter technology is fitting and reliable in the microgrid context. The setup in [1] has further applications in loss estimation for theft detection, a traditionally difficult problem. The system isolates losses from theft by summing power purchased at a given time step, subtracting the total power generated, then subtracting system losses, e.g., distribution line losses, which they calculate with GridLAB-D. Power generated but still unaccounted for is being siphoned off but not purchased. Given wire length estimates, the authors of [1] foresee localizing microgrid shorts as well as tracing open-circuits caused by downed distribution lines. They propose a meter modification that would trace resistance at each node and thereby enable quick fault detection without an RF carrier transmitter or multimeter. These many capabilities of a smart microgrid system present a rich environment for grid management as well as control and pricing schemes, but a probabilistic simulator is needed to plan such a system in the face of supply and demand uncertainty.

4 Stochastic Simulator for Smart Microgrids

LASS is a stochastic simulator built in MATLAB which assumes no distribution line losses, i.e. all generator and supply nodes are assumed to be on a single bus. For microgrids where this lossless assumption could prove problematic, e.g., with substandard distribution lines or long distances between nodes, the system should be analyzed in parallel with both LASS and GridLAB-D, the latter for line loss calculations. The simulator is currently run in the MATLAB command line, but a GUI is being developed to generate PMF inputs automatically based on parameters given by the user. Example choices for defining new PMFs would be distribution type (binomial, Poisson, bimodal, etc.) and corresponding parameters (maximum, minimum, mean, standard deviation) plus power increment for analysis, power threshold for clipping tiers, and percentage of customers in each clipping tier.

4.1 PMF Inputs and Notation

For analysis with LASS, each consumer and generator in an existing or planned smart microgrid is characterized by a PMF corresponding to the node power capacity at each time step t. We define j as the load index (of J_l total loads) and k the generator index (of K_g total generators). On the demand side, $D_{j,t}^{q}$ is the random variable corresponding to the unclipped load of customer j of class q whose demand is defined probabilistically at time step t according to $P_{D_{j,t}^{q}}$. Class c is used here for customers subject to clipping, and no superscript is used for unclipped customers in our 2-class (clipped/unclipped, single clipping level) example. $P_{D_{j,t}}$ is the probability mass function vector corresponding to an unclipped individual load. For clipping demand LASS defines a threshold T_t, a nonnegative power capacity value to which each customer in a single clipping tier will be limited when clipping is applied. $D_{j,t}^{c}$ is the random variable corresponding to the clipped load of single customer j whose demand is defined probabilistically at each time step according to $P_{D_{j,t}^{c}}$, the PMF corresponding to a clipped individual load.

Each supply node is similarly characterized by a random variable, $S_{k,t}$. $S_{k,t}$ corresponds to a single generator k whose generated capacity at each time step is defined according to the PMF $P_{Sk,t}$ of values $P_{Sk,t=s}$. A power increment value (e.g., W or kW) is specified for calculating expected energy sold.

4.2 Aggregating Inputs

S_t is the sum of supply random variables $S_{k,t}$ and D_t the sum of demand random variables $D_{j,t}$. All supply PMFs $P_{Sk,t}$ are aggregated by one-dimensional convolution at each *t*. The resulting aggregate PMF P_{St} for each time step corresponding to the probability distribution of total supply. This aggregate represents a sum of all supply random variables $S_{k,t}$. All demand PMFs $P_{Dj,t}$ are similarly aggregated into PMF P_{Dt} by one-dimensional convolution. This aggregate demand PMF is used when total supply meets or exceeds total demand, i.e. when no reduction of load is needed. Demands are separated into different payment tiers, where a given consumer's tier is decided by that consumer. Each tier is defined in LASS with a set electricity price and threshold, the maximum allowed power capacity when clipping is employed. The tier of consumers paying the highest electricity price receives the amount they demand without any clipping of their loads. Tier(s) paying lower electricity prices agree for their power to be clipped to an agreed-upon T_t at all *t* or during specific *t* (e.g., peak demand hours in the evening or high-demand days). All combinations of tiers, clipped and unclipped, are then aggregated into PMFs corresponding to aggregated clipped demand, as shown in figure 1. LASS then uses the aggregate supply PMF and all aggregate demand PMFs to calculate the probability of avoiding power cuts (quality of service) and the expected energy sold by the suppliers at each *t*.

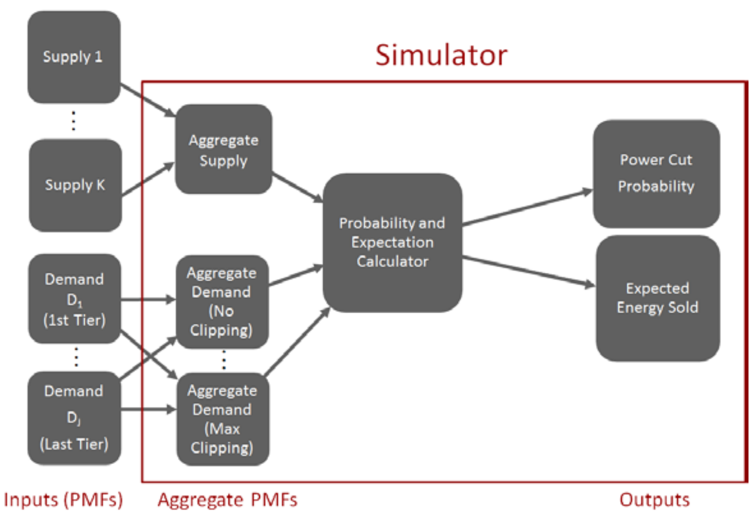

Figure 1. LASS Inputs and outputs

4.3 Clipping Demand Nodes

By clipping all loads in a tier to their threshold, the overall demand can be attenuated as needed if total capacity generated falls below total unclipped capacity demanded. Different numbers of customers are subjected to clipping depending on the limitations of the aggregate supply. As customers subject to clipping know about the clipping threshold and agree to it in exchange for less expensive electricity, the microgrid can meet its commitment to customers by providing less power to those in clipped tiers and using the power saved to supply demand nodes of higher paying or higher priority tiers (e.g., hospitals and security lights).

4.4 Case Study of Rwandan Village Microgrid

The initial case study for LASS is a theoretical microgrid for rural Rwanda presented in [2]. This simulation models standard operation rather than emergency or overhaul scenarios. The case study therefore ignores the chance of demand spikes or of supply breakdown and maintenance. Supply nodes include a solar PV array, a micro-hydro plant, and a diesel generator (total supply count K_g=3). The solar PV generation is modeled as ramping up to a maximum value depending on the hour of day and producing no power at night. At midday the PV array produces a maximum output of 3.5 kW in the absence of cloud cover. The micro-hydro plant is modeled as a binomial distribution about a mean value (the nominal or rated output of the plant) with 15 kW maximum output. The diesel generator is modeled as a 5 kW capacity input, modeled as constant given that generator failures are not being analyzed in this example. The aggregate supply is shown in figure 2.

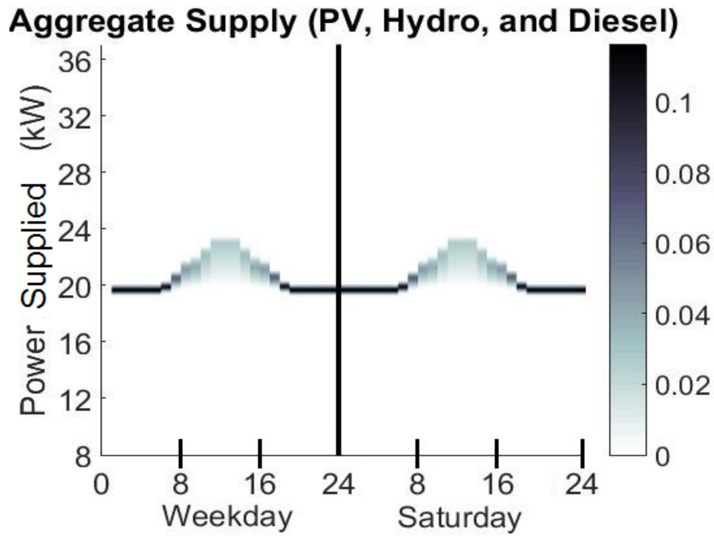

Figure 2. Aggregate supply as shaded PMFs

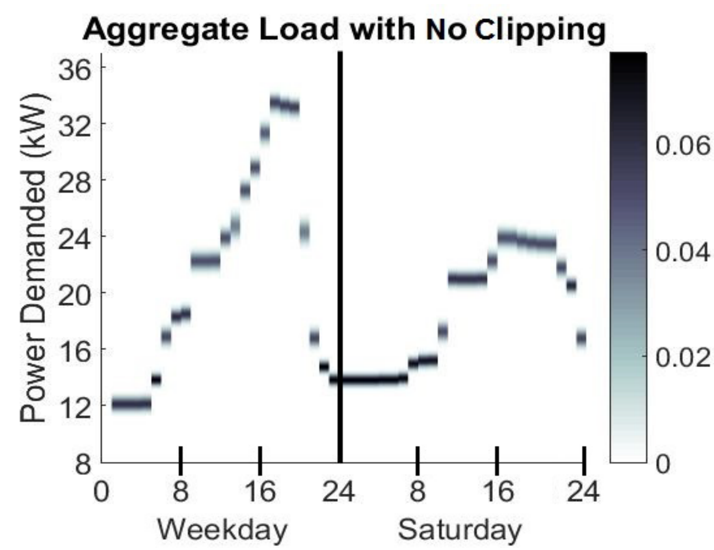

Figure 3. PMFs of aggregate demand (houses and hospital)

Demand nodes are a hospital and 100 households (total load count J_l=101). The hospital is deemed high priority and its demand is provided unclipped whenever possible. Hospital demand varies from 9 to 10 kW and is modeled as binomially distributed. Household demand is similarly binomially distributed based on published home load profiles [2]. Each household's demand varies from 0 to 250W given the low consumption of lights and cell phone charging that constitute the majority of loads in a microgrid of rural Rwanda. The 250W maximum consumption level was benchmarked from solar home kits that are popular in the region, as discussed in [2]. The households are split into clipped and unclipped tiers, the latter choosing to pay more for electricity for a higher level of service. Alternately, the unclipped households could represent nodes with traditional breakers but no smart meters. Clipped households are considered the lower tier and given last priority in this scenario, so they receive their full unclipped demand only when aggregate supply is high enough to supply all their demands plus that of the hospital and unclipped households. The aggregate demand PMFs are shown in figure 3. Peak demand before clipping far exceeds peak supply (figure 2) and occurs on weekday evenings when household consumption peaks.

When supply is insufficient to meet all demand, lower tier households are clipped to a threshold capacity of 50W until a future time step when aggregate supply is sufficient. In other words, the threshold set for low tier households under dynamic clipping is T_t=50W for all t. The 50W threshold was chosen to meet home lighting and cell phone charging needs in Rwanda, as described in [2]. The high tier (hospital and unclipped houses) has no power threshold since these loads are given priority to receive their full demand. If total supply cannot meet the reduced demand even after low tier loads have been cut, both tiers experience a power cut for that t. A well-equipped hospital would have its own backup generator for emergency scenarios, but because a node-specific backup supply like this would never feed into the rest of the microgrid we don't include such a generator in the case study.

Each time step t corresponds to one hour, and a typical week was analyzed with standard operation at all nodes – no emergency scenarios. Two days are focused on in [2], a typical weekday and a typical weekend day (Saturday).

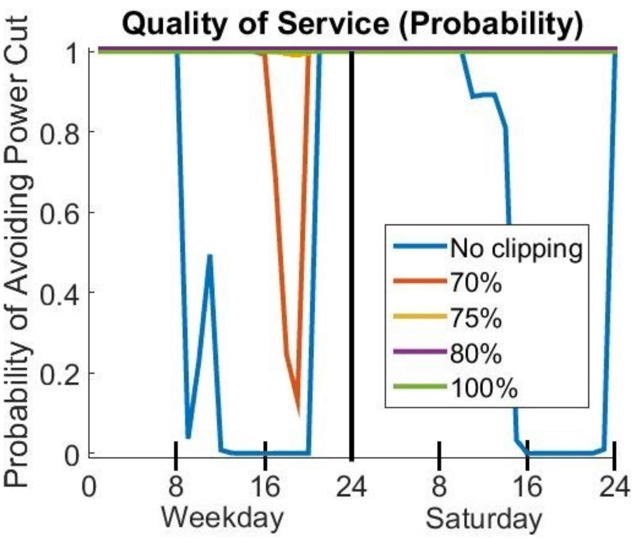

Figure 4. Prob. of avoiding a power cut with clipping varied

4.5 Case Study Simulation Results

As shown in figure 4, certain high-demand hours (especially weekday evenings) are essentially certain to experience power cuts in the absence of clipping. At such times when demand exceeds supply, the level of clipping must be carefully chosen to sell the full amount of electricity being generated. Figure 5 shows how expected energy sold grows with the percentage of customers clipped up to a certain tipping point (e.g., 75% for a weekday evening in the 2-day plots). This tipping point is time dependent and represents the percentage of customers clipped above which customers are being unnecessarily clipped and available power is not being sold to customers. Clipping fewer than this percentage of customers means risking a power cut when the total demand cannot be met.

Because microgrid income increases with energy sold, the percentage of clipping employed at each t affects both the probability of power cuts (the measure of quality of service used in [2]) and the gross income generated. In this way grid operation can be improved with a probabilistic simulator. Grid planning can also be improved by choosing generation size and type (e.g., base load plants like hydro and diesel generators) after seeing the expected value of aggregate demand (figure 3).

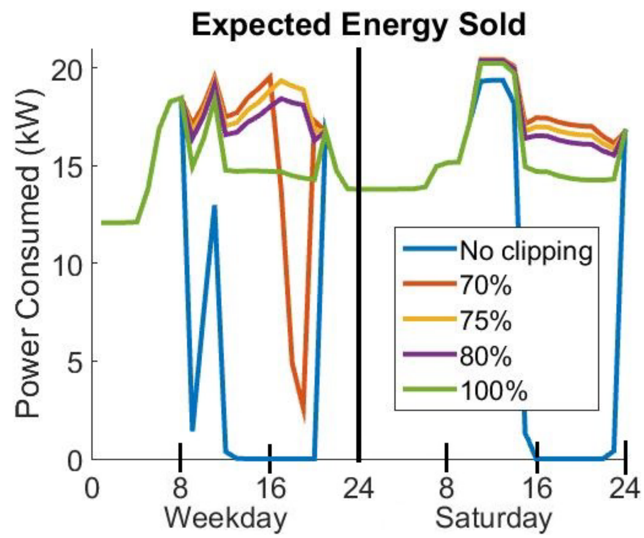

Figure 5. Expected energy sold with clipping varied

5 Conclusions

This paper presents an overview of microgrids in the developing world and the new functionalities introduced by smart meters. The smart meter and microgrid system in [1] provide an illustrative example. Given the capabilities of a smart microgrid, a probabilistic simulator can be used to account for supply and demand variation in microgrid planning and operation. LASS is the tool proposed for this purpose in [2], and its capabilities are explored in a case study based on a Rwandan village. The case study finds room for economic and quality-of-service benefits if smart meters were operated to clip consumer loads to different extents in cases of limited and variable generation capacity. Both the expected energy sold and the probability of avoiding blackouts can be increased by using a probabilistic simulator to constantly monitor supply and demand while matching demand side management levels to a dynamic generation mix. LASS provides insights for both microgrid planning and operation.

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