Siting and Sizing Distributed Storage for Microgrid Applications

Ramachandra Rao Kolluri*, Julian de Hoog, Khalid Abdulla,
Iven Mareels, Tansu Alpcan, Marcus Brazil, and Doreen Anne Thomas

***Abstract*—Energy storage systems have a key role to play in increasing the uptake of distributed renewable energy generation. In many places, reduced feed-in tariffs and declining solar incentives are making behind-the-meter energy storage a favourable option for many distributed generation owners. Parts of the grid that have sufficient local generation can be operated as microgrids. In most cases, the temporal profiles of demand and generation do not align well, making energy storage design a critical step in proper microgrid design. Moreover, significant economic and operational benefits can be achieved by appropriately sizing and operating energy storage systems in microgrids. In this work we provide a framework that can be used for the sizing, positioning and operation of batteries in ways that both reduce the cost of operating a master-slave microgrid while also maintaining a high quality of service for the network. We formulate a mixed integer linear program based optimization algorithm that considers various operational and capital costs, as well as relevant network-related constraints. The performance of our algorithm is validated using a case-study simulation.**

I. Introduction

Storage technologies play a tremendously important role in increasing the rate of renewable energy uptake, due mainly to the intermittent and unpredictable nature of renewable energy generation sources. With increasing demand on electricity networks, network operators and consumers are now finding many benefits in using energy storage and photovoltaic systems in combination. The majority of recent literature is focused on demand control for providing better power quality and voltage stability to the networks [1], [2], [3], [4]. A further important research area is the operation of energy storage (at the distribution network level [5] and the household level [6]) for economic gain, by exploiting temporal arbitrage made possible by a time-varying price signal or tariff structure. The impact of rising electricity tariffs and falling feed-in tariffs is considered in the lifetime evaluation of solar systems linked with storage [6].

Microgrids are great opportunities that arise from the trend of increased distributed generation [7]. There has been significant interest in microgrids over the last few decades [8]. They are expected to hit the mainstream energy market in a few years and are set to make a significant impact both technically and economically [9]. Microgrid configurations vary depending on the availability of energy and the type of generation asset in place. Master-less microgrids are popular in situations where robustness to loss of generation is a key criterion [10] albeit being hard to implement [11]. However, for storage-based multi-master microgrids, battery sizing is dictated by the energy requirements that come as a consequence of voltage and frequency regulations.

Master-slave microgrids, on the other hand, are a good alternative in situations where master-less microgrids are difficult to implement [12]. In master-slave microgrids, energy dispatch has to be intelligently controlled to improve the overall performance and longevity, and at the same time make the microgrid robust to energy deficits. Proliferation of storage systems together with renewable energy generation offers exciting opportunities for controllability in terms of both network-quality and cost. Optimal sizing, spatial distribution and temporal operation of these storage systems is therefore critical in these master-slave scenarios.

Researchers have considered the battery sizing problems from various perspectives. It is known that sizing and optimal operation of batteries is subject to the stochastic nature of the renewable energy supply. This fact is considered in [13] where the authors apply a mixed integer linear programming approach to find the optimal battery size that can alleviate the power imbalance in the network under forecast uncertainties. Mismatch in the response times between synchronous and inverter-interfaced generation has also been considered in the sizing of batteries [14]. A survey of different battery types and a subsequent techno-economic viability study of these batteries is provided in [15].

Many papers in the literature address the energy storage system sizing problem for microgrids from an energy/power balance perspective, [16] for example. A recent paper [17] proposes a framework that can be used for sizing energy storage systems in a distributed manner within a microgrid. Optimal battery sizing for microgrid data-centers considering financial as well as environmental constraints is discussed in [18]. Constraints on microgrid frequency deviation are used in obtaining storage decisions in [19]. Sizing for long term microgrid operation has been addressed in [20]. Unit commitment based optimal battery storage sizing for wind power based microgrids under forecast errors using particle swarm optimization has been discussed in [21].

The optimal sizing and siting of storage systems provides potential benefits not only towards improving the economics of a microgrid, but also towards achieving better network quality. Distributed voltage control, power balancing and avoidance of reverse power flow are some desirable characteristics in the operation of a master-slave microgrid. An integrated approach that solves the battery sizing and siting problem in conjunction with voltage control, power balance and operational cost minimization is not yet available, to the best of our knowledge.

A. Contribution

In this paper we address the problem of finding a way to size and operate household batteries in a radial master-slave microgrid considering the power quality benefits the

*Corresponding author email: `rkolluri@au1.ibm.com`.
R. R. Kolluri and J. De Hoog are with IBM Research – Australia, 19/60 City Road, Melbourne VIC 3006 Australia.
I. Mareels, T. Alpcan and M. Brazil are with the Department of Electrical and Electronic Engineering, The University of Melbourne, Australia.
Khalid Abdulla and D. A. Thomas are with the Department of Mechanical Engineering, The University of Melbourne, Australia.

former can provide to the latter. Instead of looking at the problem from a power balance perspective, as is typically done in the majority of the existing literature on the subject, we formulate it using an integrated approach that incorporates constraints on power quality (such as voltage drop/rise and cable thermal ratings, among others). These power quality constraints are formulated as functions of battery currents and sizes. Subsequently we solve a Mixed Integer Linear Program (MILP) based optimization to produce the optimal size, spatial distribution and temporal operation of batteries for given patterns of load and solar photovoltaic (PV) generation. The optimization problem we consider also minimises the overall microgrid costs. Furthermore, we address the uncertainty of forecasts using Monte Carlo simulation analysis.

B. Outline

The remainder of this paper is organised as follows: Section II describes the models of various systems within the network set-up. Section III describes the network configuration utilized in the formulation and discusses the various constraints that are to be satisfied for this network. Section IV presents the optimization problem in more detail. Section V shows the simulation results for an example case-study following which suggestions for future work are made in Section VI.

II. Modelling

The possibility of islanding microgrids is being increasingly considered throughout the industry, for example by commercial developers, owners of industrial parks or shopping centres, greenfield developers, energy collectives and the like. By *islanding microgrids* we refer in this case to parts of the electrical network that may be self-sufficient and not require a connection to the main grid at some times, but may reconnect to the main grid at other times.

An example of such a microgrid network is presented in Figure 1. This network contains three houses, acting as slaves, and a master generator at the beginning of the radial line. In the particular style of network under consideration, individual houses have roof-top solar PV systems and are intending to jointly go off-grid with the support of a master source. One example for this kind of scenario is that of using the communication-based master-slave system presented in [22]. Another example is a decentralized approach where the slaves unite to decide on battery sizing and operation so that they can reduce the energy consumption from the external master.

A. Modelling sources and loads

1) Master source: The grid-forming source is modelled as an ideal voltage source that is capable of supplying the entire microgrid in scenarios where local generation provides no output. This voltage source can be based on an inertial generator or converter based generation.

2) Household loads: Residential houses typically contain a variety of load types but are often represented as impedances. An ideal model would formulate houses as impedances varying over time. However, data loggers at distribution substations only measure the amount of power consumed at a transformer level, and smart meter data resolution is typically aggregated over 15 or 30 minutes, meaning that fine-grained impedance information for each house is generally unknown. As a result, it is often assumed that houses can be modelled as current-sinks varying over time. This assumption relaxes the condition

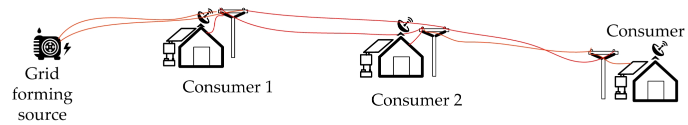

Figure 1: An example of a three consumer microgrid.

that consumption at a household depends on the local voltage pattern. Another advantage to this approach is that the power at the transformer can be averaged to find the current demand at each house. Therefore, household loads are considered as time-variant current sinks in the context of this work.

3) Roof-top photovoltaic (PV) systems: We assume a unity power factor supply from the PV system. Power injected can then be expressed as current at a given voltage. Note that a PV system produces constant power output for given insolation and does not generally depend on the voltage, if the latter is within permissible limits. For example, if the voltage at a house goes below its nominal value, current output from the PV system will increase to maintain a constant power, for a unchanged insolation. Therefore, non-linearity in modelling of roof-top PV systems is avoided by considering them as voltage-independent current sources throughout this work.

4) Batteries: In an ideal scenario, batteries are modelled as constant power loads or sources with current-limited capability from their respective DC-AC converters. In view of our present modelling paradigm, batteries can act as current sources or sinks and are considered voltage-independent. The amount of current flowing in and out of the battery is constrained by the charge capacity and charging current limitations.

III. Network and Constraints

We divide the continuous time over a finite horizon into T discrete time intervals each of length τ. The problem formulation becomes discrete and has time entries from the set $\mathbf{T} = \{1\tau, 2\tau, \ldots, T\tau\}$ where τ is the length of each time slot. We model a radial master-slave microgrid network as shown in Figure 2. We consider this a realistic representation of a typical distribution network configuration [3] (residential networks are typically radial) and any future reference to the network corresponds to a network of similar topology where the houses are connected to a voltage source in a single linear formation without loss of generality. However, our analysis can be extended to a branched network with very little modification. In Figure 2, the houses are indexed by the set $\mathbf{N} = \{1, 2, 3 \ldots n\}$. The number assigned to each house is in an ascending order, which places house 1 closest to the grid-forming source, V_s, and house n the farthest away.

Each house in the network has a local voltage V_x and is fitted with a battery and a rooftop PV. The current flowing from the network into a load at house x at time t is $h_x(t)$. The current flowing through the cable (of resistance R_x) between house $x-1$ and x is given by $c_x(t)$. The battery current at house x at time t is $b_x(t)$. Since, the current flow through the battery is bidirectional, we define charging as the period when the current is flowing into the battery i.e., $b_x(t) > 0$ and discharging when $b_x(t) < 0$. The photovoltaic current at a house x at time t is given by $p_x(t)$. According to [3], which presents data collected over an extended time period in a residential distribution network in Australia, such networks often have a high cable resistance to reactance (R/X) ratio and also operate at a power factor close to unity. We assume that this is true for the present model, thereby reducing the

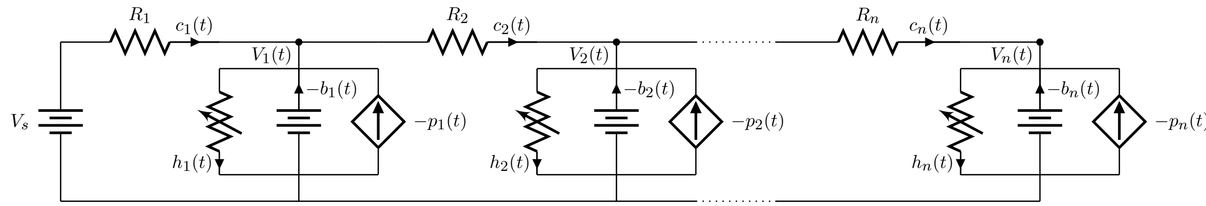

Figure 2: A radial resistive low voltage distribution network model. Each house in the network is equipped with a photovoltaic system and a battery storage system.

full complex AC network equations to their DC counterparts. This justifies the DC-type network and constraint descriptions that are to follow. Such formulation assists in applying our method to DC or AC systems. We have to mention that the transient state behaviour has not been considered in this work and all physical time-dependent variables represent rms (root mean square) steady state values.

A. Voltage Constraints

In general, it is the responsibility of the network operator (or prosumer in the decentralized scenario) to maintain the local voltage within prescribed limits. Voltage levels between 6% below (0.94 pu) and 10% above (1.1 pu) the nominal 230V rms are permissible in Australia [23]. Violating the voltage limits could adversely affect the operation/life-span of household loads and network infrastructure. From the radial model shown in Figure 2 we have the voltage at house x at time t as:

$$V_x(t) = V_s - \sum_{i=1}^{x} R_i \left(\sum_{j=i}^{n} h_j(t) + b_j(t) + p_j(t) \right). \tag{1}$$

The source voltage V_s is assumed to be generated by a reliable source and considered constant in the remainder of this paper. The voltage constraints can be written as,

$$V_{min} \leq V_x(t) \leq V_{max}, \tag{2}$$

where the suffixes V_{min} and V_{max} represent minimum and maximum permissible local voltages.

B. Nominal Current Rating Constraints

The losses on cable sections are directly proportional to the amount of current flowing through them squared. Typically, these losses are in the form of heat. Prolonged heat can cause permanent physical damage to the cables. The amount of current flowing through each cable segment has to be limited to avoid such thermal accumulation. From the system model given in Figure 2 the amount of current flowing through the cable prior to house x can be written as,

$$c_x = h_x + b_x + p_x + \sum_{j=x+1}^{n} c_j. \tag{3}$$

The current constraints can be written as,

$$-c_{max} \leq c_x(t) \leq c_{max}, \tag{4}$$

where $x \in \mathbf{N}$ and $t \in \mathbf{T}$ and c_{max} is the maximum cable current that can flow through the cables without causing any significant physical damage to them.

C. Constraints on Batteries

1) Fixed capacity: Batteries cannot charge or discharge beyond their capacity ratings. For this reason it is required to impose a capacity constraint on the battery at each house. The absolute state of charge of each battery at a specified time t', $C_x(t')$, depends on the $C_x(t' - \tau)$ of the battery and the current flowing through the battery during the time interval $(t' - \tau)$ and (t'). This can be written as shown in (5).

$$C_x(t') = \tau \sum_{t=\tau}^{t'} b_x(t) + C_x(0), \tag{5}$$

where $x \in \mathbf{N}$, $t, t' \in \mathbf{T}$, $C_x(0)$ represents an initial state of charge and τ is the length of the time slot. The associated constraint can be written as,

$$C_{min,x} \leq \tau \sum_{t=\tau}^{t'} b_x(t) + C_x(0) \leq C_{max,x}, \tag{6}$$

where C_{min} and C_{max} are the minimum and maximum charge capacity the battery can hold, respectively. The global capacity constraints can be replaced with local capacity constraints which will satisfy the above inequality. It is worth mentioning that the charge capacity in Ah, unlike in kWh, is independent of the battery voltage, which would otherwise make the problem complex, non-linear and harder to solve.

2) Optimal sizing: Alternatively, we can also find the optimal battery size by formulating the optimization problem as a combined (scaled) cost of 1) operation of battery and 2) the optimum size of battery at each house. If Γ_x is the size of the battery (typically an integer variable) at each house, we can then write the battery charge capacity constraints as:

$$C_{min,x} \leq \tau \sum_{t=\tau}^{t'} b_x(t) + C_x(0) \leq \Gamma_x \tag{7}$$

where $x \in \mathbf{N}$, $t' \in \mathbf{T}$ and $\Gamma_x \in \mathbf{Z} = \{0, 1, \cdots, C_{max,x}\}$.

3) Charge rating constraint: In general, batteries have specified charging and discharging rates. Exceeding these ratings is not always possible and, if it happens, may reduce the operational lifetime of the battery. These limits are generally imposed on the current flow from/to the battery. Therefore, it is essential to impose bounds on the amount of current that can flow to and from the battery. Let $b_{min,x}$ and $b_{max,x}$ be the minimum and maximum input and output current ratings of the battery at house x, respectively. This can be enforced by a battery current constraint which is written as,

$$b_{min,x} \leq b_x(t) \leq b_{max,x}, \tag{8}$$

where $x \in \mathbf{N}$ and $t \in \mathbf{T}$. In most cases, current limits are proportional to battery size. This characteristic is included using the constraint:

$$\delta_{min}\Gamma_x \leq b_x(t) \leq \delta_{max}\Gamma_x, \tag{9}$$

where δ_{min} and δ_{max} are the minimum and maximum charge rating factors, respectively.

$$\min_{\boldsymbol{b}\in\mathbf{R}^{nT},\boldsymbol{\Gamma}\in\mathbf{Z}^n} J(\boldsymbol{b},\boldsymbol{\Gamma}) = \tau V_s \sum_{t=\tau}^{T\tau} P_i(t) \sum_{j=1}^{n} (h_j(t)+b_j(t)+p_j(t)) + \gamma \sum_{x=1}^{n} \Gamma_x + \beta \tag{10}$$

IV. Optimization Problem

In this section we define our optimization problem, which is to minimize the cost of importing electricity, $J(\boldsymbol{b},\boldsymbol{\Gamma})$, from the grid-forming source while satisfying the network and battery constraints. Assuming that the users have unrestricted communications, unrestricted control over the batteries and some form of forecasts for load, PV and prices for a given time horizon $\mathbf{T}$ we formulate the optimization problem as shown in (10). In (10) we define the vector of battery currents $\boldsymbol{b} := [b_1(\tau),\ldots,b_1(T\tau),\ldots,b_n(T\tau))]$, the vector of battery sizes $\boldsymbol{\Gamma} := [\gamma_1,\ldots,\gamma_n]$ and $P_i(t)$ as the energy import cost. In most microgrid scenarios, the grid-forming source that is supplying energy has restricted energy import for various reasons. The optimization problem can be subsequently formulated in such a way that the overall self-consumption is maximized and the batteries are sized appropriately for the same application. This formulation results in an MILP with integer battery sizing decisions. The constraint set is reproduced in (11) and (12).

Constraint set:

$$V_{min} \le V_s - \sum_{i=1}^{x} R_i \left(\sum_{j=i}^{n} b_j(t)+h_j(t)+p_j(t)\right) \le V_{max} \tag{11a}$$

$$-c_{max} \le \sum_{j=x\neq 1}^{n} (b_j(t)+h_j(t)+p_j(t)) \le c_{max} \tag{11b}$$

$$C_{min,x} \le \tau \sum_{t=\tau}^{t'} b_x(t) + C_x(0) \le \Gamma_x \le C_{max,x} \tag{11c}$$

$$\delta_{min}\Gamma_x \le b_x(t) \le \delta_{max}\Gamma_x \tag{11d}$$

and

$$0 \le \sum_{j=1}^{n} (h_j(t)+b_j(t)+p_j(t)) \le c_{max} \tag{12}$$

if the grid-forming source has energy feed-in restrictions.

Remark 1. *The optimization problem under consideration is based on a model that is derived from mean current and voltage relationship (Kirchoff's law) assuming the network is purely resistive and operates at unity power factor. On comparison to power-based models, the current-based approach is affected by voltage changes at constituent houses. However, we find it reasonable to model the microgrid network in this manner since the optimization algorithm constrains voltage deviations (by a close upper and lower limit). This will, in-turn, contribute to improved model accuracy.*

Remark 2. *The batteries are considered to be 94% efficient throughout the period of interest. Inclusion of battery degradation based on operational regimes, chemistry based-lifetime, etc. to enhance the sizing decisions remain out-of-scope for this work. The non-linearity in battery size/price relationship has not been considered in this paper as well.*

Remark 3. *The relaxed version of* (10) *is an LP problem where battery sizes are no longer integer multiples of a given size. Solving such a problem, of course, will result in non-integer battery sizes which should eventually be rounded to the nearest available battery capacity. However, in doing so, the battery distribution and temporal operation might no longer be optimal and/or feasible, respectively, and have to be re-solved. For that reason, we have formulated the problem to be a MILP instead of an LP. However, we find it practical to solve the problem as an LP for long-term decision making for computational simplicity.*

Remark 4. *In* (10) β *is a network charge that should be paid by the customers for accessing the network and maintaining voltage. Although* β *is an uncontrollable overhead, for example, from contract between the grid-forming source and the customers, it is added to the optimization problem to indicate that the grid-forming source is always being paid for supplying the network infrastructure and maintaining the voltage that is required for the proper functioning of the network. In this work this network charge* β *is considered to be a constant over the period of interest and independent of houses' position, demand and generation profiles. The impact of a fluctuating and variable* β *would be of great interest and is left for future work.*

Remark 5. *Since there are no assumptions made on controllability and deferability of household loads, the practical realization of this optimization procedure is achievable with minimum changes to current infrastructure. With the advent of technologies like communication ready smart energy meters [24] and battery inverters [25], the proposed scheme is readily implementable.*

V. Simulations and discussion

In this case study example, we consider a microgrid consisting of 6 houses. The network and battery sizing parameters used are given in Table I. Each house has a different demand profile, as obtained from [26]. Houses 1, 2 and 5 have a 1.5 kW roof-top PV. The roof-top PV output data is obtained from [6]. The average data is extrapolated to 12 days by adding white Gaussian noise (with signal to noise ratio (SNR) = 20 when $p(t) \neq 0$) to account for variability. The generation at each house equipped with PV is made identical to capture closeness between houses, and is scaled to 1.5 kW capacity (from 2.5 in [6]) to ensure that the system is not overly constrained. For the electricity import price, we use a two part time-of-use tariff. Each kWh imported from the grid-forming source is priced at \$0.30 between 3 pm to 9 pm and \$0.20 during other times, daily (based on typical rates available in Victoria, Australia). Energy feed-in into the grid forming source is not allowed.

Table I: Numerical values for parameters used in the example case study.

Parameter	**Value**
n	6
T	24×12 (hours × days)
τ	1 hours
R_x	1/30 Ω $\forall x \in \mathbf{N}$
C_{min}, C_{max}, $C_x(0)$	0, 11, 0 Ah $\forall x \in \mathbf{N}$
V_s,V_{max},V_{min}	230, 253, 216 V
c_{max}	120 A
γ (1 year payback)	0.2 \$/Ah.day
δ_{min},δ_{max}	-1, 1 (1/hr)

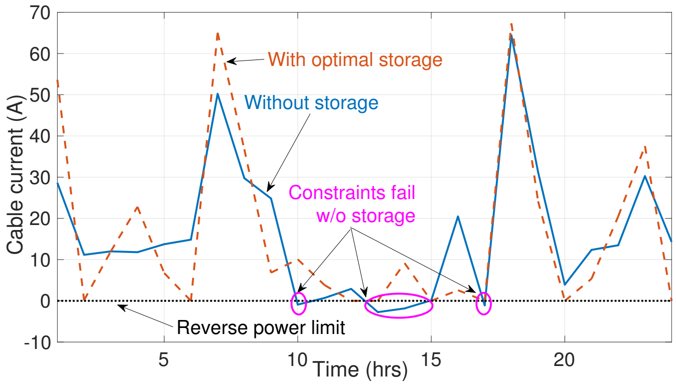

Figure 3: Cable current on segment 1, $c_1(t)$ with and without optimal storage.

Solving for battery sizes under perfect scenarios only produces conservative results in terms of operational economics for longer periods of time. This is especially true taking into account the variability of load and generation at the distribution level or the small microgrid level. It is well known that forecast uncertainty has a profound effect on sizing and installation problems in general [27]. Typically, the solution that copes with the worst case scenario is chosen in such situations. But, such decision may oversize the batteries for prolonged operation thereby reducing the overall benefit in the microgrid.

Since the availability of a grid-forming source is essential in our case, assuming that large deviations in energy are taken care of by this source, we can perform a Monte-Carlo simulation based analysis to address uncertainty in demand and generation forecasts. In this manner, we can analyze the network's response to varying demand profiles, and, choose the sizing decision that can withstand certain level of deviation from predictions. Each simulation begins on a random day of the year and runs for 12 consecutive days. A result from one simulation is shown in Figure 3 where cable current violations are taken care of by installing storage. We ran 10,000 such simulations to derive the best estimate on sizing decisions. It should be mentioned that we used linear programming to obtain the sizing decisions and rounded them to the nearest greater integer, mainly due computational constraints.

The histograms in Figure 4 show the distribution of sizing decisions over all the scenarios simulated. It can be clearly seen that house 1 needs an 11 Ah size battery to cope with the excess PV generation. The sizes of batteries at the remaining houses highly vary. However, houses 4,5 and 6 need at least a small battery (approximately 4 Ah in all cases) to satisfy local constraints.

As noted in Remark 3, once the battery sizing decisions are made using the Monte-Carlo simulation analysis, we can use our optimization algorithm with (5) instead of (7) to obtain the battery charging and discharging decisions that satisfy given constraints for varying fixed length forecasts, an approach generally known as *receding horizon control*. Observe that the complexity of the optimization problem is reduced by the number of battery sizing integer decisions, thereby reducing the overall computational overhead.

We applied four sizing choices to demand/generation changes in a year. They are:

- **Scenario 1:** $\mathbf{\Gamma} = [0, 0, 0, 0, 0, 0]$ Ah;
- **Scenario 2:** $\mathbf{\Gamma} = [11, 0, 0, 4, 4, 4]$ Ah;
- **Scenario 3:** $\mathbf{\Gamma} = [11, 0, 0, 7, 7, 7]$ Ah; and
- **Scenario 4:** $\mathbf{\Gamma} = [11, 11, 11, 11, 11, 11]$ Ah.

These results are shown in Figure 5. We compare the economics of four different sizing choices subject to ideal data and imperfect forecasts. Forecasts are generated using adaptive auto-regression models from MATLAB libraries. All available past data is fed into the regression models to obtain daily forecasts on demand/generation. Note that scenarios 2 and 3 are based on the histograms and have similar battery positions. However, the constituent battery sizes are different.

In scenario 1, no batteries are installed making the capital investment on batteries zero. The operational costs are the highest of all scenarios as the price arbitrage cannot be utilized. The reverse power flow constraint impedes PV generation in scenarios 1 and 2. The batteries in scenario 4 are over-sized for the given network. In scenario 4, the slightly lower operational costs are compromised by the huge investment upfront. Operating costs on all scenarios increase under uncertain forecasts. Heuristically, the optimal solution is scenario 3 where the PV is not wasted and the battery sizes are moderate. This leads to proper utilization of time-of-use price arbitrage as well as all the PV generation. The smaller battery sizes will also need much lower capital investment than scenario 4 adding to the overall benefit. Over the operational period (8 years, neglecting degradation), the benefit of having batteries (from not having batteries at all) is 1.9% for scenario 2, 4.9% for scenario 3 and 4.7% for scenario 4, under ideal forecasts. This benefit increases to 5.2% for scenario 2, 8.4% for scenario 3 and 8.8% for scenario 4, under forecast uncertainty used in this work, which is a more realistic scenario. This shows that larger battery sizes can cope better with uncertainty. In either case, scenario 3 remains the optimal sizing recommendation.

VI. Conclusions and Future Work

In this work we have shown how to optimally size and place batteries in a radial master-slave microgrid network. We formulated an optimization problem and solved it for a particular example of a radial network of 6 houses with realistic demand and generation profiles over one year. When the accuracy of the load, generation, and price forecasts is under question and the battery sizes are fixed, our optimization algorithm can be used for receding horizon type control or on-line optimization-based control to maximize the benefit of operating batteries. A more general result on battery sizes is obtained from Monte Carlo simulations. The solution succeeds in both (i) determining the optimal sizing, spatial distribution and temporal operation of batteries, and (ii) maintaining a high level of network quality.

In future work we aim to consider the inclusion of more detailed constraints related to battery charge and discharge, which could enable battery life extension; expanding the problem to voltage and frequency control in multi-master microgrids; and accommodating non-linear battery price profiles and inclusion of non-unity power factor loads and generation [28].

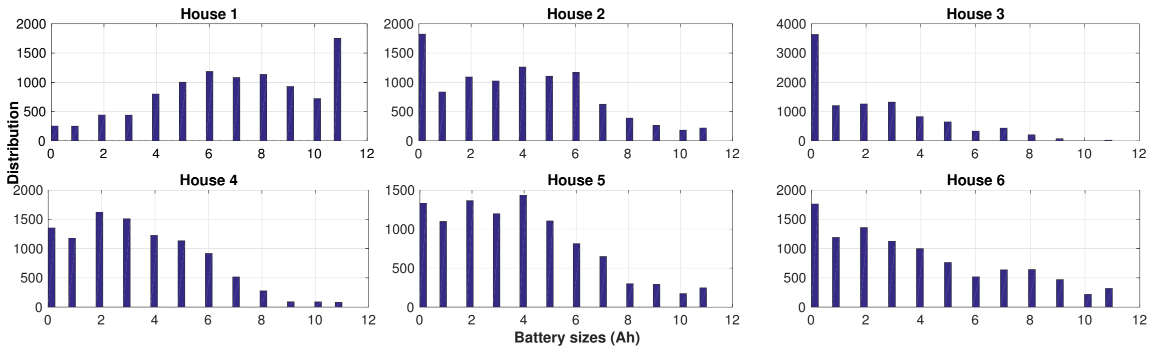

Figure 4: Distribution of battery sizing decisions from Monte-Carlo type simulations.

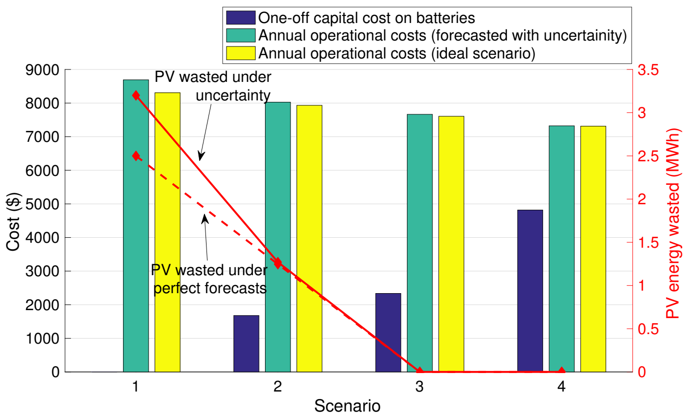

Figure 5: Cost of operating the microgrid for an year with different sizing choices.

References

[1] P. Palensky and D. Dietrich, "Demand side management: Demand response, intelligent energy systems, and smart loads," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 3, pp. 381–388, Aug 2011.

[2] N. Li, L. Chen, and S. H. Low, "Optimal demand response based on utility maximization in power networks," in *2011 IEEE Power and Energy Society General Meeting*, July 2011, pp. 1–8.

[3] J. de Hoog, T. Alpcan, M. Brazil, D. Thomas, and I. Mareels, "Optimal charging of electric vehicles taking distribution network constraints into account," *Power Systems, IEEE Transactions on*, vol. PP, no. 99, pp. 1–11, 2014.

[4] I. Mareels, J. de Hoog, D. Thomas, M. Brazil, T. Alpcan, D. Jayasuriya, V. Müenzel, L. Xia, and R. R. Kolluri, "On making energy demand and network constraints compatible in the last mile of the power grid," *Annual Reviews in Control*, vol. 38, no. 2, pp. 243 – 258, 2014.

[5] A. M. A. K. Abeygunawardana and G. Ledwich, "Estimating benefits of energy storage for aggregate storage applications in electricity distribution networks in queensland," in *2013 IEEE Power Energy Society General Meeting*, July 2013, pp. 1–5.

[6] V. Muenzel, I. Mareels, J. de Hoog, A. Vishwanath, S. Kalyanaraman, and A. Gort, "Pv generation and demand mismatch: Evaluating the potential of residential storage," in *Innovative Smart Grid Technologies Conference (ISGT), 2015 IEEE Power Energy Society*, Feb 2015, pp. 1–5.

[7] R. H. Lasseter, "Microgrids," in *Power Engineering Society Winter Meeting, 2002. IEEE*, vol. 1, 2002, pp. 305–308 vol.1.

[8] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. de Vicuna, and M. Castilla, "Hierarchical control of droop-controlled ac and dc microgrids- a general approach toward standardization," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 1, pp. 158–172, Jan 2011.

[9] N. Research, "Microgrid enabling technologies," https://www.navigantresearch.com/research/microgrid-enabling-technologies, 2013, last accessed: 03-05-2016.

[10] M. C. Chandorkar, D. M. Divan, and R. Adapa, "Control of parallel connected inverters in standalone ac supply systems," *IEEE Transactions on Industry Applications*, vol. 29, no. 1, pp. 136–143, Jan 1993.

[11] Y. Guan, J. C. Vasquez, J. M. Guerrero, Y. Wang, and W. Feng, "Frequency stability of hierarchically controlled hybrid photovoltaic-battery-hydropower microgrids," *IEEE Transactions on Industry Applications*, vol. 51, no. 6, pp. 4729–4742, Nov 2015.

[12] T. Caldognetto and P. Tenti, "Microgrids operation based on master-slave cooperative control," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 2, no. 4, pp. 1081–1088, Dec 2014.

[13] S. X. Chen, H. B. Gooi, and M. Q. Wang, "Sizing of energy storage for microgrids," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 142–151, March 2012.

[14] J. Xiao, L. Bai, F. Li, H. Liang, and C. Wang, "Sizing of energy storage and diesel generators in an isolated microgrid using discrete fourier transform (dft)," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 3, pp. 907–916, July 2014.

[15] M. Ross, R. Hidalgo, C. Abbey, and G. Joós, "Analysis of energy storage sizing and technologies," in *Electric Power and Energy Conference (EPEC), 2010 IEEE*, Aug 2010, pp. 1–6.

[16] H. J. Khasawneh, A. Mondal, M. S. Illindala, B. L. Schenkman, and D. R. Borneo, "Evaluation and sizing of energy storage systems for microgrids," in *2015 IEEE/IAS 51st Industrial Commercial Power Systems Technical Conference (I CPS)*, May 2015, pp. 1–8.

[17] I. Alsaidan, A. Khodaei, and W. Gao, "Distributed energy storage sizing for microgrid applications," in *2016 IEEE/PES Transmission and Distribution Conference and Exposition (T D)*, May 2016, pp. 1–5.

[18] C. C. Thompson, K. Oikonomou, A. H. Etemadi, and V. J. Sorger, "Optimization of data center battery storage investments for microgrid cost savings, emissions reduction, and reliability enhancement," *IEEE Transactions on Industry Applications*, vol. PP, no. 99, pp. 1–1, 2016.

[19] Q. Yaser, T. Kerdphol, and Y. Mitani, "Different optimization schemes for community based energy storage systems," in *Electric Power and Energy Conversion Systems (EPECS), 2015 4th International Conference on*, Nov 2015, pp. 1–5.

[20] H. Alharbi and K. Bhattacharya, "Optimal sizing of battery energy storage systems for microgrids," in *Electrical Power and Energy Conference (EPEC), 2014 IEEE*, Nov 2014, pp. 275–280.

[21] H. Khorramdel, J. Aghaei, B. Khorramdel, and P. Siano, "Optimal battery sizing in microgrids using probabilistic unit commitment," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 2, pp. 834–843, April 2016.

[22] Y. Zhu, F. Zhuo, and L. Xiong, "Communication platform for energy management system in a master-slave control structure microgrid," in *Power Electronics and Motion Control Conference (IPEMC), 2012 7th International*, vol. 1, June 2012, pp. 141–145.

[23] Australian Essential Services Commission, "Electricity distribution code," May 2012.

[24] T. Ganu, D. Rahayu, D. Seetharam, R. Kunnath, A. Kumar, V. Arya, S. Husain, and S. Kalyanaraman, "Socketwatch: An autonomous appliance monitoring system," *Pervasive Computing and Communications (PerCom), 2014 IEEE International Conference on*, pp. 38–43, March 2014.

[25] SolarEdge Technologies Inc., "Communication solaredge inverters," http://www.solaredge.com/products/communication, 2016, accessed: 2016-09-26.

[26] I. Australian Government Department of Industry and Science, "Sample household electricity time of use data," https://data.gov.au/dataset/sample-household-electricity-time-of-use-data, July 2014.

[27] R. Atia and N. Yamada, "Sizing and analysis of renewable energy and battery systems in residential microgrids," *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1204–1213, May 2016.

[28] M. Farivar and S. H. Low, "Branch flow model: Relaxations and convexification - part i," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 2554–2564, Aug 2013.