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Improved Air-Conditioning Demand Response of Connected Communities over Individually Optimized Buildings

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Abstract: Connected communities potentially offer much greater demand response capabilities over singular building energy management systems (BEMS) through an increase of connectivity. The potential increase in benefits from this next step in connectivity is still under investigation, especially when applied to existing buildings. This work utilizes EnergyPlus simulation results on eight different commercial prototype buildings to estimate the potential savings on peak demand and energy costs using a mixed-integer linear programming model. This model is used in two cases: a fully connected community and eight separate buildings with BEMS. The connected community is optimized using all zones as variables, while the individual buildings are optimized separately and then aggregated. These optimization problems are run for a range of individual zone flexibility values. The results indicate that a connected community offered 60.0% and 24.8% more peak demand savings for low and high flexibility scenarios, relative to individually optimized buildings. Energy cost optimization results show only marginally better savings of 2.9% and 6.1% for low and high flexibility, respectively.

Keywords: demand response; connected communities; building energy management systems; air-conditioning; coincidence factor; peak demand reduction; electricity cost reduction

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1. Introduction

The introduction of distributed energy resources (DERs), high levels of variable generation, and the common goal to reduce greenhouse gas (GHG) emissions have presented numerous challenges, both political and technical. Politically, local and national governments need to find a way to support lowering GHG emissions in a manner that is equitable to society [1]. Technically, there are an overabundance of improvements that are necessary to continue replacing fossil fuel generation while maintaining a reliable grid. The variable sources of renewable energy, solar and wind, have achieved competitively low costs in comparison to natural gas and coal; however, their impermanent and sometimes volatile nature still prevent a complete transition. Achieving this transition will not rely solely on advancements in solar and wind technologies, but more so on the creation of technologies and methods that make the grid more flexible [2]. A flexible grid can change its demand timing, plan for uncertainties, store energy, and take away many of the responsibilities that traditional generation creates. Ways of accommodating these variable sources are now being explored extensively by both utilities and the scientific community. These accommodations can take many forms including grid-connected equipment, modeling software, control schemes, and various combinations of these. One of the primary mechanisms in a flexible grid will be demand response (DR). DR is the management of the electrical demand for the purpose of meeting the goals of the supply side. DR encompasses a wide range of strategies involving different types of equipment, customers, and financial structures. It can be used in planned scenarios like peak shaving or congestion management [3], as well as to fulfill immediate needs like voltage regulation [4]. The capabilities of DR extend further through connectivity and data analysis, enabled by building energy management systems

(BEMS) and even more so in *connected communities*. Thermostatically controlled loads (TCLs) are one category of DR-capable equipment that holds a lot of potential, specifically heating, ventilation, and air-conditioning (HVAC) equipment.

Air-conditioning (AC) is one of the largest energy consumers and is projected to grow faster than all other uses of energy in buildings [5]. Heating and cooling loads have great potential as DR devices due to their inherent flexibility gained from the building's thermal inertia. The building acts as a thermal battery in which the minimum and maximum charge states, or the energy that can be manipulated, are determined by the thermal comfort region of the occupants. AC and other TCLs in buildings are already shown to have an impact in field experiments [6] and the DR market. Aggregators can manage many DR customers at once and sell their TCL's flexibility to the wholesale ancillary service market [7]. Modelling of TCL control and uncertainties for DR purposes has been extensively researched, showing its potential in many settings [8–12]. Through this research and many implemented projects, however, obstacles with AC DR have been discovered.

DR programs, through both aggregators and utilities. have been offered for several years. As such, they are an important potential asset to increasing renewable penetration and resolving grid-related issues. Therefore, it would be expected that the participation in these programs as well as the flexible capacity would grow, but this has not been the case. Customer enrollment in DR programs, between 2013 and 2019, for the commercial and industrial sector has decreased by 29% and 66%, respectively, and the actual peak demand savings have not grown in the U.S. [13]. For commercial and residential customers, AC is most likely the largest, and one of the only energy consumers that they can offer for DR. There are bound to be many reasons for such low participation, differing for each program, but little compensation along with unrealistic expectations are sure to be a cause. Commercial customers were paid on average 46.70/kW of actual peak demand savings or 1.05/kWh of energy savings in 2019 [13]. On top of this, customers are rarely called upon to provide DR. For thermostat programs, the average number of annual events is 8.9, with an average event duration of 2.6 h [14]. Such a small number of events may be necessary, as each event aims for each customer to shift a large amount of energy for the event duration. For AC, the average event duration is very long for the average building to mitigate usage, especially during the hottest times in the summer, when these events are called. Events can easily cause prolonged discomfort of occupants and could be the reason for such few events, saved only for the most critical times in the year. These high expectations of large energy shifting is a barrier to entry for the average building as well as a disincentive for those capable. In a high renewable penetration scenario, we would need to rely on DR daily and much more consistently through automated actions using building energy management systems.

To do so, AC DR needs to first transition to a more comfort-oriented position, allowing its utilization more frequently without contravening the customer. There are little known works focusing on comfort-oriented DR models; however, they show that significant load reduction is still possible for an aggregation of AC loads while minimizing the number of comfort violations [15]. Unfortunately, this route requires more data, better and simpler modeling, and a more connected structure, taking into account both the needs of the grid as well as the constraints of the customer [16]. Simplified building energy models that are data-driven are already proven to perform well against their physics-based counterparts [17,18]. The major missing elements inhibiting this reality are structure, both financial and control, as well as connectivity. There are many research-staged structures developed in the literature, resolving many of the issues discussed, while still being unique and prioritizing different objectives [19–22]. The benefits of connectivity, however, are relatively unexplored, especially for comfort-oriented control schemes.

BEMS are proficient in optimizing a building's AC energy consumption with respect to the utility rate structure and the inputted comfort settings. Its scheduled usage of equipment, however, may coincide with that of other surrounding buildings, diminishing its effectiveness from the perspective of the utility. The lack of connectivity between buildings creates random occurrences of high coincidence factors (CFs) within the population of the building. The CF is defined here as the percentage of the total population load that is active at any time. Connecting these buildings and making decisions with respect to all loads in the population creates a *connected community*. *Connected community* projects like the Alabama Power Smart Neighborhood are emerging across the U.S. and the results show great improvement in efficiency and capability to be driven primarily on renewable energy, storage, and natural gas turbines [23]. The connectivity of data from each building enables a centralized planning or agent-based system to coordinate with equipment and maximize efficiency for the entire micro-grid [24–26]. Many of these projects are based on residential buildings and most are using new construction with state-of-the-art systems (AC, lighting, etc.). It is difficult, however, to project these results onto the scenario of retrofitting existing buildings into a *connected community*. These projects mostly use the traditional AC planning scheme of peak/load shifting, pre-cooling buildings during solar hours, and riding through the evening. As mentioned earlier, this strategy is either infeasible or too undesirable for many existing buildings and occupants. A slightly different control strategy is introduced and applied in this paper.

This paper aims to answer whether or not a *connected community* offers better performance in peak demand and cost savings than individually optimized buildings. *Connected communities* with centralized decision-making may offer significantly improved benefits in certain areas of DR. BEMS have shown great results, but are blind to the operation of neighboring buildings, and it is questioned if this impacts the full potential of DR. In other words, the savings potential of a single optimized schedule for all cooling loads in a population is expected to be significantly greater than that of several individual (per building) optimized schedules. In this paper, simulation results from EnergyPlus are used to outline the capabilities and needs of a population of buildings and constrain the optimization models. The optimization models are based around a more comfort-oriented control strategy that requires very little individual load flexibility. This work will also show how individual flexibility affects the results between the *connected community* and individual BEMS.

This work contains many sections from this point on. First, all simulations and parameters used in the study are justified in Section 2.1. The following Section 2.2 describes the control scheme used in all optimization models in this paper. Section 2.3 defines the optimization models used for both the peak demand minimization and the cost minimization. The results are separated into two main sections, Sections 3.1 and 3.2. Each of these sections contains the baseline demand for the group of buildings and two optimized solutions, one for individual BEMS and the other for the *Connected Community*. Sections 4 and 5 includes insights obtained from the analysis and concluding remarks on the findings.

The main scientific contributions of this study are as follows:

- Effectiveness of a high-resolution demand planning control scheme for air-conditioning demand response for a range of building zone flexibilities;
- Theoretical demand reduction improvement potential of *connected communities* over individual BEMS for a range of building zone flexibilities;
- Theoretical nodal cost reduction improvement potential of *connected communities* over individual BEMS for a range of building zone flexibilities.

2. Materials and Methods

This section covers the methodology used for estimating the potential savings, both peak demand and cost, from the optimization models proposed. This includes an explanation of the data used for the constraints as well as the baseline energy consumption and cost. The control strategy implemented in the optimization, as well as the full mathematical formulation, will be explained thoroughly.

2.1. Description of Simulation Data

EnergyPlus is an open source building energy modeling engine developed by the U.S. Department of Energy (DOE). The buildings used in the simulation come from the

Commercial Prototype Building Models published by the DOE. The set used here is from the ANSI/ASHRAE/IES Standard 90.1-2019 prototypes [27]. These are designed with the construction and AC equipment based on data for buildings in the U.S. in 2019. A variety of building types were used in the model with the number of each type varying to create a community of buildings. Specifications on the buildings used can be found in Table 1.

Table 1. Building prototype specifications.

Building Type	Zones per Building	Buildings in Model	Total Zones
Full-service Restaurant	2	3	6
Small Office	5	7	35
Medium Office	3	1	3
Large Office	4	1	4
Strip Mall	10	1	10
Hospital	8	1	8
Large Hotel	10	2	20
Secondary School	9	1	9
Total		17	69

The simulations were conducted for 1 June 2019 for the whole 24-h period in Phoenix, Arizona, using the typical meteorological year 3 (TMY3) weather-file from Sky Harbor International Airport. We used 1 June as it has high peak temperature and solar insolation, as well as a low-enough minimum temperature that it is close to the comfort regions of the building. A 24-h period was used and seen as the maximum feasible planning period that is useful for demand response planning. Operating under independent system operators (ISOs), day-ahead pricing, and therefore planning, is very common. Run-times shorter than 24 h could also be considered in later studies, for example, to target peak-pricing periods in the day. This generates the scenario of a very high ambient temperature and solar insolation during the middle of the day, where AC must be used near capacity in many cases. The simulation was run considering 1-min time intervals, capturing a high-resolution AC energy profile for every zone. Each zone is either maintained by an independent source of cooling or a shared or centralized source. EnergyPlus results can show how much cooling energy each zone is responsible for, even for centralized cases. Most loads in the model are variably controlled and few are simply on/off operation. Figure 1 shows the baseline demand profile broken down by building type.

The variety of buildings leads to a mix of unique energy profiles, half of which do not operate for the entire day (small office, medium office, strip mall, secondary school). Many of these loads increase at different times in the day, for example, hotels peak much later in the evening than most buildings, most likely due to their housing nature. The secondary school is the second largest load in the community, but is not active all day, causing the aggregate load to drop significantly at 8:00 p.m. The number of buildings (of certain types) was increased for small load buildings, to have an aggregated load and energy cost that was not insignificant in comparison to the community. Figure 2 shows the distribution percentage of the peak demand (left) and the day's energy cost (right).

Not every building or load peaked in demand at the same time. Figure 2 (left) represents the distribution when the aggregate signal was at its highest during the day or the aggregate peak demand for the day. Although small offices have the highest number of buildings, as well as zones, they only account for 5% of the peak demand. On the contrary, the hospital and secondary school are responsible for nearly 60% of the peak demand, but only have 16% of the zones. For the most part, the energy cost distribution is reflective of the demand distribution with some significant changes.

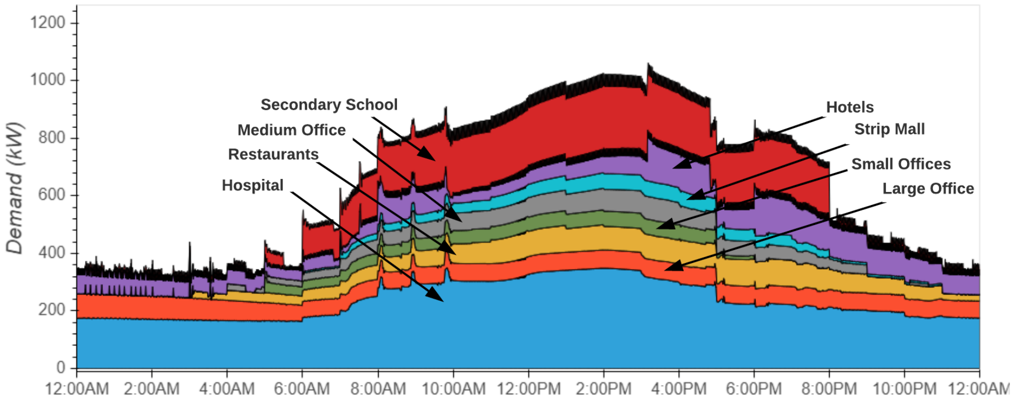

Figure 1. Baseline demand profile broken down by building type for 1 June 2019 in Phoenix, AZ, USA.

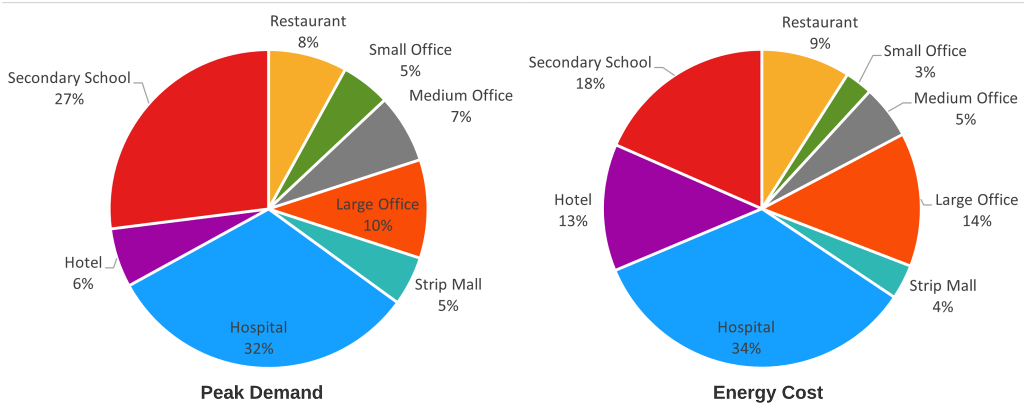

Figure 2. (**left**) Demand distribution for aggregated peak demand by building type for 1 June 2019 in Phoenix, Arizona, U.S. (**right**) Energy cost by building type for 1 June 2019 at node MESACAL 6 N004.

Two buildings see major differences from the peak demand pie graph to the energy cost pie graph. The secondary school accounts for 27% of the peak demand but only 18% of the energy cost. The hotels account for only 6% of the peak demand but are responsible for 13% of the cost. This is due to their very different profiles, where the school operates only in the middle of the day, hotels have their peak demand in the evening. A locational marginal price (LMP) node was chosen arbitrarily from the California Independent System Operator (CAISO) database. An LMP indicates the wholesale cost of electricity at a specific node in the grid. The LMP is a combination of three cost components: energy, congestion, and losses. Energy costs are primarily determined by the contracted generation sources, while congestion and losses are determined by network conditions and the flow of electricity. The node chosen was MESACAL 6 N004, and is near Los Angeles, California. California utilizes more renewable electricity generation and is thought to better represent a high-renewable-penetration scenario of nodal pricing. The 15-min ahead LMP price data for 1 June 2019 was taken to calculate the cost of electricity for the day. The baseline model, for all buildings, cost USD 416.60 for the day. Looking at the LMP for the day in Figure 3, it is apparent why the hotel has an inflated price and the school has the reverse.

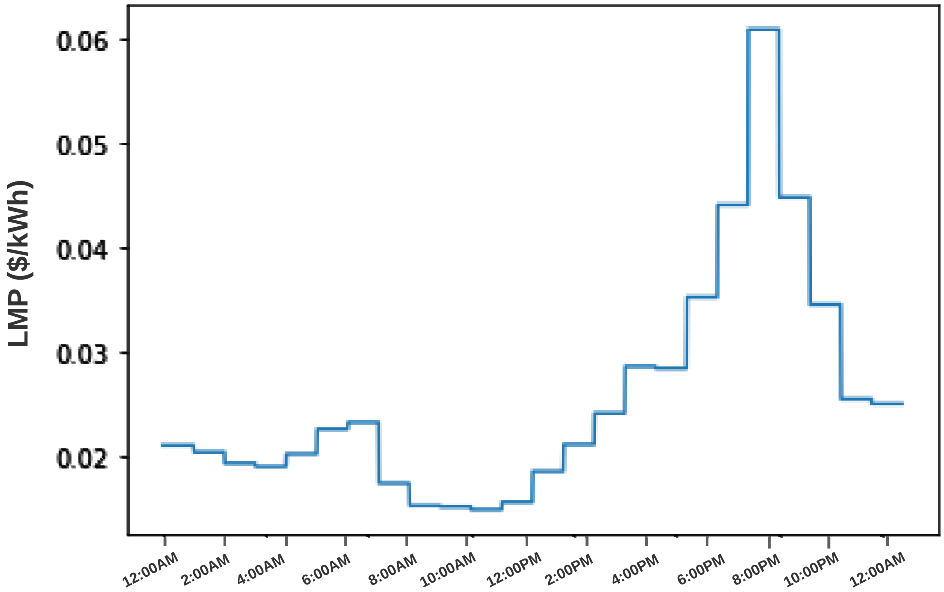

Figure 3. LMP for 1 June at node MESACAL 6 N004.

This price curve has the characteristics of the "duck curve" with its small hump in the morning followed by a dip and then an extreme ramp up to the peak in the evening. A profile shape similar to this can be expected for higher renewable scenarios; however, the minimum and maximum price contrast could extend further as more solar power is connected to the grid. Demand response, like AC management, has the potential to take advantage of these price differences throughout the day. The following section explains a control strategy that could be used for both peak demand reduction and energy cost reduction.

2.2. Control Strategy

For any number of loads, the coincidence factor (CF) describes the percentage of the full load that is in demand at any point in time. Most electrical loads will operate at partial loads, however, throughout time, high points in some loads coincide with high points in others, creating an unnecessarily high CF. In the case of AC, the CF can change drastically from one moment to the next, especially for a population of systems that have on/off operations. This is still true, but less so, for variable systems. High CFs in a population of AC equipment are, of course, very dependent on the ambient conditions of the buildings, as well as lighting, occupancy, and indoor equipment. They are also, however, caused by the lack of communication between systems. BEMS have introduced this communication within buildings for many years now, proving its capability to manage a network of AC equipment for demand response, and still has new methodologies being introduced to improve them [28–31].

In this paper, managing CF takes a different perspective on traditional load shifting strategies. The control strategy used in this paper will be referred to as coincidence minimization (CM), which is a high resolution optimal scheduling strategy. Traditional load shifting for AC has always sought to displace large amounts of energy, and thus, demand, outside of certain relatively large time regions. It is common in electricity demand response-related literature for studies to be conducted in hourly or even in 15-min intervals [31,32]. This involves buildings having extremely wide ranges of thermal comfort so that they can be pre-cooled and then passively heat up during critical times. This form of demand response is only plausible for buildings with extreme amounts of flexibility. CM only requires a small amount of flexibility to be used as a control strategy, but is, of course, much more complex in scheduling. Load shifting is typically controlled using hourly time intervals, which is in line with how most pricing schemes are established, while CM relies on time intervals as small as one minute. Load shifting and CM follow the same general concept of displacing some load and compensating it elsewhere, however, the high resolution of CM allows for smaller load shifts to smaller time shifts. There are very few studies in the literature that use intervals smaller than 15 min in this field [33–35]. Two studies utilized 5 min intervals in order to operate with the real-time energy market both for market-clearing and household scheduling [33,34]. This makes it possible for less flexible buildings to participate in demand response and still provide significant impact without compromising comfort. The scheduling is optimized using a mixed-integer linear programming (MILP) model. MILP models have been used extensively for solving scheduling problems related to energy and demand response [36–40].

The flexibility term used in this work is based on an energy budget dictated by the simulation results. Flexibility is defined differently in many published works but its basic concept is the same [41–46]. The flexibility of an electrical load is a user-defined attribute describing its ability to be manipulated. In this work specifically, the flexibility will be defined as the maximum allowable deviation from the simulated building's baseline energy consumption per zone. This energy range is essentially an energy budget that the model cannot go over or under. This is depicted in Figure 4.

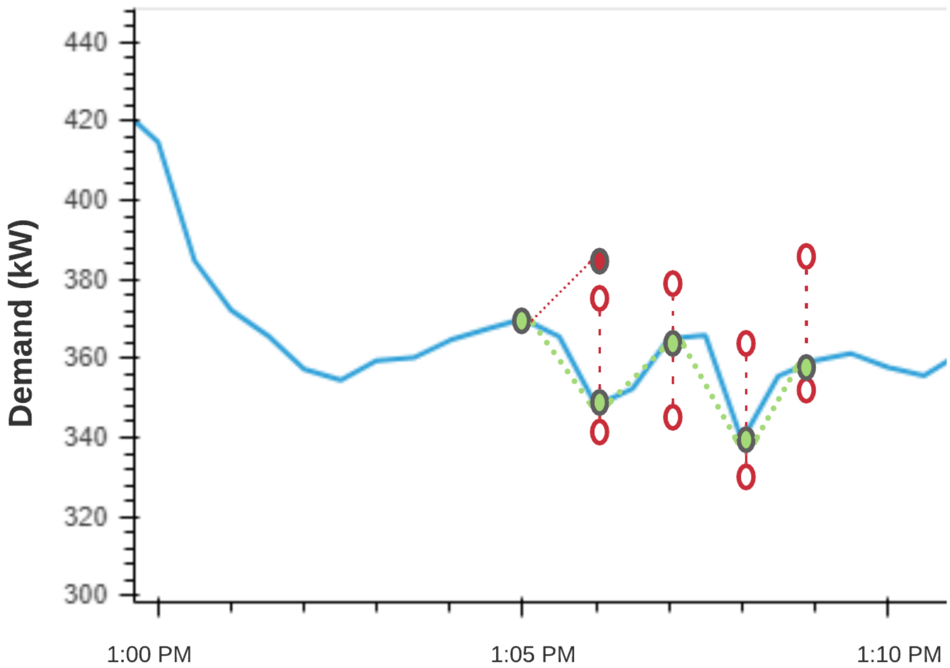

Figure 4. Example of energy budget used in model formulation.

In Figure 4, the energy budget range is indicated by the space between the two hollow red circles for each time step. This range is determined by the difference in the energy consumption of the model versus the baseline, as well as the flexibility value. At any point the energy consumption of the model could be less than or greater than the baseline. The allowable difference from the baseline is determined by the flexibility. Thus, the available decision space is dependent on both the allowable difference as well as the model's current position in energy consumption with respect to the baseline. Both the individual BEMS and *connected community* cases will have a decision for each 1-min interval and have the same operational capabilities as one another. The green filled circle in Figure 4 indicate the decision made by the optimization, and thus, the demand. The red filled circle is an example of a decision in which the demand exceeds the allowable energy budget for that time. These red hollow circles represent a major constraint in the optimization problem. The energy budget for each time step is constantly changing depending on the previous demand decision as well as the demand from the baseline data. It is assumed that if a model with low flexibility abides by the energy budget, that comfort violations are unlikely based on the fact that the baseline profile guarantees comfort. A low flexibility model will follow the baseline quite closely with minor adjustments avoiding unnecessary coincidences in demand. How the energy budget and flexibility are used will be explained more in the mathematical formulation section.

2.3. Mathematical Formulation

This section describes the optimization models for both the peak demand minimization, as well as the energy cost minimization. Both models will use the same CM control strategy and be solved for a range of individual flexibility values.

2.3.1. Peak Demand Minimization

The goal of the peak demand minimization model is to minimize the highest value of the aggregate demand,

$$\textit{minimize}\ P \tag{1}$$

where P is the peak demand (kW). The following constraint implies that P is dependent on the variable set $D_{z,t}$:

$$P \geq \sum_{z=1}^{Z} D_{z,t}, \qquad \forall t \tag{2}$$

where $D_{z,t}$ is the decision variable for demand for each zone z and time interval t. $D_{z,t}$ is a semi-continuous variable which can be written as $D \in 0 \cup [lb, ub]$. This means that $D_{z,t}$ can equal 0 or any value between lb and ub. This is tied to the loads' operational constraints. AC equipment will typically have minimum operating loads which are represented by lb. The load will have to go to zero if it needs to go below lb, and of course, there is an upper bound, ub, representing the maximum loading. lb and ub were determined from the prototype models that generate the data, and loading that was due to obvious inrush current was not considered as ub.

Zones are categorical, so the summation includes all zones within the building for the individual BEMS optimization, and all zones entirely for the *connected community* case. This is strictly the only difference in the optimization models between the two cases. This forces P to equal the maximum value of the aggregate demand found in all time intervals. The rest of the following constraints focus on constraining $D_{z,t}$ further. The first constrains $D_{z,t}$ within the energy budget range as shown in Figure 4:

$$f_l \times EB_{z,t} \leq EM_{z,t} + D_{z,t} \leq f_u \times EB_{z,t}, \qquad \forall z, t \tag{3}$$

where $EB_{z,t}$ is the energy consumed by the baseline for zone z at time t, $EM_{z,t}$ is the energy consumed by the model for zone z at time t, and f_l and f_u are the lower and upper flexibility values, respectively. Flexibility values will vary between $\pm 0.5\%$ and $\pm 10\%$. For example, a flexibility of $\pm 10\%$ makes $f_l = 0.90$ and $f_u = 1.10$. The next equation simply ensures that the total energy from the baseline and the model are equal by the end of the day:

$$EB_{z,T} \equiv EM_{z,T} \qquad \forall z \tag{4}$$

where T is the last time interval to be scheduled. As mentioned previously, the energy budget is also determined by the previous decisions of the model which are reflected in $EM_{z,t}$:

$$EM_{z,t} \equiv EM_{z,t-1} + D_{z,t-1} \qquad \forall z, t \tag{5}$$

The next constraint is strictly to control the variability of the decisions. Without it, there is no deterrent for the signal to ramp up and down at extreme rates. This is imposed on the aggregate signal rather than the individual zones z:

$$C_l \times \sum_{z=1}^{Z} D_{z,t-1} \leq \sum_{z=1}^{Z} D_{z,t} \leq C_u \times \sum_{z=1}^{Z} D_{z,t-1} \qquad \forall t \tag{6}$$

where C_l and C_u are the lower and upper control fractions. It was found that a C_l of 0.97 and a C_u of 1.03 were suitable, controlling the variability without making the problem infeasible. Greater values showed repeated spiking both upward and downward in demand that was unnecessary. There were a few cases in which $\sum_{z=1}^{Z} D_{z,t-1} = 0$, specifically for buildings that did not operate the entire day. In this case, a very small constant was added to the term $C_u \times \sum_{z=1}^{Z} D_{z,t-1}$ only to start operating. Most loads continued operating after starting.

To summarize, the peak demand minimization model formulation can be simplified as minimizing Equation (1), subject to constraints (2)–(6).

2.3.2. Energy Cost Minimization

A locational marginal price (LMP) node was chosen arbitrarily from the California Independent System Operator (CAISO) database. The node chosen was MESACAL 6 N004, and is near Los Angeles, California. The 15-min-ahead LMP price data for 1 June 2019 was taken to calculate the cost of electricity for the day. The baseline model for all buildings cost USD 416.60 for the day.

All constraints for the energy cost minimization model are the same as the peak demand minimization model, excluding Equation (2). The objective equation is the primary difference:

$$min \sum_{t=0}^{T} \sum_{z=1}^{Z} LMP_t \times D_{z,t} \tag{7}$$

where LMP_t is the LMP for time t.

To summarize, the energy cost minimization model formulation can be simplified as minimizing Equation (7), subject to constraints (3)–(6).

3. Results

3.1. Peak Demand Minimization

The first important result is to show the difference in management of the loads throughout the day for all three cases: baseline, individual BEMS, and *connected community*. Figure 5 shows a comparative graph of demand profiles from the optimization models.

The individual flexibility had a large impact on the demand reduction for both the individual BEMS and *connected community* cases. The individual BEMS case was capable of reducing the peak demand by 6.8% in the low flexibility case ($f = \pm 1\%$). This increased significantly to 23.3% peak reduction for the high flexibility case ($f = \pm 10\%$). In comparison, the *connected community* substantially outperformed the individual BEMS in the low flexibility case, attaining a peak reduction of 17.0%. However, the performance difference is not so drastic in the high flexibility case. The *connected community* reduced its peak demand by 31.0%, only 24.8% better than the individual BEMS. This is quite the contrast to the 60.0% increased performance seen in the low flexibility case.

In both flexibility cases, the *connected community* schedules more energy consumption prior to the peak demand. This is equivalent to a small amount of pre-cooling, a typical load-shifting strategy. The effect of the increased energy budget in the high flexibility case can be seen, with both the *connected community* and individual BEMS having a larger amount of energy consumption, higher than the baseline before 8:00 a.m. With low flexibility, both optimal schedules follow the baseline energy consumption closely after the peak demand. With high flexibility, the optimal schedules both allocate significant increased energy consumption after 8:00 p.m., which is previously a region of very low demand for all cases.

To further investigate these changes in performance, the optimization was run for several different flexibility values between $f = \pm 0\%$ to $f = \pm 10\%$. The results are shown in Figure 6.

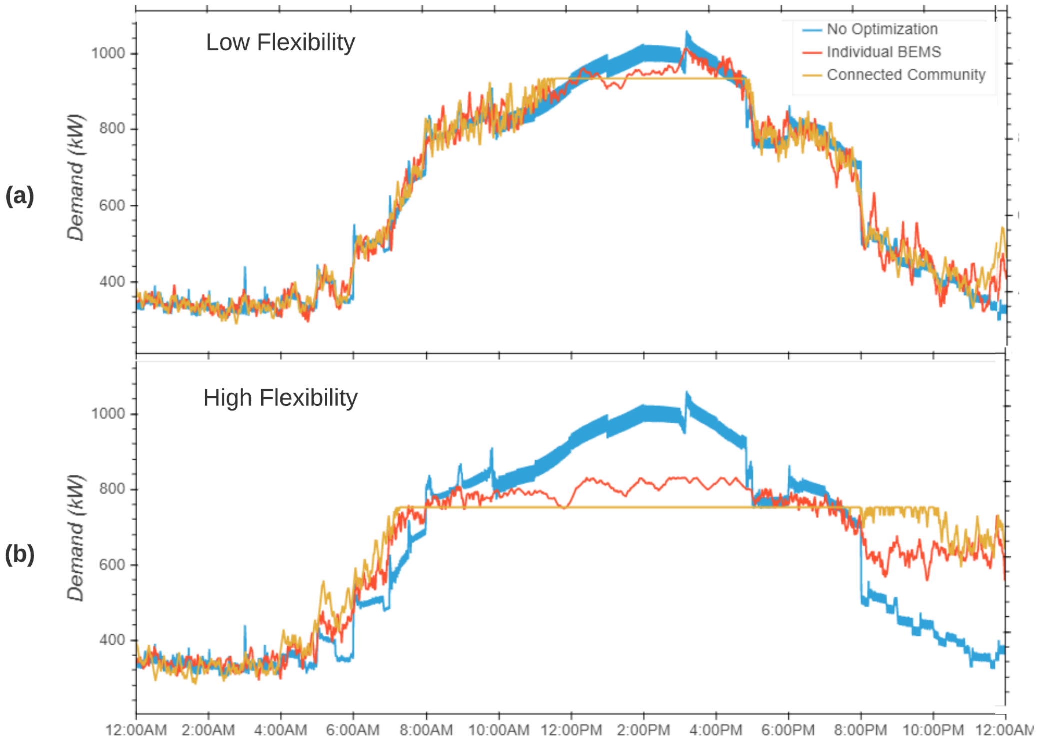

Figure 5. (**a**) Baseline and optimized (for peak demand) demand profiles under low flexibility ($f = \pm 1\%$) conditions. (**b**) Baseline and optimized (for peak demand) demand profiles under high flexibility ($f = \pm 10\%$) conditions.

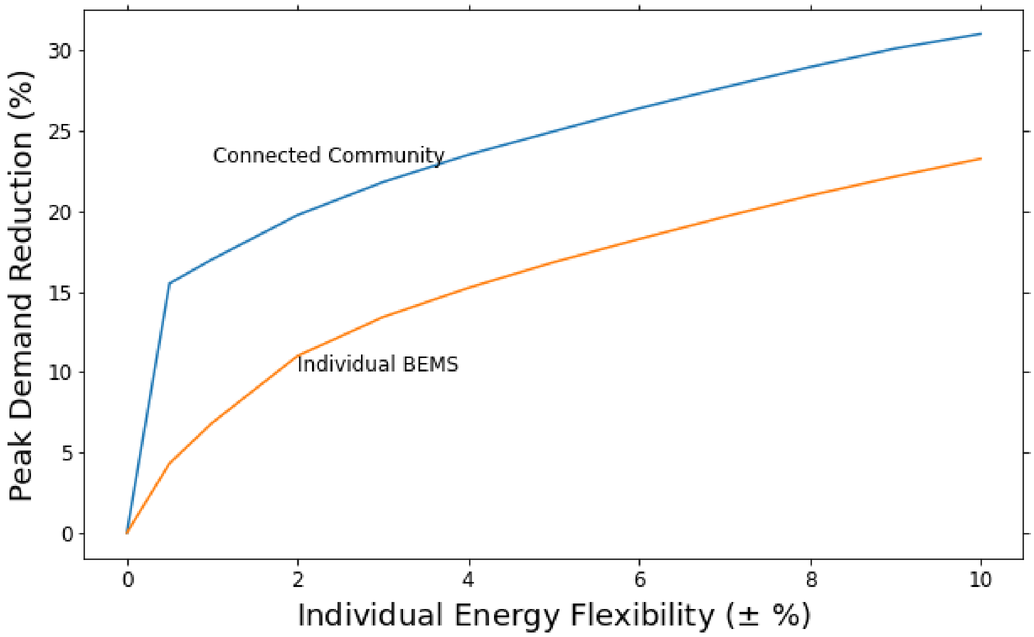

Figure 6. Peak demand reduction in individual BEMS and a connected community as a function of individual zone energy flexibility.

As depicted by Figure 5, there is a significant difference in the initial jump in demand reduction for the two cases. The individual BEMS slowly gets closer to the *connected community* reduction as flexibility increases. This makes sense because in a case where all the energy is flexible, the optimum result would be a flattened demand equal to the average demand of the baseline. This is the absolute minimum demand with complete flexibility. This would be achieved by both the *connected community* and the individual BEMS optimization. The *connected community* can manipulate all the loads to make a flattened demand. In the individual cases, the result of each optimization would be a flattened demand of that building. Aggregated, this would be equal to the average demand of the group, and result in the same answer.

For the *connected community* to achieve an aggregated peak demand that is lower than the baseline, there is a higher number of choices than individual BEMS. For example, the *connected community* may force a particular building's loads to all increase in demand to 100% CF in preparation for mitigating the group's demand later. This would go against the objective of the individual BEMS. Closer inspection of the individual building controls that were applied was performed, and the peak demand of each building for every case is displayed in Table 2.

Table 2. Individual building performance for peak demand minimization (C.C. = Connected Community).

Building Type	Baseline	Demand (kW)			
		C.C. ($f = 0.01$)	BEMS ($f = 0.01$)	C.C. ($f = 0.01$)	BEMS ($f = 0.01$)
Full-service Restaurant	129	99	84	96	72
Small Office	56	56	49	56	42
Medium Office	79	81	72	81	57
Large Office	85	109	83	109	75
Strip Mall	71	55	50	55	41
Hospital	350	373	321	372	258
Large Hotel	178	198	120	198	96
Secondary School	289	292	232	292	190

The difference in control is quite clear in most building types. For only two buildings the *connected community* had a lower individual peak demand than the baseline. In contrast, the individual BEMS acquired lower peak demands in every building; however, this is obvious as it is the objective to lower its peak demand. The connected community adopts the additional flexibility of raising the demand of certain buildings beyond typical CFs in order to mitigate the aggregate demand later. This can still occur on a zonal basis for each building, where a zone would exceed the expected baseline demand; however, the limited number of zones in each building creates less opportunities. An opportunity is created when a zone is capable of increasing demand while another decreases, shifting some individual load, while keeping the aggregate load from increasing significantly. The range of time that the shifted load can be scheduled is a function of the flexibility and, in other words, how long the zone can refrain from using that energy while staying within the energy budget. The individual BEMS have the additional constraint of their respective building's baseline demand. Opportunities to shift the load, while increasing a building's demand past its baseline demand, only exist for the *connected community*.

3.2. Energy Cost Minimization

The energy cost minimization results are in the same format as the prior results. Figure 7 shows the low and high flexibility demand profiles for all three cases.

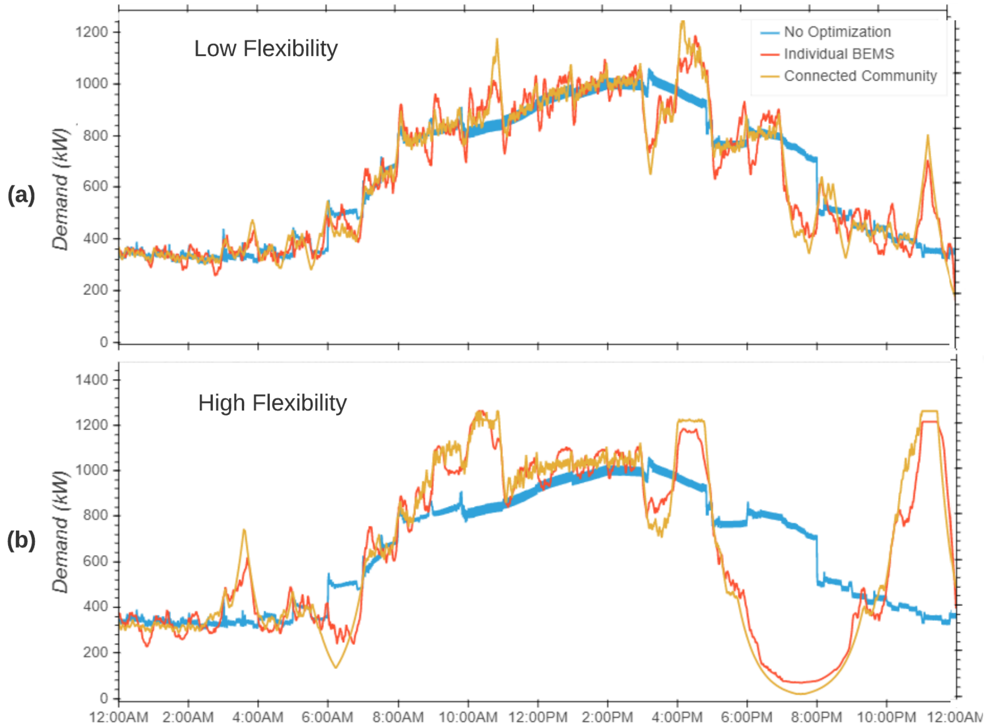

Figure 7. (**a**) Baseline and optimized (for cost) demand profiles under low flexibility ($f = \pm 1\%$) conditions. (**b**) Baseline and optimized (for cost) demand profiles under high flexibility ($f = \pm 10\%$) conditions.

It is very clear from both the low and high flexibility demand profiles that the *connected community* and individual BEMS case performed similarly when energy cost is minimized rather than peak demand. For the low flexibility case shown in Figure 7a, the *connected community* attained energy cost savings of 6.9% while the individual BEMS attained 6.7% savings. An area of intended DR can just barely be made out in the evening of the low flexibility case. This is where the LMP peaked according to Figure 3. There was still significant necessary load, according to the baseline data, in this area, and with such low flexibility, it would be impossible to capture the whole higher-priced time region.

The high flexibility case shows results similar to that of a traditional load shifting problem. A very large amount of energy is shifted to either side of the peak price point. This was accomplished by both the *connected community* and the individual BEMS cases, attaining 18.1% and 17.0% energy cost savings, respectively. This is only an improvement for the connected community of 2.9% and 6.1%, respectively. The similarity in results can be seen in Figure 8.

In the low flexibility region, the energy cost savings are roughly the same for the two cases. The difference grows, in favor of the *connected community*, very gradually as the flexibility increases. This is opposite to the peak demand minimization in which larger flexibility resulted in closer values between the two cases. The results were further broken down to the per building level. As expected, this similarity in the aggregate demand is reflected in the comparison of each building. In all building types, the *connected community* and individual BEMS produced approximately the same demand profile and, therefore, the same cost. This is due to the objective function being rooted in energy consumption rather than demand manipulation. Savings based on energy consumption do not rely on any coordination between zones. The actions of each zone are independent, and the savings value of each zone can be measured. The nature of the objective is quite different to peak demand savings, where savings are only counted by the actions of every zone.

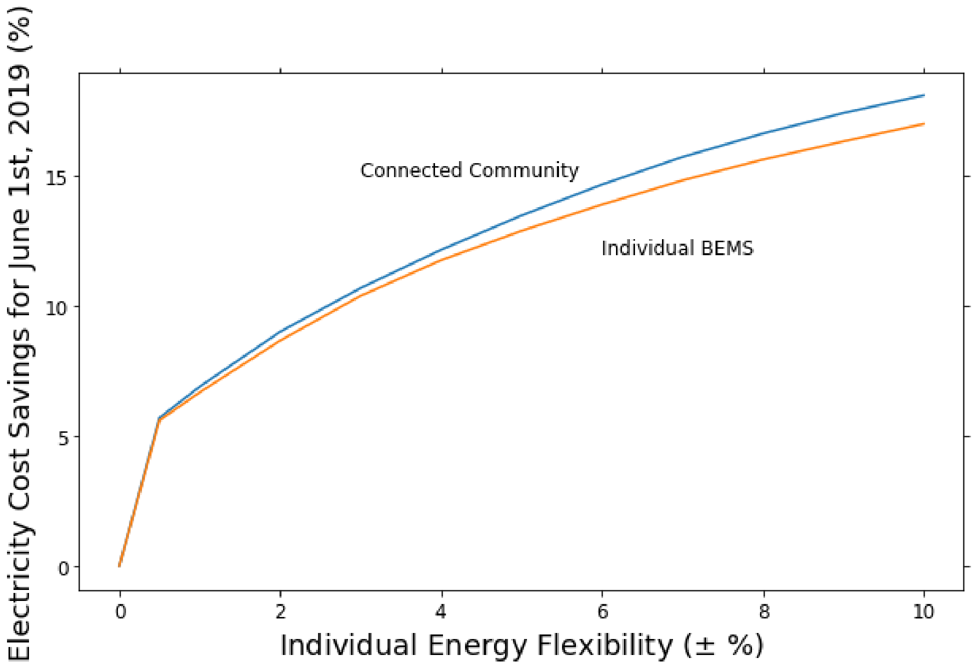

Figure 8. Electricity cost reduction in individual BEMS and a connected community as a function of individual zone energy flexibility.

4. Discussion

The results of this work showed that the *connected community* performed better in peak demand reduction and only slightly better in energy cost reduction, relative to individual building control. Even in the case of low individual flexibility, the visibility of every load in the population still seemed to enhance the capabilities of the *connected community*. Although many of the buildings' peak demands coincided with the aggregate peak demand, the individual BEMS case failed to flatten the demand in the area where it needed to. It is highly likely this is due to the lack of information transfer between buildings, since all buildings had the same capabilities in both cases. Buildings with few loads had greater trouble mitigating the peak demand on their own. As mentioned previously, it is thought that a high resolution control scheme can provide more flexibility, especially to highly constrained loads. This increased flexibility could be attributed to the increase in decision variables, and, in other words, possible combinations. In that case, more zones would also increase the flexibility. This is not to say that increasing the total time period of the problem results in more flexibility. In a low flexibility case, the decisions made an hour prior will not have an effect on the current state. It is likely the system had already bounced off both comfort boundaries several times within the hour. It is more likely that decisions close to the surrounding ten minutes has an effect. Let us assume a system must run four of those minutes at 70% part-load in order to stay within the energy budget. If the load can be variably driven, there are an infinite number of combinations, taking into account which time slots are active, as well as what partial loading it will be on. With increasing flexibility, the amount of surrounding time where the decision has an effect will also increase. Traditional load-shifting fails to capture additional flexibility, typically because the time intervals considered are too large and it takes a great amount of individual flexibility to attain more available time slots. To summarize this point, individual flexibility only determines the time range that is effective, which is maximum at the time it takes to go from one comfort boundary to the other. The scheduling resolution can increase flexibility further, although this will be computationally more expensive.

In the high flexibility scenario for peak demand reduction, both cases achieve a flattened demand, but the *connected community* leads to a bit lower than the individual BEMS. In this scenario, it is clear that most of the loads are approaching their upper flexibility limit. This is assured by the large amounts of demand still being drawn for 2 h after the baseline has dropped significantly. The ±10% flexibility is certainly enough for large load-shifting, or peak shavings, as it achieved both the peak reduction and the cost reduction cases. It creates fantastic results; however, how feasible is it to the buildings that are around now is unsure. It is likely that only newer and modern buildings could accomplish this comfortably. Projects like the Alabama Smart Neighborhood will provide a lot of knowledge in the systems being used; however, their performance cannot be representative of normal buildings. To reach the goal of a highly renewable energy-driven world will require buildings to be retrofitted with new technologies and provide the services needed to supplement renewable sources. There needs to be more emphasis on accessibility in regards to both DR technologies as well as DR methodologies and frameworks. Growth in DR capacity is practically stagnant according to EIA reports and the compensation is minuscule to most participants, other than industrial and very large commercial [13]. Compensation may improve through new frameworks, and through direct wholesale participation; however, the accessibility of control schemes and DR in general is not discussed enough. A highly accessible and highly rewarding market could increase participation substantially and considerably improve the flexibility of the grid.

This paper focused on finding potential savings with the CM control strategy, hindsight of building energy consumption, and nodal pricing. The energy budget framework of the control is only applicable in the case of knowing baseline consumption. In practice, control in this manner would be much more complex, as would any community-wide or individual BEMS long-term scheduling optimization. Both cases would rely on predictive models of energy consumption and nodal prices. Building energy modeling using data and reinforcement learning is developing quickly [47–50]. It is possible that electricity customers will be moved to a real-time rate structure in the future. Real-time pricing is well-reflected in both hour-ahead and 15-min ahead wholesale pricing. Following those wholesale prices is likely to be a good indicator of real-time prices, which can be utilized in models. These models will enable the advanced scheduling needed to realize the full potential within AC DR.

The energy cost savings of the *connected community* were marginally better than the individual BEMS. In the low flexibility case, they were nearly identical. Both the demand reduction and energy cost reduction problems are rooted in allocating demand; however, there is a stark difference in results. The reason is thought to be due to the nature of the objective functions. In the peak demand minimization formulation, the objective is to minimize the variable, P, representative of the aggregate peak demand. The issue for the individual BEMS case is that no singular building will have knowledge of where the aggregate peak will lie. Instead, they only reduce their own peak demands, when, if the building had knowledge of the aggregate peak location, it would prioritize reducing demand in that time period. This is exactly what the *connected community* is good for: having knowledge of the peak demand, and adjusting each zone to prioritize efforts toward the aggregate, rather than their own buildings. The reason that the energy cost minimization results are so different is because the LMP generates that time-interval priority list for the individual BEMS. Every 15 min is essentially ranked by cost of energy, allowing the individual BEMS to allocate demand to each 15-min segment just as well as the *connected community*. It should be emphasized that demand profiles within each interval do vary between the *connected community* and individual BEMS; however, energy consumption does not. The peak demand does not matter with respect to the LMP, but it is unknown what rate structures or customer-market relationships will exist in the future. The *connected community* and individual BEMS will perform nearly identically for objectives that are based on energy consumption rather than demand. With any sort of demand component, it is thought that the *connected community* should still outperform when scheduling within those 15-min segments, handling conflicting operation between buildings that the individual BEMS could not. A larger difference is expected if using hour-ahead price data. It is expected that the *connected community's* ability to avoid conflicting scheduling between buildings would have more of an impact in comparison when the priority time resolutions are lower. In that case, individual BEMS would still prioritize the correct times for energy consumption, but have a higher chance to fail, to avoid coincidences in demand. In general, it seems the *connected communities* must have an objective demand to have any increased performance. In addition, given a demand-related objective, it will handle more low-time resolution objectives significantly better than individual BEMS, but perform similarly given high resolution objectives.

5. Conclusions

Summarizing this work, the aim was to compare the potential peak demand and cost savings between a *connected community* (central optimization) and individually optimized buildings, considering different levels of flexibility and a high resolution scheduling control scheme. The results have brought about great insights on where a *connected community* excels and where the additional connections may become redundant. With the focus of reducing the peak demand of a community of buildings, the *connected community* performed exceedingly well over the individually optimized buildings. The difference is greater when looking at a low flexibility scenario, which shows potential for more accessible control strategies that do not rely on large amounts of flexibility, afforded by modern buildings and expensive storage devices. The 15-min-ahead locational marginal price (LMP) data used, created a more targeted objective function than the peak demand minimization. The energy cost minimization results showed almost the same savings from both the *connected community* and the individual building energy management systems (BEMS). Further investigation into the exact variables that caused it is needed. *Connected communities* show great promise in providing additional savings over individual BEMS, in some cases. The future of DR planning, nodal pricing, and the participants' role will have a big impact on whether or not *connected communities* will become a great asset or just an unnecessary expense.

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