Microgrid Energy Management with Load Clipping DSM and Small Hydro Dispatch

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I. Introduction

Smart meters deployed in microgrids are starting to enable real-time load aggregation measurements as well as fine-grained monitoring and control, including load clipping to prevent power cuts. This new functionality makes it possible to envision and implement new operating strategies for grid managers. Current grid simulation tools do not allow offline assessment and evaluation of supply dispatch and load clipping strategies, which leaves microgrid operators relying on broad rules of thumb, real-time experimentation, and intuition when implementing load clipping. This research focuses on developing demand side management and dispatch planning options for smart-meter-enabled microgrids, along with tool support to choose between these options.

Load clipping is a new functionality of smart meters to prevent power cuts when system demand exceeds supply. Microgrids in the developing world, specifically, often suffer from insufficient supply when customer loads exceed the levels anticipated during grid planning. By using smart meters, dispatchable supplies can be controlled and demand limited to avoid power cuts [3], [11]. The demand-side smart meters referenced in this research are equipped to limit power consumed (i.e. clip load) to a maximum power capacity specified by a central gateway controller. This controller communicates wirelessly with the meters. This load clipping is a type of demand side management (DSM) now being tested in Haiti, Nigeria, Tanzania, and Bhutan [2], [6].

To flatten the load curve and prevent rolling blackouts from limited generation capacity, electricity pricing can be tied to peak power limits, enforced as needed by load clipping. Price incentivizes lead consumers to accept lower limits at times of clipping, which flattens the load curve and reduces the likelihood of power cuts. Schemes to dynamically dispatch generation and energy storage can be paired with load clipping to decrease the incidence of power cuts [10].

One factor that has limited the scope of microgrid simulation is the preponderance of deterministic simulators and those focused on transmission-level systems. To address inherent variation in supply and demand levels, probabilistic modeling and dynamic control options are needed to prevent system power imbalance. To model microgrids probabilistically, this research provides tool support in the form of a PMF-based stochastic simulator. This tool models single bus, distribution-level real power dispatch and uses Monte Carlo methods to assess performance probabilistically over a full range of supply and demand levels.

Energy storage, clippable demand, unclippable (high priority) demand, and supply together constitute the microgrids modeled in the simulation tool. The summed power levels of these components determine the level of demand clipping and dispatchable supply needed at the next time step. An initial case study introduces an energy manager (EM) that compares the cost of different strategies in real time and chooses the lowest cost option. In the physical systems being approximated, clipping levels can be changed remotely and wirelessly based on customer preferences and microgrid inputs (weather conditions, equipment failures, etc.). The priority levels (i.e. order of dispatch) for load clipping and dispatchable supplies are also controlled remotely and can be easily changed depending on generator conditions and grid economics (e.g., fuel prices). The EM being proposed and modeled compares dispatch options that are enabled by this functionality.

II. Optimization Problem

For the EM, an optimization problem was defined to choose the dispatch order of generation, storage, and load clipping. Assumptions approximate the rural microgrid scenarios and generator options of East Africa. In the rural areas few generation options are typically available, with very limited choice of technologies. A fixed slope cost curve (cost vs. power output) for each generator approximates the supply mix well. This approximation makes the optimization problem straightforward to solve. Generator ramping limits don't affect the EM in these scenarios because the EM's response time is 10 minutes, longer than the max 1 minute ramp-up or ramp-down time of the relevant dispatchable supplies (hydro, diesel, and battery discharging).

AC generators that are routinely run below a power bandwidth (around the nominal power overheat and fail prematurely. The simulator therefore limits both the hydro and diesel generator output capacities to be either off (zero output) or within a positive power bandwidth (between power limits $P_{i,min}$ and $P_{i,max}$ specific to generator i). Initially we assume that hydro flow and diesel supply is plentiful, so the desired power within a bandwidth (65%-70% of rated max power) can always be generated.

The optimal generation mix given these constraints entails dispatching the lowest cost generation source (to the demand level or the generator's maximum instantaneous output) then dispatching the next lowest cost generation source, etc., until the full demand is met. Battery operation includes a binary decision. Depending on the battery storage energy level, the battery will either be allowed to discharge (treated as a supply) or commanded to charge (treated as a load). I modeled this in an Excel toy model and in the Simulink microgrid model. From the optimization problem we find that, given sufficient flow year round to provide maximum rated output for the hydro plant, hydro is always the lowest cost generation source (in terms of efficiency, fuel cost, O&M, etc.) and thus hydro should always be dispatched first given these assumptions. With limited flow and thus the need to manage a changing hydro reservoir, battery discharging should precede hydro dispatch in certain scenarios for the lowest overall cost to meet instantaneous demand.

III. Cost Analysis

Dispatch costs were evaluated in terms of the benefit or penalty for different actions and states (e.g., charging the battery, clipping load, or generating diesel power) even when the monetary costs of most actions are negligible. The nominal cost ($/kWh) of small hydro generation or battery discharging, for example, is negligible when we ignore periodic maintenance and capital costs [4]. Initially, therefore, the penalty on diesel generation was set according to fuel costs, with smaller penalties or incentives on other actions based on their level of desirability. Clipping load was demonstrated to decrease the cost when loads must be cut in the absence of clipping.

IV. Case Study

To demonstrate scenarios where clipping and/or partial cuts are needed, a case study was designed with a total supply capacity that stochastically falls above and below the peak power demanded at hours of high system load. This case study contains the inputs described in Table 1 and shown schematically in Fig. 6. The simulated microgrids are assumed to be single-bus, lossless, balanced power systems that meet all reactive power requirements internally [1]. Only with these assumptions can we move forward with a straightforward, real-power-based model.

Clipping is standardized for the purposes of the case study. When the metered loads are clipped, their power consumption is limited to a 50W peak power limit. The metered load is kept clipped to this power limit until a future time step when aggregate supply is sufficient and the state is changed back to unclipped by the energy manager. The 50W limit was chosen to meet home lighting and cell phone charging needs in a rural Rwandan household [8]. Households are expected to consume up to 250W without clipping, slightly higher than the maximum allowed to first-access Rwandan homes with widely used solar home kits [5]. The high priority loads (hospital, factory, and high-tariff houses) have no power limit since these loads are given priority to receive their full demand. If total supply cannot meet the reduced demand even after clippable loads have been cut, all loads experience a power cut for that time step. In practice a well-equipped hospital would have its own backup generator for emergency scenarios, but because a node-specific backup supply like this would not feed into the rest of the microgrid such a generator is not included in the case study.

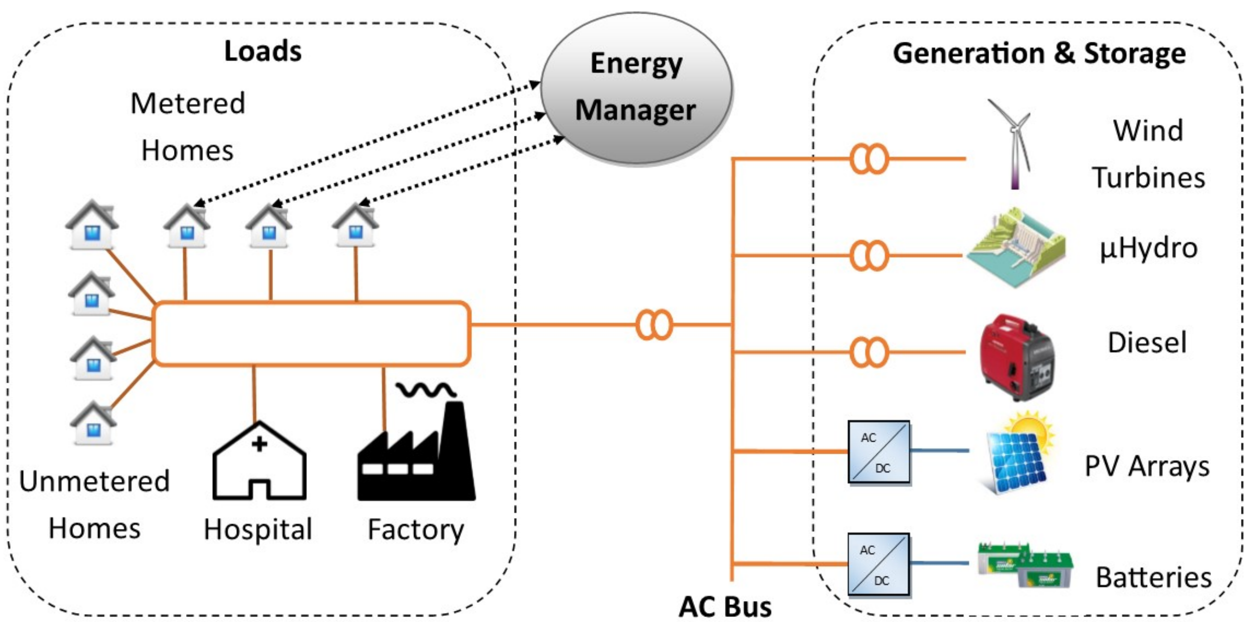

Figure 1: Schematic of case study microgrid

V. Initial Assessment Results

Fig. 7 shows the expected numbers of days for which there would be a full power cut, partial cut, clipping, or no limits enforced. This is an important statistic since customers tend to rate the quality of service based on their daily experience. The table shows that with no metered customers, full power cuts result nearly 30% of the days. With only 20% of the homes metered, days with full power cuts are

Table 1: Microgrid inputs and their sizing for case study based on rural Rwandan village without utility grid access

Loads	Supplies
• 1 hospital (max 10 kW) • 1 factory (max 10 kW) • 300 homes - max 250 W (unclipped) - 50 W clipped	• PV array (max 7 kW) • Wind (max 15 kW) • Hydro (max 23 kW) • Diesel generator (max 14 kW)
Storage	
• Battery - Controlled - Charging/discharging limits • Hydro reservoir - Semi-controllable - Limited by river flow	

reduced by more than half, and with 60% of the homes metered, power cuts are eliminated entirely. On the other hand, metered customers should expect cuts for some time on most days until at least 60% of the homes are metered. This means customers will likely expect a significant reduction in their rates when they agree to be metered [7].

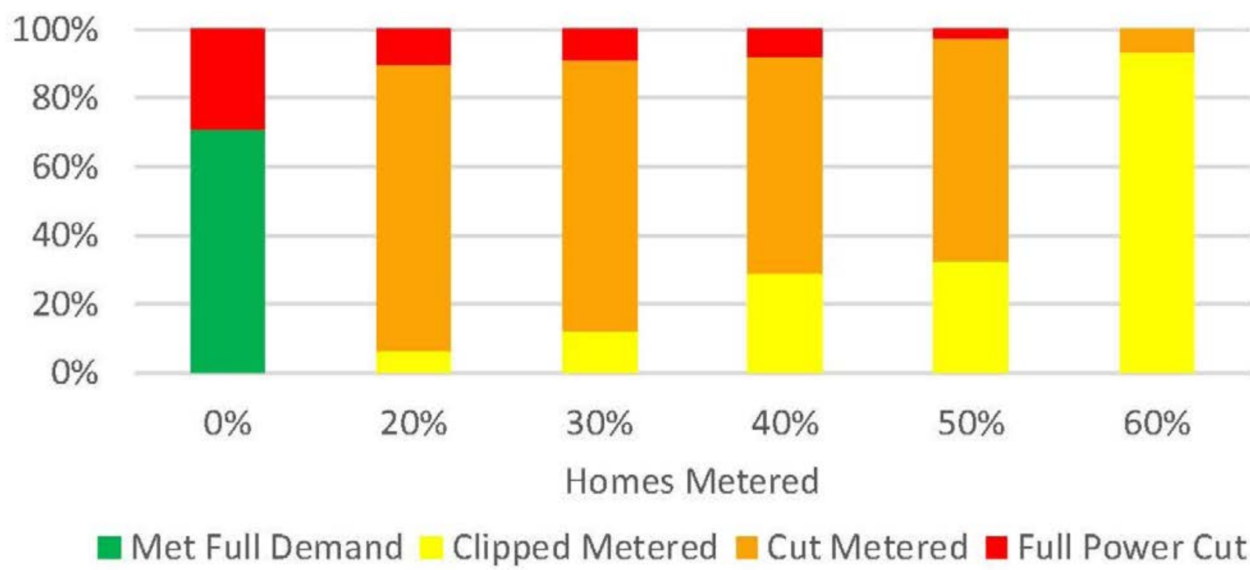

Figure 7: Percentage of days with full power cut, partial power cut, clipping, and no interruption

Fig. 8 shows the average length of time per day in the cut and clipped conditions. The duration of full and partial cuts are steadily reduced as more customers agree to be clipped. The duration of full and partial cuts is relatively small. In fact, with 60% of the homes clippable, the duration of power cuts for clippable customers is less than the duration of power cuts experienced by all customers when none are clippable. Thus the primary concession made by clippable customers is to accept clipping to basic service levels (the agreed-upon peak power limit) for approximately 40% of the time. This may not be a deterrent for rural customers, provided clipping times are predictable and the reduction in tariffs is significant enough. These results have not shown time-of-day analysis, which is introduced below in Section VI.

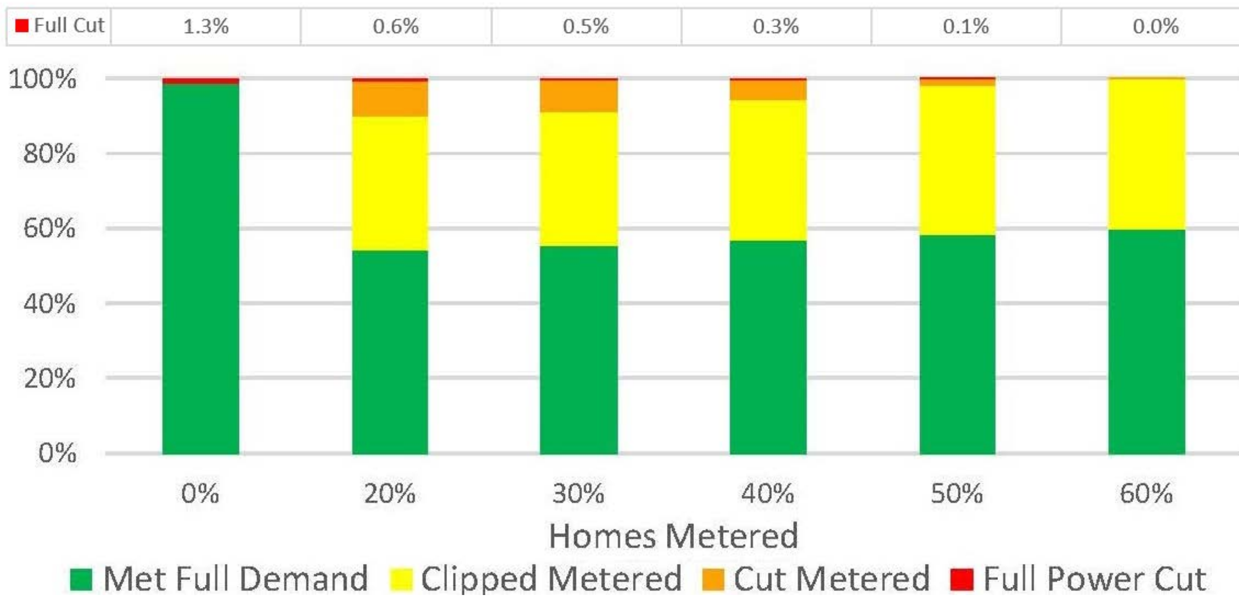

Figure 8: Average daily duration of full and partial power cuts, clipping, and no interruption

VI. Implications for Dispatch - Renewable vs. Fuel-Burning

For the microgrid manager, the critical factor is what savings can be achieved in fuel costs for various operating policies and customer distributions. Table 2 provides initial data on the operating costs by showing the fraction of the demand that is met by the renewable sources (which have very low cost) vs. diesel generation. The table shows that when there are no clippable customers, the demand is being met by consuming the most diesel fuel for the cases shown in the table. By adding clippable customers (making it possible to clip or cut metered demand without a full power cut), the diesel fuel consumption can be reduced significantly.

Table 2: Percentage of unclipped demand met with renewable (PV+hydro+wind+battery) and non-renewable (diesel) power

Homes Clipped	Average Demand Met by Hydro, PV, Wind	Average Demand Met by Diesel	Average Unmet Demand
0	92.7%	5.6%	1.7%
20%	93.6%	2.7%	3.7%
30%	93.8%	1.5%	4.7%
40%	93.9%	0.7%	5.5%
50%	94.0%	0.3%	5.7%
60%	93.7%	0.1%	6.3%

VII. Implications for Clipping Choices

The results for expected energy sold offer a non-intuitive result. At each time step there exists an ideal level of clipping, or tipping point, that is often neither the maximum nor minimum clipping possible. For example, Fig. 9 and 10 show the probability of a power cut and the expected power consumption levels, respectively, for a 100-household case study [8].

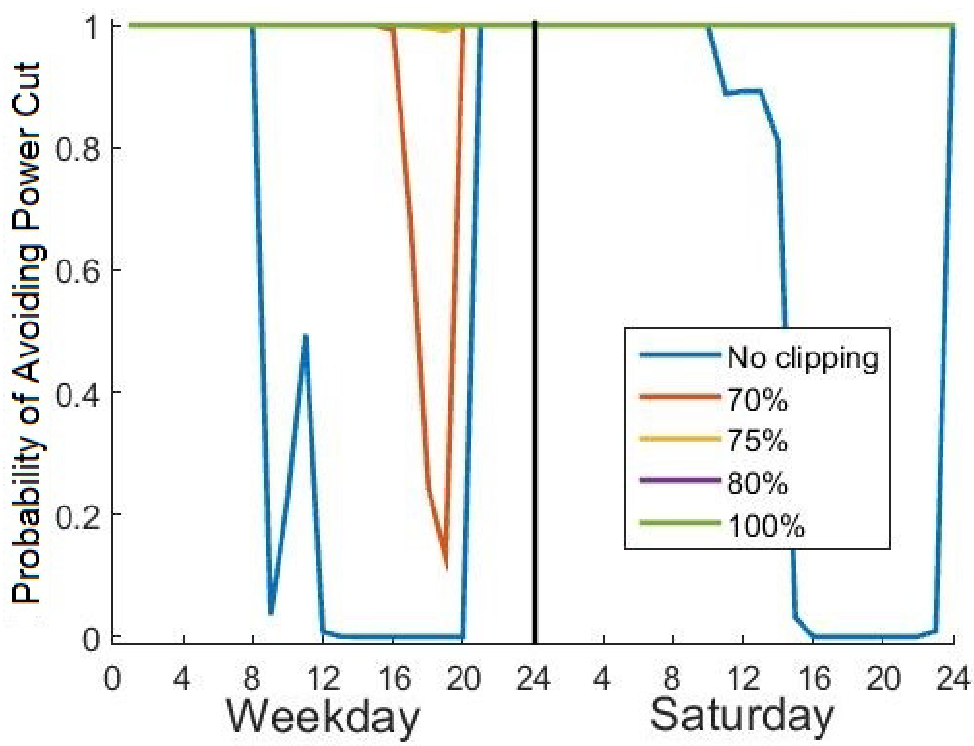

Figure 9: Probability of avoiding power cuts with clipping varied

As shown in Fig. 9 and 10 certain high-demand hours (especially weekday evenings) are essentially certain to experience power cuts and deliver no energy unless clipping is instated. At such times when demand exceeds supply, the percentage of houses clipped must be carefully chosen to sell nearly the full amount of electricity being generated. Fig. 10 shows how expected energy sold grows with the number of customers clipped, up to a certain tipping point (e.g., 75%=75 homes for a weekday evening). Tipping points are time dependent and represent the percentage of customers clipped, above which customers are being unnecessarily clipped and available power is not being sold to customers. Clipping fewer customers means risking power cuts when demand cannot be met.

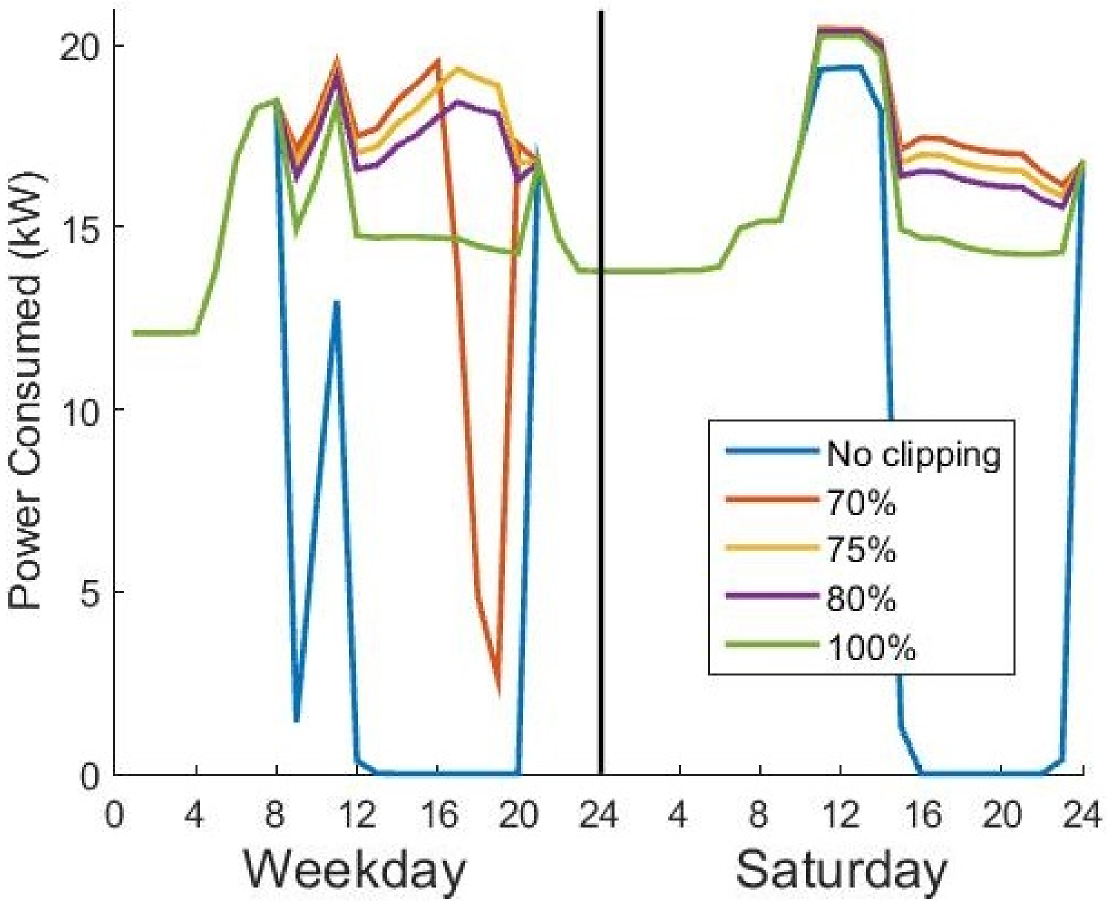

Figure 10: Expected energy sold with clipping varied

Note that early in each day, the aggregate supply is essentially certain to meet the unclipped demand without a power cut. As expected power cuts become more likely as supply decreases and demand increases (Fig. 2), so that clipping is needed most in the late afternoon and evening. From Fig. 9 note that from hours 1-8 all clipping levels (including no clipping) will result in no power cuts with probability 1. As the weekday demand increases from hours 9-17, more clipping is needed to avoid power cuts, and only clipping at or above 75% of homes will ensure no power cuts with probability above 0.99. Clipping at least 80% of homes ensures aggregate supply is sufficient but also results in less power sold to customers than 75% clipping (see Fig. 10).

Because microgrid income increases with energy sold, the percentage of clipping employed at each time step affects both the probability of power cuts (the quality of service metric used in [9]) 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., hydro and diesel generators) after seeing the expected value of aggregate demand (Fig. 2). Note from the cumulative results in Table 3 that while clipping 75% of homes results in the max energy sold on a weekday, clipping fewer homes results in more energy sold on a Saturday, when the typical home demand is lower. The optimal clipping level, therefore, is time and day dependent.

Table 3: Cumulative results for two days, highlighting the max energy sold on each day.

	Percentage of homes clipped (of 100 homes)	Expected power cut duration [hrs/day]	Expected energy sold [kWh/day]
Weekday	0 (No clipping)	11.2303	197
	70%	1.9474	361
	75%	0.0137	392
	80%	0.0005	385
	100%	0.0005	356
Saturday	0 (No clipping)	9.4835	240
	70%	0.0005	397
	75%	0.0005	393
	80%	0.0005	389
	100%	0.0005	373

VIII. Conclusions

The probabilistic simulator with DSM modeling capability is shown through this case study to evaluate quality of service for smart grid operating strategies while analyzing variability in the system's supply and demand inputs. The case study demonstrates that dynamic clipping of loads reduces the incidence of power cuts and increases the income potential of an isolated microgrid. Energy storage, both from a hydro reservoir and battery banks, can be managed dynamically with load clipping and supply dispatch to further increase grid reliability and prevent power cuts.

Comparing the different generation options, the most cost-effective supply evaluated is small hydro. Hydro can serve as both base load and (with a reservoir and dispatch control) as peaking generation. Given limited and variable generation capacity that is often time-dependent, the simulator shows economic and quality of service benefits come from time-dependent clipping of demand. The expected energy sold and probability of avoiding power cuts can increase with a stochastic simulator to match DSM levels with a dynamic generation mix. The demonstrated simulator informs microgrid planning and operation for better service both to customers and grid managers.

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Works Cited

[1] P. Buchana and T. S. Ustun. The role of microgrids and renewable energy in addressing Sub-Saharan Africa's current and future energy needs. IEEE IREC, March 2015.

[2] M. Buevich, D. Schnitzer, T. Escalada, A. Jacquiau-Chamski, and A. Rowe. Fine-grained remote monitoring, control and pre-paid electrical service in rural microgrids. ACM/IEEE IPSN, pages 1–11, April 2014.

[3] F. Kupzog, T. Zia, and A. A. Zaidi. Automatic electric load identification in self-configuring microgrids. In Proceedings of the IEEE AFRICON, Nairobi, Kenya, January 2009.

[4] Basic economics of power generation, transmission and distribution, EME 801: ENERGY MARKETS, POLICY, AND REGULATION, Penn State Department of Energy and Mineral Engineering, 2017. <https://www.e-education.psu.edu/eme801/node/530>.

[5] J. Mugabo. Mobisol solar system to help Burundian refugees. The New Times, October 2015.

[6] T. G. Quetchenbach et al. The gridshare solution: a smart grid approach to improve service provision on a renewable energy mini-grid in Bhutan. Environmental Research Letters, 8(1):014018, 2013.

[7] J. Thornburg and B. Krogh. Simulating energy management strategies for microgrids with smart meter demand management. In Proceedings of the IEEE Power and Energy Society PowerAfrica, Accra, Ghana, June 2017.

[8] J. Thornburg, B. Krogh, and T. S. Ustun. Stochastic simulator for smart microgrid planning. In Proceedings of the ACM Symposium on Computing and Development (DEV), Nairobi, Kenya, November 2016.

[9] J. Thornburg, T. S. Ustun, and B. Krogh. Smart microgrid operation simulator for management and electrification planning. In Proceedings of the IEEE Power and Energy Society PowerAfrica, Livingstone, Zambia, June 2016.

[10] T. S. Ustun, J. Thornburg, and B. Krogh. Smart pricing implementation/simulator with ICT infrastructure. In Proceedings of the Africa-EU Symposium on Renewable Energy Research and Innovation, Tlemcen, Algeria, March 2016.

[11] M. Welsch et al. Smart and just grids for Sub-Saharan Africa: exploring options. Renewable and Sustainable Energy Reviews, 20:336–352, 2013.