Optimized Microgrid Power Management for Minimal Electricity Costs

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1 Motivation & Context

The growth of the solar industry, along with energy storage research and development, has placed increasing focus on microgrids as alternatives to traditional power distribution models. Use cases for microgrids range from military bases[1] to rural African villages[2] to middle-class neighborhoods[3]. Depending on the exact use case, a microgrid can be configured to operate in many different ways. But before getting into that, we must first clarify what exactly a microgrid is, and what it is needed for. As defined by the US Department of Energy (DoE)[4],

> "[a] microgrid is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode."

These "interconnected loads" are the devices and equipment that run on electricity: air conditioning units, lighting, data centers, etc. Each requires certain amount of electric power to perform a given function. How these loads interact with each other, relative to their times of use, dictate how much power must be available to the system. In each instant, the power required by the loads must be provided by the "distributed energy resources". The energy resources are the suppliers of electric current that power the loads. The key term here that gives microgrids their utility is "distributed". There are multiple sources of electric power, of different types, thereby decreasing the effect of faults on power delivery continuity. If one source goes down, there are others to pick up the slack. The final part of the DoE's definition, the ability to "connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode", is self-explanatory.

These three aspects of a microgrid are intrinsically interrelated, and together define the requirements for the efficient operation of the microgrid. This project assesses the relationships between the load, resources, and grid to define the optimal allocation of resources in the microgrid, and implements a method for determining these allocations.

[1] "New Secretary of Defense James Mattis Supports Solar Military Microgrids To 'Remove Tether of Fuel'." Microgrid Media. February 14, 2017. Accessed August 14, 2017. http://microgridmedia.com/new-secretary-of-defense-james-mattis-supports-solar-microgrids-to-remove-tether-of-fuel/.

[2] Anmar Frangoul. "In Kenya, micro grids are boosting access to electricity for rural communities." CNBC. June 15, 2017. Accessed August 14, 2017. https://www.cnbc.com/2017/06/15/in-kenya-micro-grids-are-boosting-access-to-electricity-for-rural-communities.html.

[3] "Solar Experiment Lets Neighbors Trade Energy Among Themselves." The New York Times. March 13, 2017. Accessed August 14, 2017. https://www.nytimes.com/2017/03/13/business/energy-environment/brooklyn-solar-grid-energy-trading.html.

[4] "Microgrid Definitions." Microgrid Definitions — Building Microgrid. Accessed August 13, 2017. https://building-microgrid.lbl.gov/microgrid-definitions.

The term “optimal” is not a precise term, as it depends heavily on the subject of optimization. Here, an optimal allocation of resources in a microgrid could have a variety of solutions. For example, a microgrid resource allocation optimized for carbon footprint would likely resemble a rule-based control flow, where clean energy resources are used as default, and only using carbon-based resources as necessary. The inherent independence of microgrids makes them attractive for use cases where reliance on grid-power is discouraged. This could be for lack of confidence in the grid's reliability; an outpost in an austere environment or developing nation may very well not have access to a stable grid network. Or, this could be for a desire to preserve the reliability of the grid by lightening the load[5] — so to speak — or more likely, to minimize the cost of using grid-power.

However, truly minimizing the cost of electricity cannot be achieved by simply minimizing the use of the grid. Electricity prices fluctuate throughout the day as demand and availability change. Thus, cost is not only affected by how often the microgrid connects to the grid, but also by when it does. This project uses hourly prices of electricity to minimize a microgrid's cost from grid-power consumption by finding the optimal times to use the grid. And while this method will likely be most attractive to companies and firms looking to control costs, it has the additional benefit of preserving grid reliability. From a classical economic standpoint, electricity prices, like all other prices, are signals to consumers regarding availability. Prices rise as power consumption increases towards generator capacity, and drops – sometimes to negative prices[6] – when there is a surplus of power availability. The method implemented in this project, in its attempt to minimize costs, responds to the price signals exactly as electric power providers desire: avoiding grid-power consumption during periods of scarcity, and allowing the use grid-power when the supply is most available.

In this project, a general microgrid is considered with no particular application in mind. It may power an EV charging station, hospital, refugee camp, military outpost, etc. The individual loads are not defined; only the net load on the microgrid is considered. The sources at its disposal include a 22 kW solar panel array, an 8 kWh battery system, and a connection to the grid. It is assumed that daily load profiles for this microgrid, as well as reasonable forecasts in electricity spot prices can be can be predicted. Methods for these tasks are not in the scope of this project, but have been investigated by others[7,8]. Con-

[5] Brandon Davito, Humayun Tai, and Robert Uhlander. “The smart grid and the promise of demand-side mangement”. McKinsey and Company. December, 2009. https://www.smartgrid.gov/document/smart_grid_and_promise_demand_side_management.

[6] “Rising solar generation in California coincides with negative wholesale electricity prices.” Today in Energy. April 7, 2017. Accessed August 13, 2017. https://www.eia.gov/todayinenergy/detail.php?id=30692.

[7] Dominik Lieble. “Modeling and forecasting electricity spot prices: a functional data perspective”. The Annals of Applied Statistics. 2013. Vo. 7. No. 3, pg 1562-1592.

[8] M. Chanza, P. Ramjith and G. Van Harmelen, “Forecasting domestic hourly load profiles

ceptually (albeit, over-simplified) this information can be generated from data such as 24-hour weather forecasts, historic energy-use data, scheduled operation of equipment, etc.

This project assumes electricity markets are of similar structure to those of today, where the price per kWh peaks in the mid-afternoon, and is cheaper overnight, when consumption is low. Obviously, if changes is electricity consumption patterns are significant enough, these changes will manifest in the pricing of electricity. For example, if large-scale energy storage systems charge overnight using power from the grid, the increased demand of electricity at these hours will raise the price, effectively eliminating the incentive for nightly charging. This project places itself in the situation where the storage of energy from the grid remains small in scale, such that the pattern of electricity consumption is not significantly different from present conditions.

Arbitrary power requirements and electricity prices are used to demonstrate functionality of the optimization routine. Real data, if made available, can be used in its place to generate more meaningful results. The optimization algorithms are implemented in Python using the SciPy, NumPy, and pandas libraries.

2 Initial Cost Minimization

The process begins with a load profile, an array of the microgrid's daily power requirements in one-hour increments and the corresponding spot prices of electricity, as shown in Figure 1, respectively. The allocations of solar, battery, and grid resources must be allocated such that the load requirements are met each hour, and that the cost incurred by using grid power is minimized. One component of minimizing grid cost, is reducing the use of it. This can be achieved by using all of the available solar power. This leaves the microgrid with a remaining demand, characterized by Equation 1, where L and S_A are 24 dimensional arrays of the hourly load profile and solar power availability, respectively.

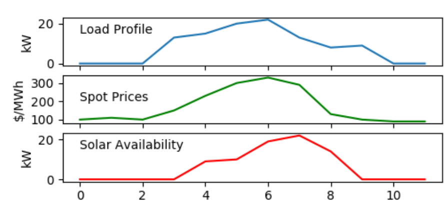

Figure 1: Example load profile, electricity spot prices, and solar power availability

$$D = L - S_A \tag{1}$$

At this stage, available solar power in excess of the load requirements is not of

using vector regressions," 2013 Proceedings of the 21st Domestic Use of Energy Conference, Cape Town, 2013, pp. 1-5.

concern, thus any negative values of D must be capped at 0.

$$D'_{(i)} = \begin{cases} D_{(i)} & \text{if } D_{(i)} >= 0 \\ 0 & \text{if } D_{(i)} < 0 \end{cases}$$

This new array, D', can be thought of as the load profile relative to the battery and grid resources. Thus, we will construct two 24-dimensional arrays B_u and G to represent the hourly use of the battery and grid, respectively, in Watts. The cost of using the grid is defined by

$$c = P \cdot G^T \tag{2}$$

(Note that because the values in G, and all usage arrays for that matter, are hourly, an element in G has both the unit W and Wh. Thus, the prices in P, listed in $\$/Wh$ can be dotted with G to obtain the cost.)

Since

$$D' = B_u + G \tag{3}$$

the cost can be equivalently written as

$$c = P \cdot D'^T - P \cdot B_u^T \tag{4}$$

And since D' is a constant array, minimizing c is equivalent to maximizing the term $P \cdot B_u^T$. This makes sense conceptually, in that by maximizing the equivalent dollar value of energy used by the battery, the most money is saved compared to using the grid.

In order to perform this maximization, constraints must be set to prevent the battery from over-delivering power, and from exceeding its power rating B_{max}, or capacity K. First,

$$0 <= B_{u(i)} <= z_{(i)} \tag{5}$$

where,

$$z_{(i)} = min\{D'_{(i)}, B_{max}\} \tag{6}$$

and second,

$$\begin{bmatrix} 1 & 1 & 1 & \dots & 1 \end{bmatrix} \cdot B_u^T <= K$$

With these constraints set, the optimal values of B_u can be found using the linear programming simplex algorithm. Once B_u is known, G can be found via Equation 3. Figure 2 shows the optimal allocation of resources for the example load profile and spot prices given above.

3 Handling Excess Solar

The solution above is not final, as it neither treats the battery system as rechargeable nor attempts to handle any solar power in excess of the load.

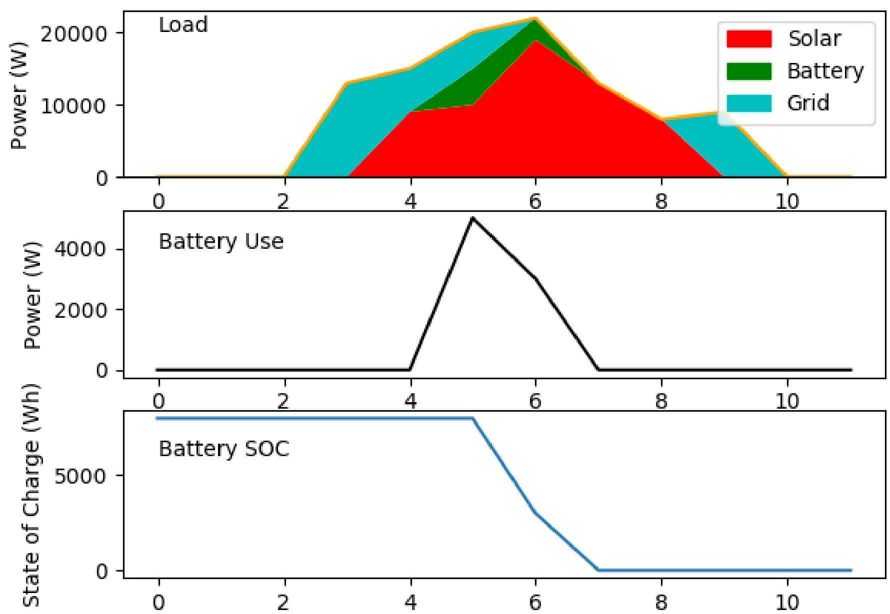

Figure 2: Load profile allocation among the three resources, along with the hourly battery use and state of charge

When available solar power is in excess, it is beneficial to store it, if possible, for later. To accomplish this, an array of the battery state of charge at each hour must be calculated through the cumulative sum of B_u as such:

$$\Pi_{(j)} = K - \sum_{i=1}^{j} B_{u(i)} \tag{7}$$

With Π known, any excess solar power can be allocated to charging the battery if it is in need and not in use.

$$\begin{aligned} \text{For each } i \text{ s.t.} \quad D_{(i)} &< 0, \\ B_{u(i)} &= 0, \\ \text{and} \quad \Pi_{(i)} &< K; \\ \text{let} \qquad & \\ B_{u(i)} &= max\{-B_{max}, D_{(i)}\} \end{aligned}$$

It is possible for there to be enough hours of solar power exceeding the load profile that the above method will result in B_u ,as it stand now, overcharging the battery. Thus, after recalculating Π, over charging must be eliminated.

Let I be an n-dimensional array of the indices i where $\Pi_{(i)} > K$.

$$\begin{aligned} B_{u(I[0]-1)} &= K - \Pi_{(I[0])} \\ B_{u(I[1:n]-1)} &= 0 \end{aligned}$$

After these operations, the power consumption of the battery demanded by B_u will not result in the overcharging of the battery.

Any additional excess solar power not used to recharge the battery, is unused. The remaining solar power could be injected back into the grid, generating revenue and further decreasing electricity costs. However, since a secondary goal of this project is reducing the use of the grid, grid-injection of excess solar is not performed. The result of applying the above methods to the example scenario in this project is displayed in Figure 3.

4 Further Use of the Battery

Up until this point, the microgrid has used the entirety of available solar power, used the battery to reduce consumption of expensive electricity and has used excess solar power to recharge the battery if necessary. The next step is to use the newly stored energy to further decrease the cost, and finally, to ensure the battery is fully charged at the end of the day.

The method outlined in Section 2 is used again to optimally allocate the newly

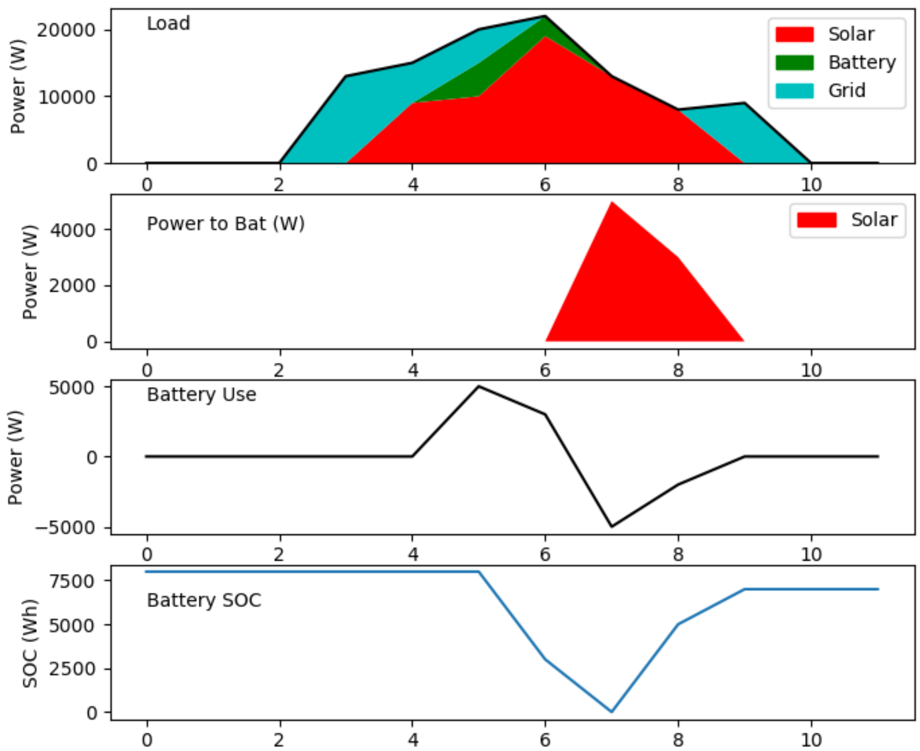

Figure 3: Load profile allocation among the three resources, along with the hourly battery use and state of charge. Note the inclusion of battery charging with excess solar.

stored solar energy. However, it is only applied to the data subset following the charging of the battery.

At the end of the day, the battery must be recharged to full capacity to allow for operation the following day, but at minimal cost. With cost calculated by

$$c' = P' \cdot B_u'^T \tag{8}$$

where P' and B_U' are the electricity price and battery use arrays of the data subset, an optimal B_u' must be found, subject to the following constraints

$$0 <= B'_{u(i)} <= B'_{max}$$

$$\begin{bmatrix} 1 & 1 & 1 & \dots & 1 \end{bmatrix} \cdot B_u'^T = \Delta K$$

where ΔK is the battery SOC deficit. Applying these final two optimization routines, results in the final optimized resource allocations. The results are shown below in Figure 4.

5 Overall Performance

With the set of spot prices and load profile used in this project, the cost of using the grid alone is \$24.37. Use of the solar panel array decrease the cost to \$8.22. Using the battery system in the optimized manner determined by Section 2 decreases the cost to \$5.73. Recharging the battery with excess solar, and using the power later further decreases the cost to \$5.23. Charging the battery back up to 100% state of charge at the optimal times found in Section 4 increases the cost to just \$5.66, still less than the cost of Section 2. This final cost achieved by optimizing the use of a battery system represents a 31% reduction in cost compared to using solar alone.

Method	Cost	Savings
Solar Only	\$8.22	0%
Battery (peak only)	\$5.73	30.3%
Battery (further use)	\$5.66	31.1%

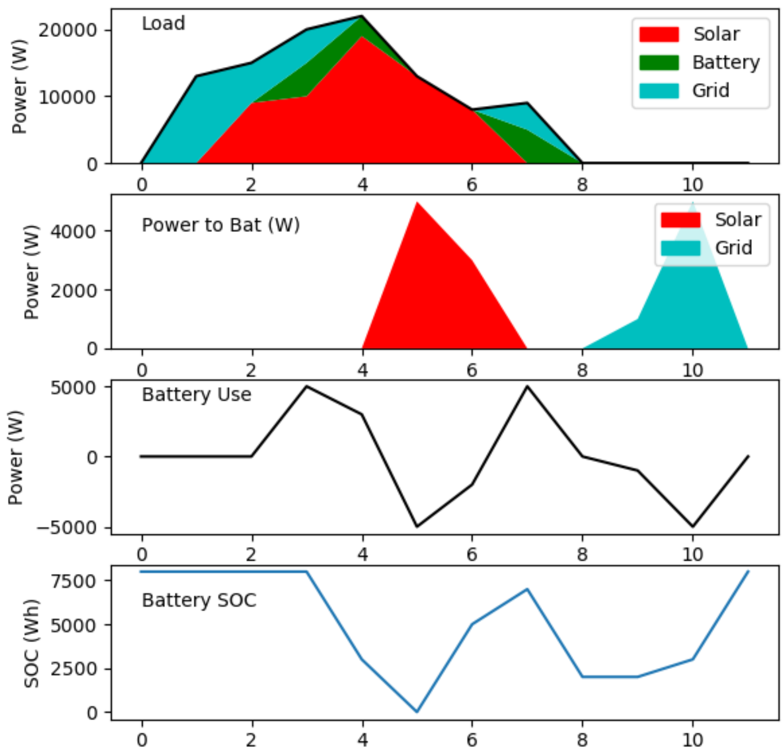

Figure 4: Load profile allocation among the three resources, along with the hourly battery use and state of charge. Note the additional use of the battery and the complete charging of the battery at the end of the day.