Aggregating Levelized Cost Functions In Microgrids For Transmission Grid Operation

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***Abstract*—While much research effort has been devoted to operation of microgrids, how the economic benefits of microgrids can be integrated into the transmission-level main grids remains as an open question. Motivated by this observation, we position the microgrid operation problem that is compatible with the main grid operation problem. This paper first presents an economic structure where multiple microgrids can be aggregated into the transmission-level main grids through load serving entities. Assuming that a microgrid energy manager (MEM) can bid into the market through a load serving entity, we solve the optimal scheduling of various distributed energy resources (DERs) in a microgrid. We construct detailed cost functions for DERs taking into account the costs of aging and fuel. The resulting cost functions can be non-increasing in terms of power, which is significantly different from cost functions of traditional bulk power producers, and can hinder MEMs from participating in the market. However, we show that as a result of the optimal scheduling of DERs, a MEM can obtain a single linear bid, which is the marginal cost of the microgrid system for each time step. This is compatible with the market structure at the main grid level. We also show the impact of including levelized costs of DERs compared to a case assuming zero short-term costs.**

I. Introduction

The concept of microgrids emerged around two decades ago [1], [2] and has garnered increasing attention since. Falling prices of distributed energy resources and their growing penetration as its result made microgrids more economically viable. Needs for more secure power supply is also one of the main reasons for building a microgrid system. As a result, many technical and economical questions regarding how to operate a microgrid system have been widely studied. The focus in this work is geared toward the economical perspective.

Some previous work has considered long-term costs of components such as operation and maintenance (O&M) costs into its short-term scheduling, which includes costs of aging and repair of the equipment. One of the most studied topics regarding these *levelized costs* is degradation of batteries in electric vehicles in, for example, [3]–[5]. We consider this type of costs into short-term scheduling for operating a microgrid. In doing so, we provide detailed models on how we calculated the levelized costs.

Most literature regarding resource scheduling of microgrids concerns components within one microgrid. Game theoretic methods have been widely studied [6]–[9]. [10] gives an overview of the game theoretic approach applied to smart grids. [7] explores cooperation between multiple microgrids, but does not consider the application of the results onto the main grid. It is also not clear if coalition among microgrids is realistic. [11] considers scheduling of storage in a microgrid in relation to the day-ahead and real-time market prices. This work proposes that the distributed generation resources submit their bids with respect to their production cost. This is equivalent to individual distributed generation resources bidding directly into the market. However, since these resources are tied within a microgrid, the bid has to be calculated in relation with the other resources and demand of the particular microgrid that it is serving. In other words, the bids of a generation resource in a microgrid should come as a result of scheduling it with the other resources in the same microgrid.

This paper has three main contributions. First, we provide detailed models of levelized O&M and aging costs for distributed energy resources (DERs) in a microgrid such as small generators and batteries. We use these costs to schedule the components to meet given loads in a microgrid system. Secondly, we analyze the bidding prices and quantities of microgrids to the transmission-level market. We observe that the levelized costs of DERs may not be monotonically increasing, especially in the case of storage devices. The costs can be piecewise linear with different ranges by components and the optimization model of scheduling involves binary variables. We calculate the bidding price and quantity of a particular microgrid to participate in the main grid operation. Lastly, by simulating cases with and without assuming levelized long-run costs of a storage system and comparing the results, we discuss the impact of scheduling a microgrid with levelized costs.

II. Background

The overall system environment we consider in this paper consists of microgrids, load serving entities, and a transmission-level market, as shown in Fig. 1. Microgrids are overseen and operated by microgrid energy managers (MEMs). MEMs are responsible for safe and economic operation of the microgrids. Their economic objective is to minimize the cost of meeting demand in their microgrid, either by utilizing the resources in their own grids or by purchasing energy from a load serving entity. Load serving entities (LSEs) provide electricity not only to individual consumers but also to microgrid

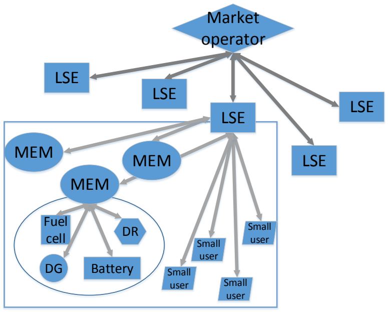

Fig. 1. Overview of the system

loads. They purchase energy from the market and/or can have bilateral contracts with power producers outside of the market. Since most consumers do not purchase energy directly from the market or power producers, LSEs aggregate small loads of consumers including microgrids and make transactions with the market and power producers in large amounts. An MEM can choose to have contracts with her LSE so she can sell surplus energy production from her microgrid to the LSE. The LSE can then purchase energy from the MEM and provide that energy to the other loads or sell it in the market. The market/system operator oversees the energy transactions and operation at the transmission grid level.

The problem we solve in this paper is the one by a MEM who schedules energy transaction in a microgrid and calculates bids to submit to the market and purchase amount from the market through a LSE. We assume that the LSE simply acts as a mediator between the MEM and the market operator, and the market is a perfect competition. Even though these assumptions do not perfectly model the reality, it gives an insight as to what a MEM would bid in the market, and how it would affect the transmission-level grid operation.

We solve a problem of scheduling resources in a microgrid a day ahead of operation, before submitting bids into the main grid. We assume that a MEM can either purchase or sell electricity from/to the market, at the market price. In future work, we plan to relax these assumptions by including surcharges by the load serving entity such as distribution costs and market transaction costs.

III. Cost models for distributed energy resources

In this section, cost models for small distributed energy resources (DER) will be studied. Derivation of cost models for small DERs is slightly different from larger power plants. In large power plants, the cost is calculated based on various criteria and has a direct relation with economical conditions. However, in smaller plants, cost model is mainly driven by the capital cost and costs of fuel. Hence, after the initial investment, this model is often not updated except for the cost of fuel (in the case of small fuel cell resources or diesel generators). For instance, a battery resource does not require fuel and hence, its cost model is derived based on installation and maintenance costs.

The return on investment (ROI) portion of the cost is calculated based on the profit that an investor would make if funds were deposited in an average investment plan. In this case, capital cost for installation of an item, $\mathfrak{c}_{\text{cap}}$, will reach a total of $(1+i)^y\mathfrak{c}_{\text{cap}}$ after y years with a fixed interest rate i. By investing $\mathfrak{c}_{\text{cap}}$ in a DER, the investor will receive a fixed annual revenue of $\mathfrak{c}_y$ which can be invested in the market. Assuming that the collection of revenue occurs at the end of each year, the annual revenue to completely compensate for the capital cost in y years is

$$\mathfrak{c}_y = \frac{\mathfrak{c}_{\text{cap}}(1+i)^y}{(1+i)^{y-1}+\cdots+1} = \frac{\mathfrak{c}_{\text{cap}}i(1+i)^y}{(1+i)^y-1} \tag{1}$$

In order to compensate for annual inspections and incidental damages to this system, a fixed operation cost of $\mathfrak{c}_o$ is added to this model. In order to utilize this model in grid markets, per kWh cost of the resource is defined as

$$\mathfrak{c}_{/\text{kWh}} = \frac{\mathfrak{c}_y+\mathfrak{c}_o}{C_{\text{nom}}\times 8760} + \mathfrak{c}_r + \mathfrak{c}_f \tag{2}$$

where C_{nom} is the nominal capacity of the unit in kW, $\mathfrak{c}_r$ is the cost of repair dependent on the power output level, and $\mathfrak{c}_f$ is the cost of fuel required to generate a kWh of energy. It should be noted that this cost is calculated based on the investment and does not include any revenue. However, economical competitiveness usually enforces an investor not to expect any net revenues during the ROI period.

Due to the high price of equipment, these systems are designed and constructed to operate for a long period of time. In fact, the incentive for investment in an energy resource is the profit period that comes after the ROI period. After the ROI period, the unit will continue to operate and generate a net revenue higher than that during the ROI period. However, heavy usage of the DER can reduce its expected life span which is levelized in this work as an additional short-term cost. In this paper, the aging cost, $\mathfrak{c}_a$, is defined as the equivalent cost associated with accelerated aging of an energy resource.

The failure rate of equipment is modeled as a random variable. Statistical studies have shown that failure of electrical equipment is well described with exponential, Weibull, or bathtub random variables [12], [13]. For a random variable, a failure rate function λ_t can be defined so that the survival rate of a unit is a random variable with a survival distribution function of $e^{-\int \lambda_t dt}$ [14]. Based on statistical inference, it has been observed that the failure rate for majority of electrical equipment is an exponential function of electrical stresses. In low stress conditions, mechanical failures such as overall aging of equipment is the dominant factor of incidents. However, high electrical stresses can dominate mechanical stress factors. For this reason and without loss of generality, a reduced-order failure rate function of a DER is defined as

$$\lambda_t(P) = \max\{\lambda_0, k_\lambda e^{k_p|P|}\} \tag{3}$$

where λ_0 is the base failure rate factor calculated in safe nominal operating conditions, k_p and k_λ are correction factors, and P is the power transferred by the equipment, respectively.

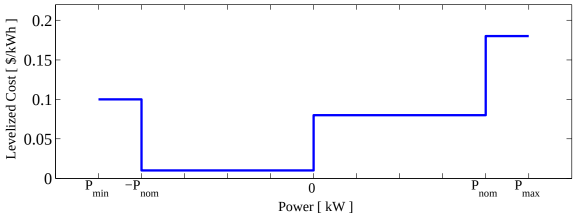

Fig. 2. An example of the proposed levelized cost model for a battery storage system.

Intuitively, if electrical equipment is not used, it is still prone to failures due to aging and wear-down with a rate of λ_0. Aging can be defined as the cumulation of a failure rate over time (i.e. $Age = \int \lambda_t/\lambda_0 dt$) [14]. Hence, the overall cost of generating P kW during a unit time by a DER can be derived as

$$\mathfrak{C}(P) = \mathfrak{c}_{/\text{kWh}}P + (\mathfrak{c}_{\eta_+}1_{P\geq 0} + \mathfrak{c}_{\eta_-}1_{P<0})P \\ + \mathfrak{c}_f 1_{|P|>P_0} e^{k_P|P|}P \tag{4}$$

where $\mathfrak{c}_{\eta_+}$ and $\mathfrak{c}_{\eta_-}$ are costs associated with efficiency during generation and storage, respectively. An indicator function is denoted as 1_{logic} where its value is 1 when $logic$ is true and 0 otherwise. $\mathfrak{c}_f$ and k_P are the costs associated with early failures and the correction factor, respectively. P_0 is the maximum safe operation region of the unit. In case of wind and solar resources, this is the maximum limit of the unit. However, some DERs such as battery resources or small generators can be forced to operate higher than their nominal ratings for short periods of time. In this case, model proposed in this paper will consider an additional cost of $\mathfrak{c}_f$ to compensate for accelerated aging of the unit.

If an investor decides to use a DER, then no costs associated with the investment should be considered. In this case, the investor have already taken the risk of investment and therefore, cannot charge the sunk cost. In this case, (4) is calculated with $\mathfrak{c}_y = 0$. Also, investment in low-capacity DERs are likely not competitive in the market because of their high cost per capacity. Therefore, it is assumed that if they have already invested in a DER, they do not consider $\mathfrak{c}_y$ in their cost model. Therefore, our cost models only include the costs of fuel and aging. The result, however, can help verify the effectiveness of the investment by comparing the expected net annual revenue and the revenue required to compensate for their investment from (1).

The cost function defined in (4) is nonlinear and cannot be used in market operations. Hence, levelized costs can be derived by linearizing this model in multiple operation regions. The levelized cost of this DER is calculated as

$$\mathfrak{c}(P) = \mathfrak{c}_j 1_{P_0\leq P<P_1} + \cdots + \mathfrak{c}_n 1_{P_{n-1}\leq P<P_n} \tag{5}$$

where c_i is calculated by linearizing (4) in the region $P_{j-1} \leq P < P_j$. An example of this levelized model for a storage system is shown in Fig. 2.

For a microgrid energy manager who has various DERs already installed, it is economically feasible to supply its loads with the local non-dispatchable DERs such as solar and wind. Therefore, these resources are considered as negative loads with no costs associated to them. For storage systems, the MEM will only consider the cost of repair, and for diesel and gas generators, the costs of repair and fuel can be included.

IV. Problem of a microgrid energy manager

A. Scheduling distributed energy resources

A MEM schedules DERs in her microgrid before a day-ahead market at the transmission level opens. Given the expected price for this market, either forecast by her own intelligence or given from another entity, she can schedule DERs over a day in the time interval consistent with the market. In this work we assume that the market price forecast is given to the MEM and the time interval is 15 minutes.

$$\text{minimize} \sum_{t=1}^{T} \left[\hat{\lambda}(t)P_{\text{grid}}(t) + \sum_{i=1}^{N}\sum_{j=1}^{n_i} c_{ij}P_{ij}(t) \right] \tag{6}$$

$$\text{subject to } P_i(t) = P_{i,\min} + \sum_{j=1}^{n_i} P_{ij}(t) \quad \forall i, \forall t \tag{7}$$

$$\sum_{i=1}^{N} P_i(t) + P_{\text{grid}}(t) = \hat{P}_D(t) \quad \forall t \tag{8}$$

$$P_{\text{grid,min}} \leq P_{\text{grid}}(t) \leq P_{\text{grid,max}} \; \forall t \tag{9}$$

$$P_i(t) = P_{i,\min}(t) + \sum_{j=1}^{n_i} P_{ij}(t) \; \forall i, \forall t \tag{10}$$

$$P_{ij,\min} \leq P_{ij}(t) \leq P_{ij,\max} \; \forall i, \forall j, \forall t \tag{11}$$

$$E_i(t+1) = E_i(t) + \Delta t P_i(t) \; \forall t, \text{ for } i \in \mathcal{S} \tag{12}$$

$$E_{i,\min} \leq E_i(t) \leq E_{i,\max} \; \forall t, \text{ for } i \in \mathcal{S} \tag{13}$$

$$U_i(t)P^+_{i,\min} \leq P^+_i(t) \leq U_i(t)P^+_{i,\max} \text{ for } i \in \mathcal{S}, \forall t \tag{14}$$

$$(1-U_i(t))P^-_{i,\min} \leq P^-_i(t) \leq (1-U_i(t))P^-_{i,\max} \\ \text{for } i \in \mathcal{S}, \forall t \tag{15}$$

$$P^+_i(t) = \sum_{j\in j^+} P_{ij}(t), \; P^-_i(t) = \sum_{j\in j^-} P_{ij}(t), \\ P_i(t) = P^+_i(t) + P^-_i(t) \text{ for } i \in \mathcal{S}, \forall t \tag{16}$$

$$U_i(t)\text{: binary varable for } i \in \mathcal{S}, \forall t \tag{17}$$

The decision variables are P_{grid}, P_{ij} P_i, and E_i, P^+_i, P^-_i, U_i for $i \in \mathcal{S}$ where $\mathcal{S}$ denotes the set of storage components. The reason for introducing binary variables for storage is because it can be either charging or discharging, but not a combination of both. An idle state of storage can be considered as P_i being zero with U_i either 0 or 1. Additionally, the costs at charging and discharging states can be further divided into multiple segments as shown in Fig. 2. The relationship between the segmented power level and charging/discharging state is modeled in (14)-(16). All the other values are assumed to be given deterministically, including the market price forecast $\hat{\lambda}$ and expected demand $\hat{P}_D$. In particular, $c_{ij}P_{ij}$ in (6) corresponds to our cost model developed in (5).

If component i is a storage device such as a battery, i.e., $i \in \mathcal{S}$, then the energy dynamics of the component should also be considered, as in (12). The initial state of the device $E_i(1)$ (e.g., the initial energy level of a battery) is given.

This is a scheduling problem over T time steps, of N components. The nonlinear cost function of each component is approximated as a piecewise linear function with n_i segments for component i, and the piecewise linear cost coefficient is c_{ij} for segment j of component i. P_{grid} can be negative when sale to the market through the LSE is allowed.

B. Bids to market through load serving entity

In a perfect market, the optimal bidding price for a participant is their marginal cost [15]. Without considering any surcharges for bidding, we can find out the marginal cost of a microgrid that was scheduled in the previous subsection IV-A. The marginal cost of this system at time step t is defined as $\lambda_m(t)$, which is the Lagrange multiplier associated with (8). One of the Karush-Kuhn-Tucker optimality conditions when the constraint (9) is nonbinding is

$$\frac{\partial \mathcal{L}}{\partial P_{\text{grid}}(t)} = \hat{\lambda}(t) - \lambda_m(t) = 0 \;\forall t \tag{18}$$

where $\mathcal{L}$ is the Lagrange function of the problem (6)-(17). This implies that at the optimal operation of a microgrid, the marginal cost of the microgrid system and the expected market price is the same, and this will be the bidding price of the MEM in a perfect market. Since the expected market price determines the bidding price, the accuracy of the market price forecast is essential. Therefore, further research on including stochasticity of the market price to calculate the optimal bids is planned for future work.

The quantity of bids are decided as $P_{\text{grid}}(t)$ at the optimum. Note that P_{grid} can have a sign either negative or positive. At the time steps when P_{grid} is positive, the MEM offers to purchase electricity at the marginal cost, and when it is negative, a sale offer is made.

It is also worth noting that regardless of the number of components in the microgrid system and the complexity of their cost functions, the MEM can submit one bid, either purchase or sale, with a bidding price and quantity per time step. Since the components of the microgrids are not visible to the system operator, this is particularly important in order to comply with the market rules at the transmission level.

V. Numerical example

The microgrid system we consider for a numerical example is a modified version of the real microgrid system in the Solar Village of Missouri University of Science and Technology [16]. The system we modeled consists of five residential houses with solar panels, a fuel cell, a battery, and a diesel generator. Since the usage of a diesel generator requires meeting environmental regulations and is usually limited for emergency cases, we impose a higher cost than its fuel cost to penalize its output. The levelized costs and capacities of the components considered are shown in Table I. The peak load of the system was about 9.8 kW.

TABLE I
THE LEVELIZED COSTS OF THE MICROGRID COMPONENTS

	Cost ($/kWh)	Output range (kW)	Total capacity
Solar	0	0 to 5	5 kW
Fuel cell	0.15	3 to 5	5 kW
Battery	0.03 0.1 0.035 0.1	0 to 1 (charge) 1 to 1.5 (charge) 0 to 1 (discharge) 1 to 1.5 (discharge)	5 kWh
Diesel generator	0.31 0.5	0 to 1 1 to 1.3	1.3 kW

We obtained data of the total solar output and load in the system during the month of October 2014 in 15-minute intervals and averaged the values at each interval, which are depicted in Fig. 3. For the expected market price, we averaged the 5-minute real-time locational marginal price of node AMMO.UE in the Midcontinent Independent System Operator (MISO) region on the October 13th, 2014 [17]. This is shown in Fig. 5 with the right-hand side y-axis. As discussed in Subsection IV-B, this price becomes the bidding price of purchase or sale.

Given these data, we optimized the scheduling of each component to meet the load with the given expected market price and the costs of the components. We used the mixed-integer linear programming solver `intlinprog` of MATLAB® Optimization Toolbox™ to solve the problem, and the simulation time was trivial. The optimal power from/to the main grid P_{grid} for each time step is shown in Fig. 4. Power coming out of the battery is depicted in Fig. 5. We ran simulations for both cases where we assumed the levelized cost for battery operation, and where a zero marginal cost for the battery was assumed.

As is obvious from Fig. 5, when we consider the long-run levelized costs for battery operation it was used less frequently. This also affects the purchase and sale from/to the main grid, as shown in Fig. 4. It is worth nothing, however, that the result of the battery schedule assuming no cost not only degrades it faster, but also requires a higher fluctuation of P_{grid} to meet the load. In other words, choosing the right cost models for scheduling microgrid components not only is crucial for the long-run microgrid health and economy but may also have implications for stability at the point of common coupling with the main grid.

Interestingly, the total operational cost with the nonzero levelized battery cost was 38.78 dollars, which was only 0.9% higher than that with the zero battery cost. As expected, the MEM can sell surplus power from solar during the daylight hours and purchase power to meet peak demands in the morning and the evening. When the levelized cost of battery was included in the model, it was used to avoid the market price spikes, as shown in Fig. 5.

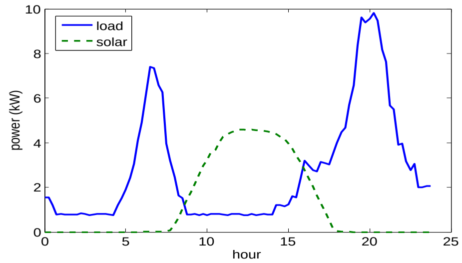

Fig. 3. Solar power output and load

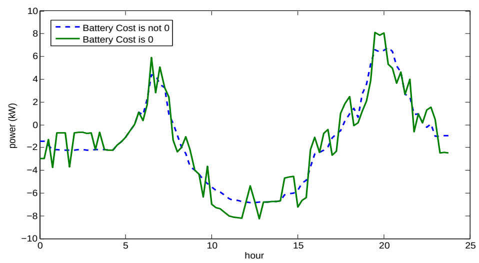

Fig. 4. Power drawn from(+) and injected to(−) the main grid

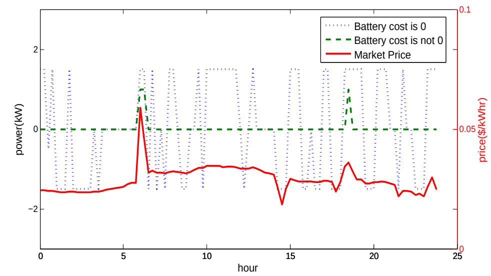

Fig. 5. Power used for charging(−) and discharging(+) the battery, and expected market price (= bidding price)

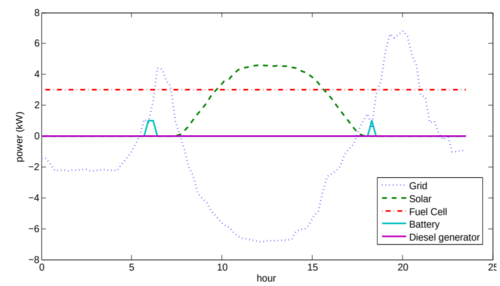

Fig. 6. Dispatch results of all components with levelized cost of battery

VI. Conclusion

In this work we scheduled components in a microgrid with their levelized costs, and calculated their bidding price and quantity to that can be incorporated into the transmission market. Our simulation results show that including the levelized costs of components in a microgrid results in a vastly different schedule of a storage system and power exchange with the transmission-level system.

We plan to extend this work to include a variety of microgrid components and configurations, and see the impact of an aggregate of a number of microgrids in the transmission grid operation. In order to assess the impact of levelized costs in short-term scheduling with better accuracy, we expect to obtain solar and load data for a longer time period to run numerical examples with multiple days and seasons. More realistic strategic models of load serving entities and microgrid energy managers can also be studied based on this work.

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