The Role of Demand Side Management in the Economics of Microgrids

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Abstract:

Microgrid design entails the selection and sizing of appropriate energy generation and storage technology to meet a known or proposed load profile. For traditional generation technology (i.e. thermal generating plants), it is well known that the incremental costs of meeting high peak demand is much higher than the average cost and hence negatively impacts microgrid economics. On the other hand, for microgrids with high renewable penetration, the situation is more complicated. The times of greatest resource constraint are generally not coincident with peak demand. In this study, we will discuss techniques of identifying the times of greatest resource constraint, methods of addressing them through efficiency measures and demand response, and the economic impacts of this approach. Studies to date have indicated that demand response programs that are implemented as little as 5% of the time can save nearly 50% in capital costs.

Introduction & Background:

In many respects, the process of microgrid design echoes the process that electric utilities have been following since Edison begin the first commercial operation in 1882[1]. With a knowledge of the load, the generation and distribution systems have to be sized to accommodate the worst case condition, the peak load. In addition, since the grid demand has historically been consumer driven, grid operators are required to provide a capacity surplus (operating reserve) to accommodate unanticipated loads and/or outages[2].

While the simplest solution would be a single power plant with nameplate capacity 10% higher than the known peak, this solution is also quite impractical for a number of reasons. Single large power plants typically don't follow load very well and new load is not easy to accommodate without significant capital expense for new plants. Utilities approach the problem with a fleet of generators with various characteristics. On one end of the spectrum are large thermal plants (typically coal or nuclear) that are expensive to build but can generate electricity at a relatively low per kWh rate. On the other extreme are single cycle combustion turbines that are capable of much better variable performance and can be built in small increments (10's of MW) with lower up-front costs but the variable costs are relatively higher. The optimal combination can be found using load screening curves that compare the annual load arranged from peak to valley (Load Duration Curve) with curves representing the variable and fixed costs of each generation technology.

One of the most consistent results of these economic optimization exercises is that the cost per kWh to meet peak demand is often much higher (integral multiples) than the costs to meet the so-called base load, or “always on” portion of the demand profile[3].

The concept of the microgrid has become a mainstream concept over the past two decades, largely driven by the potential for better integration of renewable resources and their inherent variability. The vast majority of the literature, and indeed, the experience of microgrids presupposes a tie to the larger grid, thus minimizing the need to provide 100% of the generation, capacity reserve and the additional constraints needed to maintain reliability[4].

Much has been written on relationship between microgrid control and cost of operations. An extensive review of the literature in this area can be found in [4] . The work by Chen et al. [5] presents an economic optimization with both renewable and traditional generators and Alvarez discusses a fast optimal dispatch scheme using a heuristic approach[6]. All of these works focus on optimization of the grid operation in the absence of Demand Response.

Several researchers have developed optimal approaches to microgrid operation utilizing demand response. Cha demonstrated a multi-agent control scheme utilizing fuzzy logic for both generation dispatch and demand response[7]. Korkas [8] looks and demand response and thermal energy storage while a discussion of DR and biomass generation can be found in [9] . These works contribute to the body of literature that is helping to define the economic value of demand response as an operational concept. However, the ability of DR to reduce capital cost is not considered in any of these.

The initial design of the microgrid is not often discussed, largely because it is considered as an add-on to an existing, and expansive electric grid. In other words, the microgrid contains the number and capacity of generation that happen to be installed and the challenge is to control the grid in such a way that minimizes overall cost, often dominated by power purchases from the larger grid. For stand-along grids, the design constraints are more demanding. One can approach microgrid design in a similar manner, but in the process, one discovers that the screening curve approach assumes that the operator has control of when and how much each generator produces. Such is clearly not the case for wind and solar resources.

Another approach to microgrid design would be to simply estimate (or measure) how many kWh are required in a given year, compare that to the typical solar and wind resources of the region and size the generation (solar panel array or wind turbines) so that the expected output meets the demand, plus some reserve to account for atypical climate and unforeseen loads. This approach is flawed because it rests on the assumption that the timing of the consumption is arbitrarily flexible and can be altered to accommodate generation. In fact, we find that a large portion of demand takes place when (and often because) typical renewable sources are not available.

In order to compensate for those times when the demand cannot be met with the solar and wind resources, energy storage is introduced to the system. Batteries are currently the most effective means of spreading the demand of the load throughout the day. This is true because that during the peak solar production hours of the day, an excess of electricity is produced. The batteries act as a buffer between the energy production, determined by natural processes and the load, determined by consumer behavior.

An important point in microgrid design with storage is to account for the performance characteristics of the batteries themselves. Even the best batteries have their limitations such as: the rate at which the batteries can fully charge may be too slow to capture all or even the majority of excess electricity, the batteries can only hold 100% of their charge for a certain time, a batteries condition (along with its effectiveness) deteriorates over time from use and operation, and even size, cost, and weight constraints. That last three constraints meaning that if there was a perfect battery, it wouldn't matter if one did not have enough room to store it, it cost too much, or if it was too difficult to handle due to weight.

The combination of variable generators (solar and wind) and storage adds complexity to the design scenarios. Like traditional grids, we find that an inordinate amount of cost is incurred in meeting a small portion of the load. However, unlike traditional grids, the timing of the load which has high economic impact is not when the load is at its peak. In fact, it's often at low-load times (pre-dawn) which occur during prolonged times of low resources (December/January in the northern hemisphere). Improving the economics of microgrids relies, in large measure, on the ability to identify and ameliorate these resource constraints.

In addition to the difficulty in meeting demand during low resource times, an even more subtle characteristic of microgrids should be addressed to maximize economic efficiency. Microgrids designed to meet a predetermined load while minimizing the levelized cost of electricity, as HOMER does, will nearly always produce significant amounts of electricity at times when there is no demand and no storage capacity. In other words, the 'excess generation' is simply wasted and the opportunity to make use of that resource is lost. This counterintuitive result emerges as a result of the relative costs of storage compared to PV panels. If the situation were reversed, excess generation would not be an issue. Nonetheless, a truly efficient use of resources should lead us to a microgrid design that minimize or eliminate excess generation.

This study will investigate these issues relative to two microgrid design problems. On a smaller scale, we will look to provide power for a small residence hall on a college campus. At a larger scale, we design a microgrid for a geographic region that is home to 14,500 people and a world-class winter resort. The impact of efficiency measures and demand response on grid economics and excess generation will be explored.

Methodology:

In this study, we will consider two microgrid design projects which span most of the scales encountered in potential applications. The smaller project is Morrison Hall (MH), a 72-bed residence hall located on the campus of Boise State University. The large scale project is an isolated region in south-central Idaho known as the Wood River Valley (WRV), home to approximately 14,500 people spread among the communities of Ketchum, Hailey, Bellevue and the Sun Valley resort. The two locations are separated by a distance of 125 miles and similar latitudes. They share nearly identical clearness index and daily radiation values allowing us to satisfactorily compare different designs regardless of the load profile.

To create our designs we utilized the Hybrid Optimization of Multiple Energy Resources program (HOMER) developed by the National Renewable Energy Laboratory (NREL). Given an annual load profile, wind and solar resource information and capital and maintenance costs for various generation technologies, HOMER searches the combinations of generation and storage options to find the solution with the lowest Levelized Cost of Energy (LCOE). Additional optimization and sensitivity analysis algorithms not only determine the feasibility and economics of the system to be considered, but allow the user to input variable costs [10].

The microgrid design process begins with knowledge of the electrical load that must be met. In HOMER the user must either enter in a weekday/weekend daily load profile for each month or import the load in the form of a file that defines the hourly demand for an entire year. Like most campuses, Boise State University has sub-metered most of its buildings, including Morrison Hall, so the load profile is available as a starting point. On the other hand, such a file does not exist for WRV and additional steps were taken to construct a useful load profile that is dependent on several drivers.

Load Profile Development for WRV:

The hourly demand profile for a group of customers being served by an electric utility comprises the proprietary information of each of the customers in the region. While it can be argued that releasing the aggregate data does not compromise the confidentiality of individual customers, many utilities are still reluctant to provide data this is not required by the regulatory bodies to be released. In such situations, other methods must be developed to obtain realistic load profiles.

Community leaders in WRV were able to provide minimal information regarding the load profile, namely that their region experiences a peak load of nearly 50 MW in the wintertime and just under 20 MW in summer. Using this as a starting point, we propose that the load can be decomposed into various subclasses, each of which follows a known pattern. The process then takes these various 'basis functions' and finds the relative weight of each component to find a load pattern that matches the information we have about the load.

For this region the following basis functions were considered:

- Baseload: Minimum continuous energy demand that must be supplied.
- Temperature: Accounts for the region's space conditioning needs.
- Business Hours: Takes into consideration the usage in the region on a normal business schedule, typically 9am-5pm.
- Residential Activity: That portion of the load due to discretionary activities in residences.
- Resort Activity: WRV contains touristic attractions, namely the Sun Valley Ski Resort, whose operational hours will greatly influence a portion of the load.

The process as to how the actual basis functions were created is summarized in the following paragraphs.

The baseload function will be a constant value for every hour of the year. During the hours of low electrical usage the total power may be near the baseload range but will never go below it.

According the U.S. Department of Energy, heating and cooling account for roughly 45-50% of the energy use in a typical building. For the WRV load, the average daily percentage of power due to space heating was at 47.6%, well within the DOE-anticipated range. The basis function for outdoor temperature was established by taking the difference between the 2015 NOAA-reported temperature for Hailey, ID (interpolated for hourly timestamps) and the nominal HVAC balance point, which is generally taken to be 65°F.

Business and residential basis functions were created by mirroring the daily load profile behavior of a typical office and residence. The different load profiles were obtained after plotting datasets containing a year's worth of hourly simulated data in MATLAB. Within those plots, Fig.1-2, each colored line represents a full day and facilitates seeing the day-to-day fluctuations that occur. Datasets for all typical meteorological year (TMY3) locations across the United States are publicly available through the Open Energy Information website.

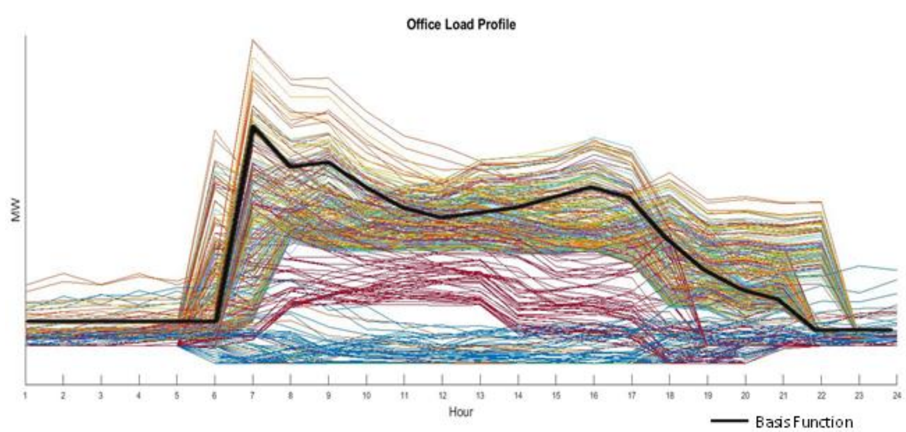


***Figure 1**: Basis Function for commercial load.*

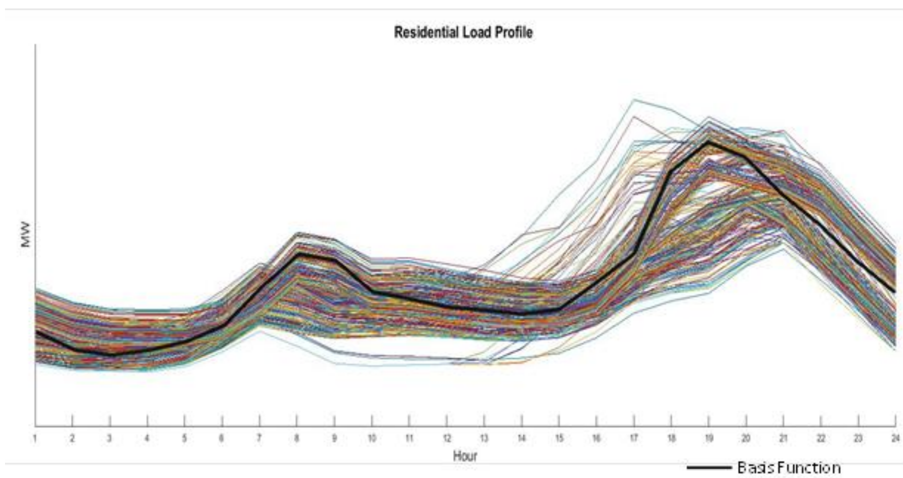


***Figure 2**: Basis Function for residential load.*

Given the lack of information surrounding the operating conditions of the ski resort, a negatively skewed distribution curve was created to peak during the afternoon. This was done to account for heavier usage of ski lifts and heavier traffic overall. An important assumption that was made for this function is the fact that it will be only applicable during the months of December – March, the typical skiing season.

To control the overall make up that each function had over the total power, a constant was paired with each basis function. Through trial-and-error and by evaluating the resultant load profile to similar profiles, the following average daily load profile was obtained.

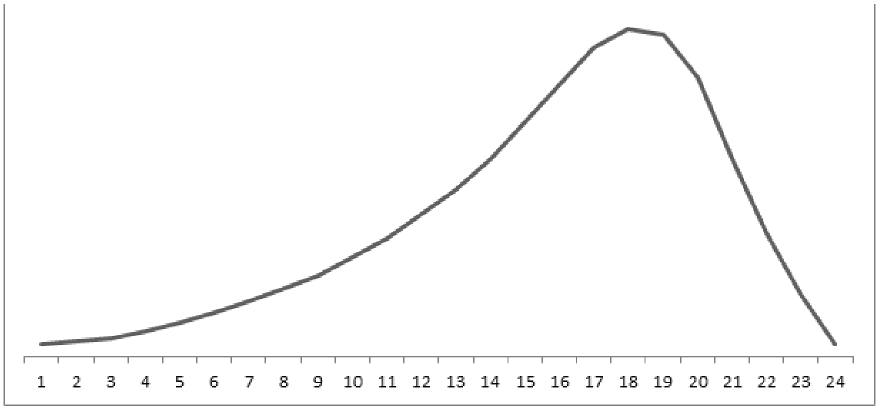


Figure 3: *Basis Function for ski resort.*

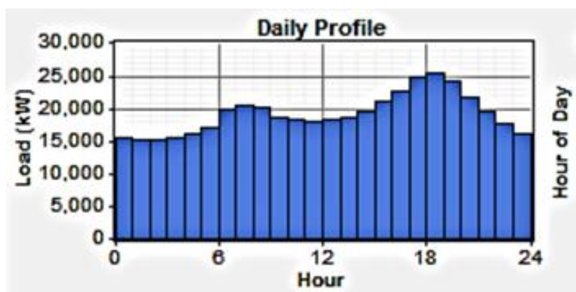


Figure 4: *Average Daily Load Profile for the Wood River Valley*

In addition to the load profile, HOMER offers a way to visually represent a year's worth of data that proved extremely beneficial for our methods. Known as a DMap, it contains 8,760 colored pixels that display the intensity of energy usage. Starting from the bottom left corner, our x-axis goes from Jan-Dec while the y-axis shows the time of day starting and ending at midnight. The DMap obtained appears to meet the conditions we know exist. The winter time peak is set in the afternoon hours in January and December (50 MW) while the summertime peak is met in the afternoon hours of June and July (20 MW). The variations in between are dominated by the ambient temperature and the operations of the resort.

Load Profile Development for Boise State University's Morrison Hall (MH):

A load profile for MH was recorded in 2015 via smart meter data taken in 15 minute increments, and so the process used for the WRV load was not necessary. In order to convert from 15-minute smart meter data to hourly data, the average of every four entries was taken resulting in the required 8,760 data points, which corresponds to the number of hours in one year.

As previously stated, MH is a small scale application design. That is easy to see when comparing population size, power consumption, square footage, peak loads, and peak load times. MH houses approximately 72 students in an intimate collegiate setting featuring mostly single rooms with some

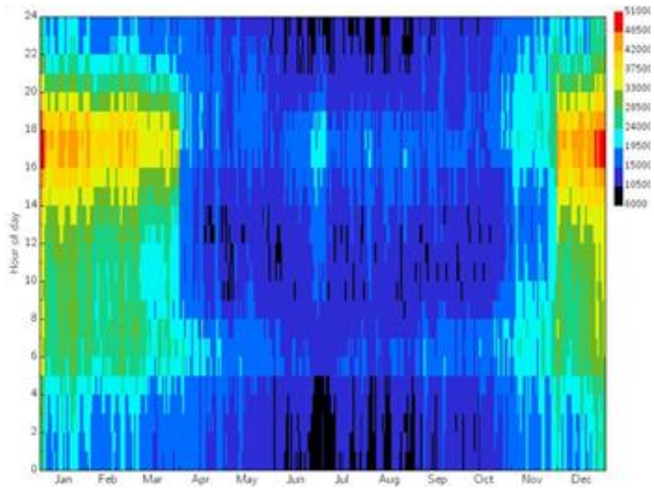


Figure 5: *DMAP representation of the hourly load for the Wood River Valley (WRV).*

double rooms, arranged in suites for 8 to 12 residents. In addition, there is a large main lounge equipped with study tables, a community recreation room, kitchen, and laundry room that are accessible to residents at all times. This accessibility paired with different class schedules across the entire day and offset sleep cycles results in load profile which is much flatter than typically encountered in residential or commercial settings, as seen in Figure 6.

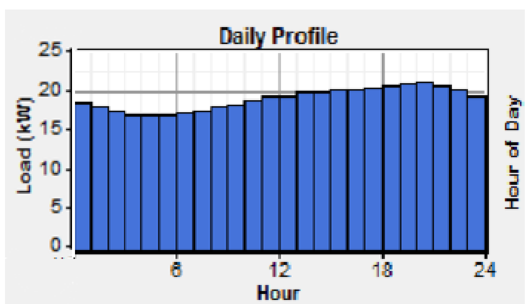


Figure 6: *Average Daily Load Profile for Morrison Hall*

Widening our range from a day to an entire year, one can clearly identify regions of concentrated demand that closely follow the academic calendar, Fig. 7. For example, starting in August there is a noticeable rise in power consumption that corresponds to residents moving into the dorm as well as to the warmest time of the year, requiring additional space conditioning. Other major school year breaks can be identified by the decline in demand during summer break, May-Aug, winter break, Dec-Jan, and even smaller breaks such as spring break and Thanksgiving break which occur in November and March respectively.

When comparing Fig. 5 and Fig. 7, the most noticeable differences are the different load concentrations. The load for WRV is concentrated heavily in the winter months, during the skiing season, and in the evening. The load for MH is more spread out throughout the year, but there is a distinct dip in the load around May, and in the early morning.

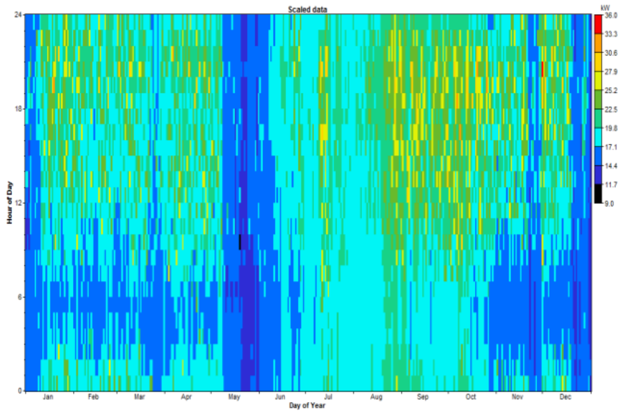


Figure 7: *DMAP representation of estimated hourly load intensity for Morrison Hall*

Design Scenarios:

The ultimate goal is to design a microgrid supplied by 100% renewable energy. However, to explore the potential for combined heat and power (CHP) applications, a design requiring on 67% renewable was also designed with the remaining load being supplied by a natural gas generator on the assumption that the gas generator would also supply some of the thermal load (which was not modeled in detail).

For MH and WRV, each design scenario was modeled with a small battery, the Tesla Powerwall 7 kWh, and a large scale battery the Cellcube FB 200-1600, which holds about 1600 kWh. The specifications of these two batteries were added to HOMER so that the program could choose the number of batteries each system would need. To adequately compare the economic impacts of each design, regardless of the renewable fraction, the same cost parameters and system configurations were used when applicable. When using the Cellcube, HOMER specifies that the converter must be modeled as 100% efficient and very large. However, for all other batteries, a converter efficiency of 85% was introduced as a more conservative constraint. The cost and performance assumptions for used in the HOMER models are listed in the appendix.

In addition, to designing microgrids to meet the loads, we explored variations on the design to explore the impact of both energy efficiency measures and demand response.

Under the category of Demand Response Scenarios (DRS) lie several cases that consider a combination of capacity reserve and capacity shortfall values. Capacity reserve is defined as a set percentage of the hourly load that will be always available to provide reliable service. On the other hand, capacity shortfall is the percentage of the hourly load where the system is not required to meet 100% of the electrical demand. The default setting in HOMER for an optimal system has a standard 10% hourly reserve with a 0% capacity shortfall. To see how DRS impacts the initial capital costs shortfalls of 0, 5, 7, and 10 percent with no operating reserve will be considered.

To determine whether DRS offered the most impactful decline in capital costs the results were compared to other common approaches taken to reduce power consumption. The Energy Efficiency Scenarios (EES) that were considered are as follows:

- Baseload Reduction: This approach identifies and eliminates a portion of the load which is constantly consuming power (i.e. turning off a light that is historically always on). To represent this effect, a set amount is taken off of each hour.
- Load Duration Curve (LDC): This method categorizes hours by their consumption rate and removes a portion from the largest hours effectively leveling off the upper portion of the LDC. This represents what utility companies do in an effort to reduce supplying peak demand power, which is often thought to be the most costly portion of the load.
- Overall Scaled Reduction (OSR): The fundamental principle of this approach is to simulate making an entire region/building more efficient and thereby eliminate the need to use as much electricity. To accomplish this, all hours of the year will be multiplied by a constant scaling the load by a predetermined amount.

To make the various scenarios comparable, the same number of kWh were removed from DRS and EES at each percentage (0, 5, 7, and 10). Because of this, all scenarios tested can be compared by looking at the LCOE.

Results:

As different scenarios were analyzed for WRV it was found that HOMER limits the overall number of batteries that can be modeled to 32,500 and thus, any design for the WRV utilizing a Powerwall with a 100% renewable solution was unfeasible. Ultimately, this was for the best seeing that for a 67% renewable solution with natural gas generators the cost of using Powerwalls would be approximately 15 times greater than using the Cellcube.

On the other hand, results for MH showed that the Cellcube quickly became impractical as the maximum capacity shortage percentage grew above 0%. The Cellcube was less expensive for a 0% capacity shortage system, but at 5% capacity shortage we see a drastic drop in initial capital using the Powerwall and only minor drops for the system using the Cellcube. To get the system to reach a 67% renewable fraction, to fulfill our first design criteria, HOMER rejected the Cellcube due to fact that the sheer size of the battery would not allow a renewable fraction of less than 71%. These two results were a clear indicator that the Cellcube was too large to use for the residence hall.

The following tables summarize the scenarios modeled along with their appropriate constraints.

Table 1: Optimized design *configurations* for the WRV using the Cellcube FB200-1600

Scenario	Operating Reserve (%)	Annual Capacity Shortage (%)	COE ($/kWh)
67% ren. solution w/natural gas generators	10	0	0.314
100% ren. solution	10	0	1.043
	0	0	1.039
	0	5	.761
	0	7	.691
	0	10	.621

Table 2: Optimized design configurations for MH using the 7kW/h Tesla Powerwall

Scenario	Operating Reserve (%)	Annual Capacity Shortage (%)	COE ($/kWh)
67% ren. solution w/natural gas generators	10	0	0.420
100% ren. solution	10	0	1.112
	0	0	1.111
	0	5	0.618
	0	7	0.553
	0	10	0.483

As seen in Tables 1-2, the biggest drop in the levelized cost of electricity occurs when there is a 0% operating reserve with a 5% demand response program in place. The percent change of each table beginning from Table 1 is 27% and 44% respectively.

Using the capacity shortfall constraint in HOMER can easily assess the impact of a demand response program, however, further investigation is required before an effective demand response program can be designed. To that end, the data are further analyzed to discover when in the year the DR program would have to be engaged.

Figures 8-10 show the D-MAP view of when and how much the DR program would have to be deployed throughout the year under the various scenarios.

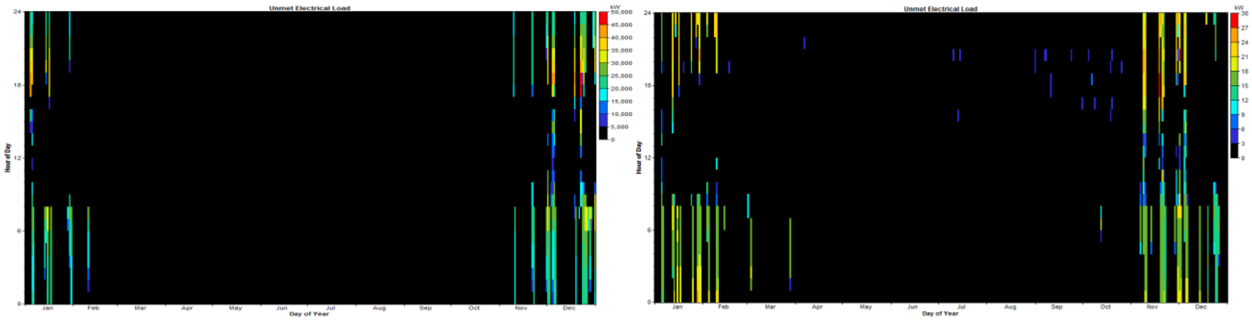


Figure 8: *Hourly occurrences where the load was not able to be met for a 100% renewable system with no operating reserve and an annual capacity shortage of 5%. WRV on the left, MH on the right*

The data were further analyzed using spider graphs, which focus on each particular month and easily shows the time of day that is most affected by load shortages along with how frequently those shortages occur (Fig. 11-18). January and May were chosen because out of all the months January changed the least, and May changed the most. For that reason, these months are the most interesting for us to study and use in example.

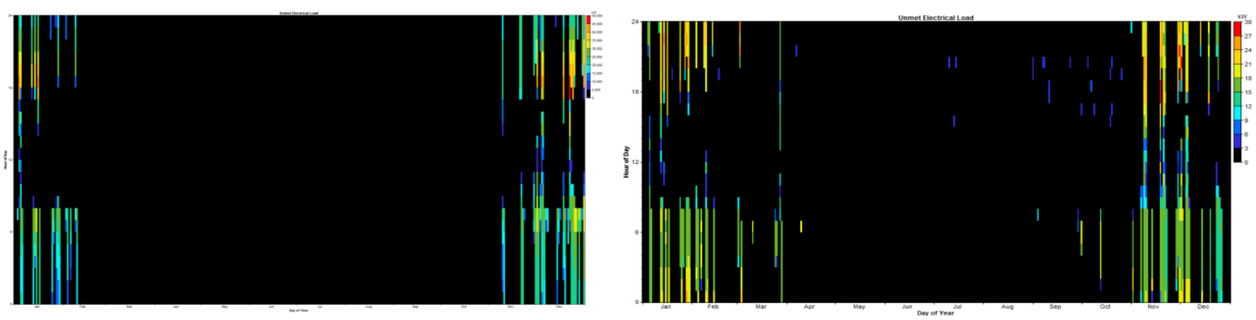


Figure 9: *Hourly occurrences where the load was not able to be met for a 100% renewable system with no operating reserve and an annual capacity shortage of 7%*

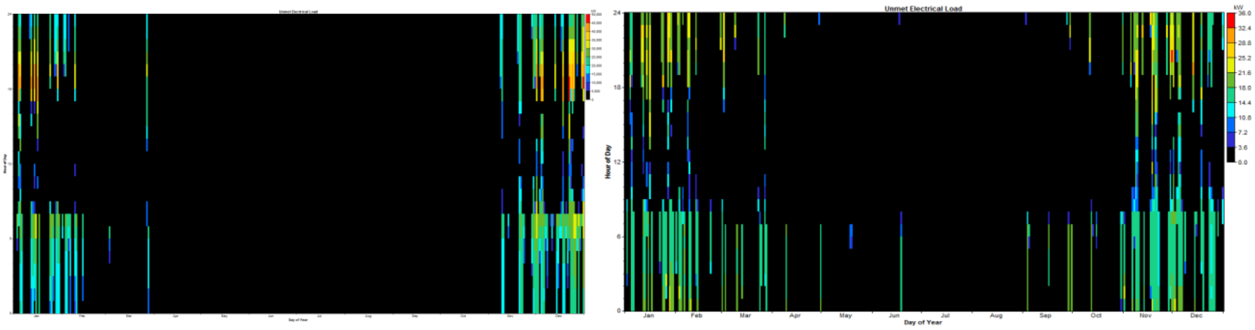
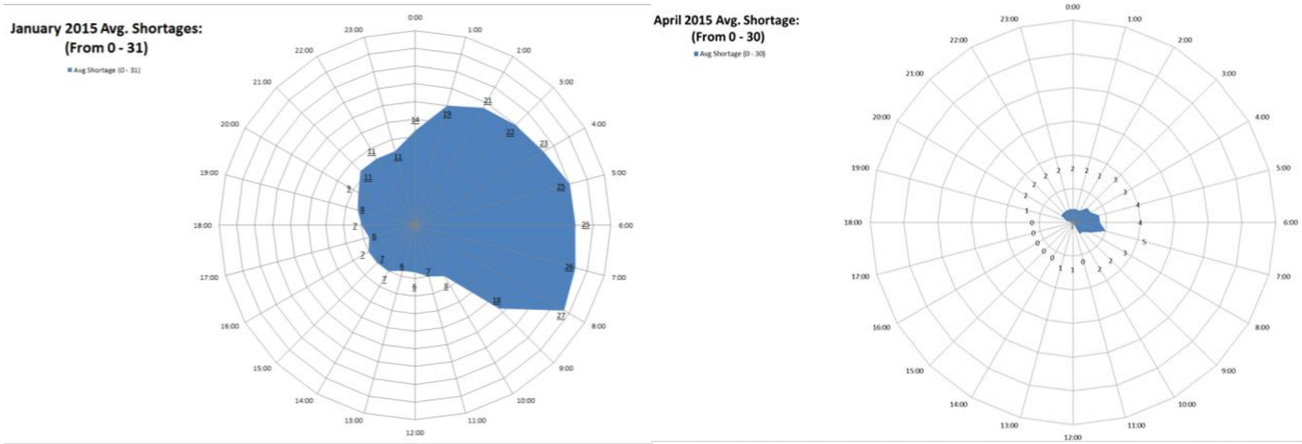
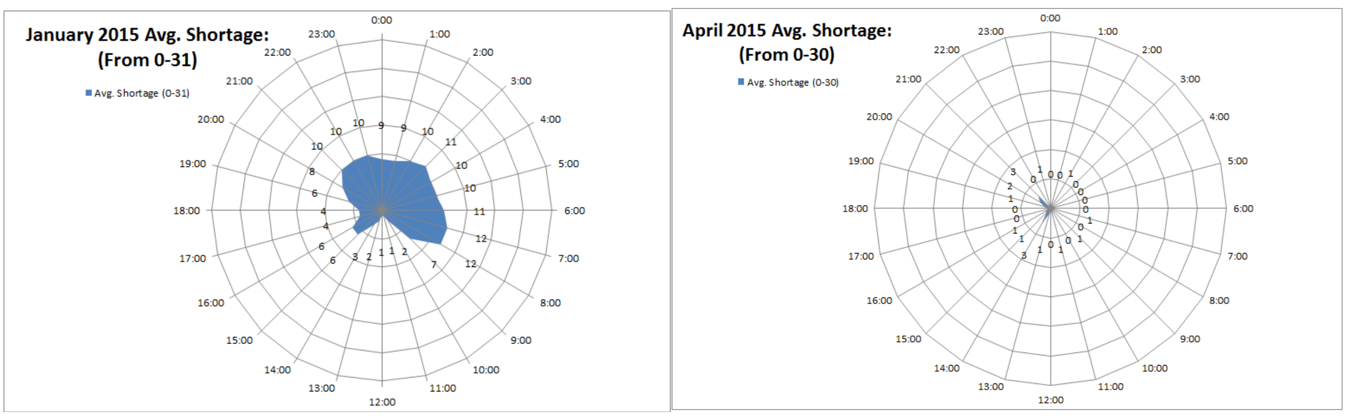


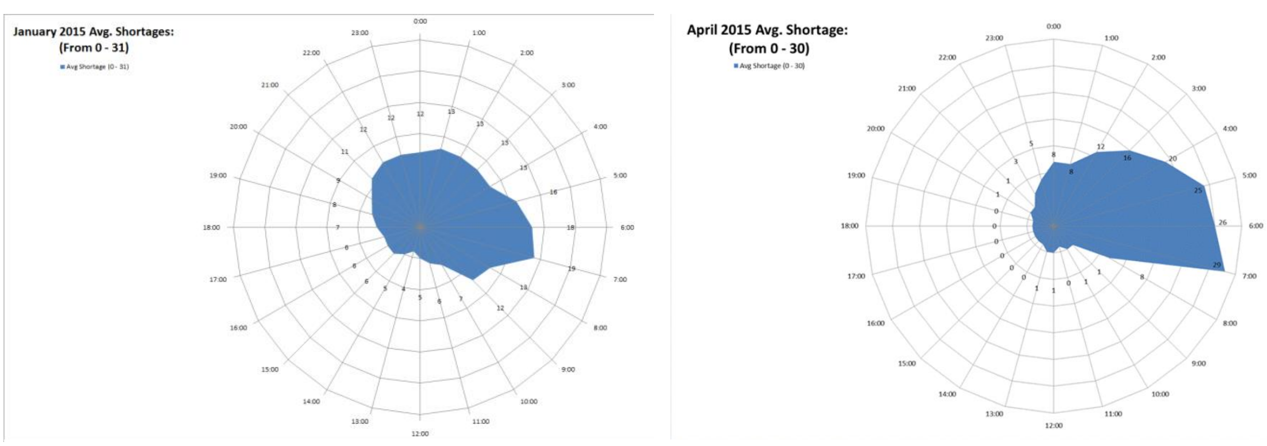
***Figure 10**: Hourly occurrences where the load was not met for 100% renewable system with no operating reserve and an annual capacity shortage of 10%*



Figures 11,12: *Number hours of unmet load in MH in January(L) and April(R) 2015, 5% shortage capacity.*



Figures 13,14: *Number of hours of unmet load in MH for January (L) and April (R); 7% shortfall*



Figures 14,15: *Number of shortages in MH in January(L) and April(R) 2015, 10% shortage capacity*

It was found that the main time that there was a shortage in power supply is during the early mornings between 1:00 A.M. - 9:00 A.M. as seen in Fig. 10-15, where the peak demand was during the evening at around 8:00 P.M. which is noticeable from Fig. 3.

HOMER finds the combination of resources in a user0defined search space that minimizes the levelized cost of electricity (LCOE). For renewable systems with minimal maintenance and no fuel costs, the combination that minimizes LCOE also minimizes capital costs for the installation. Figure s 16 and 17 show the LCOE for the various design scenarios for the WRV (Figure 16) and MH (Figure 17).

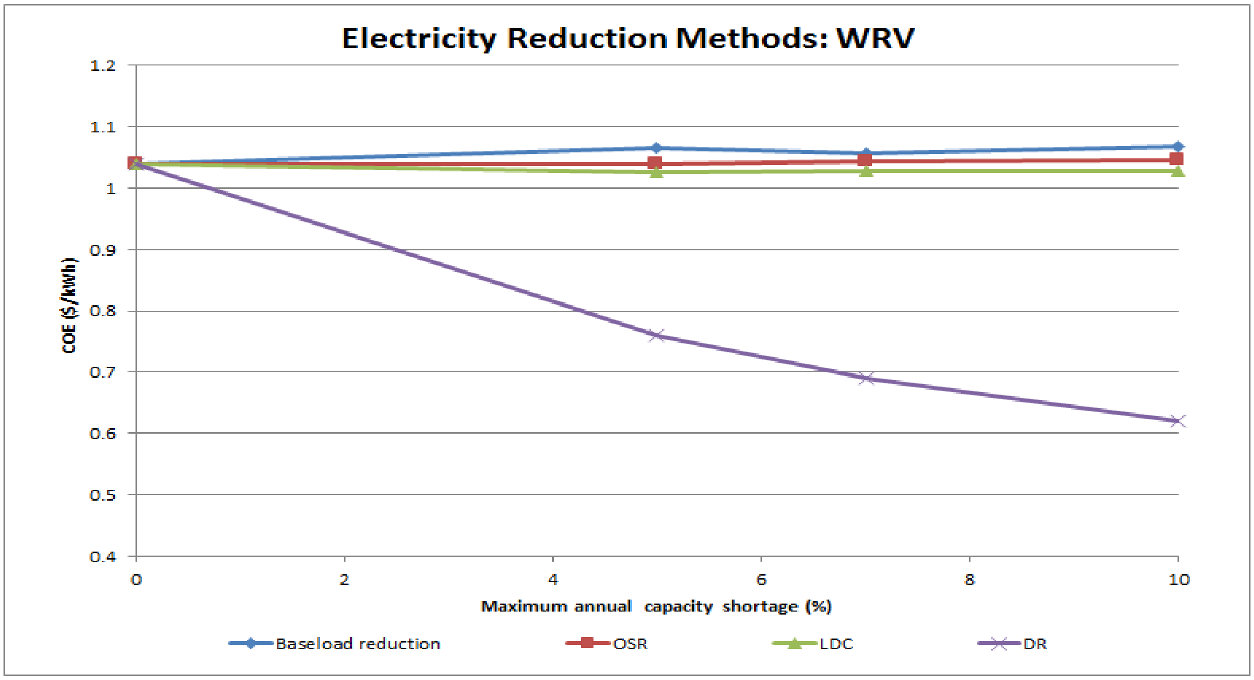


Figure 16: *Results of the four reduction methods on the WRV system*.

Note that both grid designs are nearly insensitive to attempts to decrease the load by traditional energy efficiency means that may lower the baseload, lower the peak demand or scale the entire load. This result, though initially counter-intuitive, is consistent with the results of the previous section that show that the constraining condition for the design is not related to the peak load.

The sensitivity to demand response focused on the hours of maximum constraint however, show a profound impact on the overall costs of the resultant microgrid.

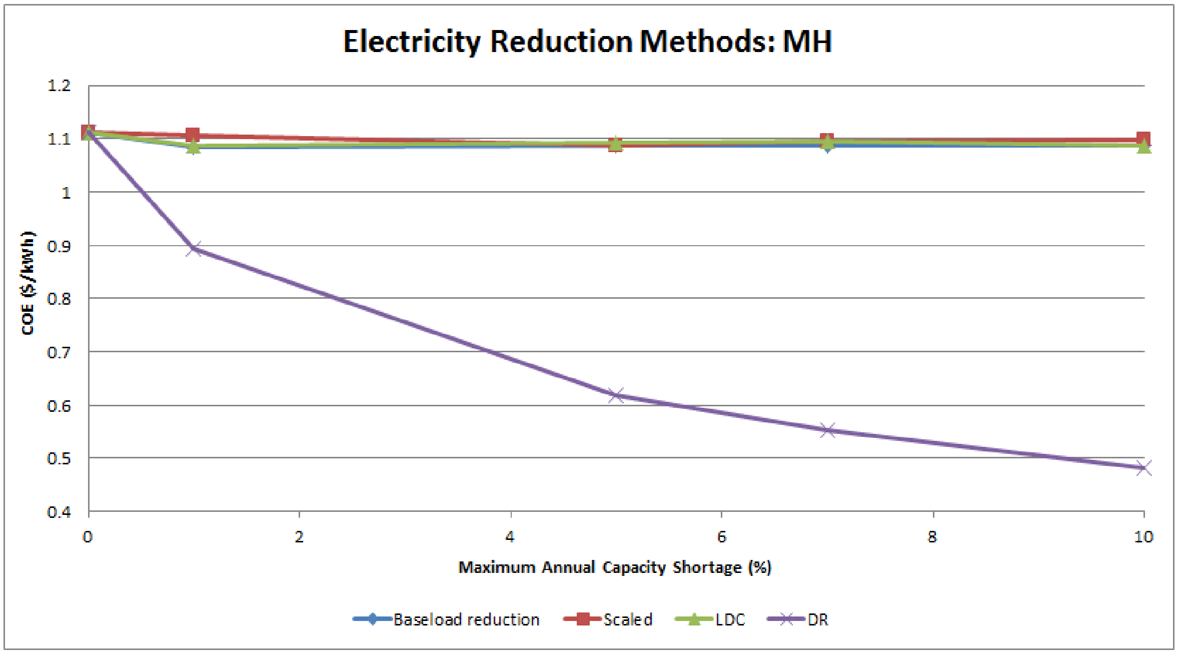


Figure 17: *Results of the four reduction methods on the MH system.*

Conclusion

The study reveals some very important implications for solar-based, islanded microgrid design. The most important result is that a well-designed demand response program can have a significant impact on the overall economics of the microgrid. A DR program that can shed only 10% of the load reduces the LCOE by as much as 40% (for the residence hall) or 56% (for the valley). Equally notable is that the impact of overall load reduction through traditional efficiency measures has minimal impact on the economics.

The study can also be used to inform the design of a DR program. In the case of the residence hall, the times where DR would have to be employed are nighttime hours in the winter whereas the peak load is clearly summer afternoons. This runs contrary to the traditional approach to demand response which is focused on shedding or shifting peaks. A campus or business that was serious about adapting to a more renewable energy supply might even consider changing their operations in such a way that minimizes the need for energy during the depth of winter. For example, a college campus could consider an extended winter break through much of December and January in favor of semesters that occupy more of the summer months.

On the other hand, the Wood River Valley microgrid design, while more sensitive to the DR scenarios, revealed a pattern that was somewhat less surprising. The demand response required to accommodate the capacity shortfalls had significant overlap with the peak consumption times. Given than peak consumption is largely driven by the ski resort, a significant economic driver, much more creative DR programs are called for than simple load shedding/shifting.

The sensitivity of microgrid economics to the timing of the load suggests that effective microgrid designs must include detailed understanding of the load being served and effective DR programs will be more complex and customized that those currently being considered.

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Appendix

Item	Quantity	Capital ($)	Replacement ($)	Operating & Maintenance ($/yr)
Cellcube FB200-1600	1	600,000	600,000	12,000
Tesla PowerWall	1	3,000	3,000	5

Item	Size (kW)	Capital ($)	Replacement ($)	Operating & Maintenance ($/yr)
Commercial PV System	1	2,500	2,000	1
Residential PV System	1	3,000	1,500	1
Converter used for PowerWall	1	525	212	0
Converter used for Cellcube	1	0	0	0