Dynamic Energy Management Needs in Low-Energy Buildings Imposed by Stochastic Solar Resources

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***Abstract*—This paper introduces various electrical and thermal energy generation, consumption, and storage components in solar powered low-energy buildings. Dynamic management of such energy components is essential given the stochastic solar resources. Emphasis is put on power electronic HVAC (heating, ventilation, and air-conditioning) drives, which can act as an effective electric swing bus to mitigate solar power variability. In doing so, grid power flows become substantially more constant, reducing the need for fast grid resources or dedicated energy storage such as batteries. The concept is equivalent to using building thermal energy as virtual dynamic storage in support of power grid operation. The paper defines a bandwidth over which such HVAC drives can operate. A practical band-pass filter is realized that provides 1) lower frequency bounds such that the building maintains consistent room temperature via the HVAC system as demonstrated by a thermal modeling study, and 2) upper frequency bounds that ensure commanded HVAC fan speeds do not update arbitrarily fast. The latter primarily avoids acoustic discomfort to users. The combination is illustrated by experimental results based on various update rates of a variable frequency fan drive over a sample of actual stochastic solar data. Building electrical and thermal energy systems modeling by MATLAB is addressed throughout the paper, including solar and HVAC systems as well as batteries and water tanks.**

***Index Terms*—Low-energy buildings, frequency domain analysis, grid-level energy storage, HVAC systems, solar energy, thermal storage, power electronic drives, complex system energy management**

I. Introduction

Low-energy buildings, including several net-zero-energy commercial buildings, have been constructed around the globe. Research activities on this topic have increased in recent years [1-4], and many occupants have shown interest in having net-zero energy buildings as their future offices such as the new Apple "Spaceship" in Cupertino, California [5]. Low-energy buildings, from an electrical engineering perspective, allow onsite generated renewable energy, such as solar power, to support a portion of the energy demand, and therefore, to reduce the power drawn from or send excess power back to the electricity grid. Net-zero energy buildings bring this concept one step further. The onsite generated renewable energy should be sufficient such that on average a zero-net building does not consume any energy from the grid and may provide excess power to the grid [6]. Other engineering disciplines, such as mechanical and civil engineering, are also active in improving construction materials, lighting systems, air condition and thermal insulation, for example, to reduce building energy consumption. In the long run, it is envisioned that low-energy buildings will become integrated systems where renewable energy generation, electric vehicle charging, and onsite energy storage function together and interact effectively with the electricity grid. Given the various energy generation and consumption devices in a building, it is vital to manage energy flow dynamically in such complex systems.

This paper discusses approaches to dynamic energy management, based on time-domain interfacing with heating, ventilation, and air-conditioning (HVAC) equipment. The conceptual framework and methods follow from ideas in [7-8]. This paper emphasizes systems issues related to electrical and thermal usage and storage in low-energy buildings. A companion paper [9] quantifies HVAC as a virtual storage opportunity and presents implementation details.

Low-energy or net-zero-energy buildings often include onsite photovoltaic (PV) solar panels. Panel power can vary rapidly due to weather conditions, local intermittent shading, passing clouds or flocks of birds, differential soiling, and time of day. Considering this inconstancy to represent an unwanted ac signal from a PV system, a suitable filter could be implemented but energy storage would be required. Although the most familiar challenge is the diurnal solar cycle (imposing substantial energy storage requirements for evening and night loads), rapid dynamic changes in solar energy are more difficult to address. Batteries or supercapacitor banks are often discussed, but their installed size and expense can be substantial [10-12]. Also mentioned are hot or cold water tanks. In fact, water heating already accounts for about 6% energy usage in commercial buildings [13]. However, water tanks are better suited for energy storage intervals of minutes to hours. If instead one utilizes the thermal storage capacity or thermal inertia inherent in a building, then HVAC system adjustments can implement electrical storage, much like an electric swing bus [7-8], [14-17]. Such an electric swing bus could offset fast variations of local solar power from a grid perspective while reducing the need for conventional storage. The scaling potential is sizeable, given that nearly 40% of annual U.S. energy is consumed in residential and commercial buildings [18] with nearly half of that consumed by HVAC systems [19]. This proposed dynamic energy systems management is summarized in Figure 1. The various storage devices operate on different time scales relative to stochastic solar resources.

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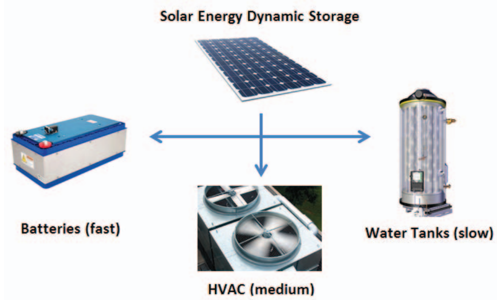

Figure 1. Electric-thermal dynamic storage units in response to stochastic solar resources in low-energy buildings.

This paper is focused on demonstration of intelligent control of HVAC drives that compensates, within predetermined frequency and amplitude limits, for onsite solar power variation over short time intervals without disrupting building temperature and comfort. In particular, [7-8] show how bandwidth concepts can take advantage of HVAC dynamic adjustment to offset energy resource variability. Power electronics enables this control via dc-dc converters, inverter-based drives, and other existing hardware, as illustrated in Figure 2. The results formally take advantage of thermal energy storage, but in this paper the emphasis is on mitigating fast dynamic variability, akin to treating HVAC as accessing thermal inertia. Utilizing thermal inertia can alleviate the need for inherently expensive, fast-varying, grid-side (or building-side) resources. This is nearly equivalent to placing a low-pass filter on a building's net generation and usage, requiring grid-side assistance only when changes in load persist beyond an extended interval [20]. Given the slow thermal response of a building, we might anticipate that times scales of a few minutes or faster can be used to advantage to offset resource variability without noticeable impact on occupants.

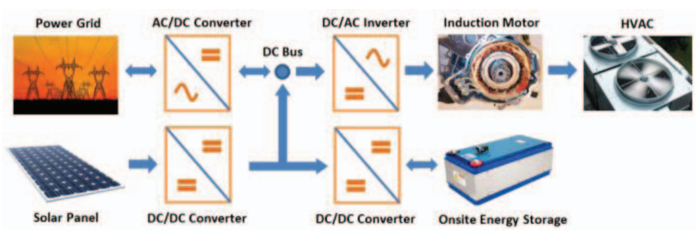

Figure 2. Energy flow inside a building with various types of converters that may be utilized to implement dynamic energy filtering.

A fundamental advantage of HVAC adjustment for effective dynamic thermal storage is that it is relatively easy to implement. Conventional building energy management systems and thermostats are designed to perform in slow control loops, on time scales of minutes. HVAC adjustment can use time-scale separation and stay away from this "effective dc" loop action. In this sense, an ac feedforward signal is injected into a drive to adjust power flow on fast time scales, while avoiding interference on slow time scales. The average performance of the HVAC system remains intact, and the fast adjustment is invisible to users.

II. HVAC Dynamic Filtering Bandwidth Determination

Frequency domain analysis can be performed to illustrate the dynamic energy filtering concept. This analysis takes advantage of two years of data collected from solar panels and recorded at sample rates up to 5 kHz. It is important to recognize that HVAC-implemented energy resource filtering has both upper and lower frequency band limits. The lower frequency limit, meaning the lowest update rate for HVAC speed and power commands, is established to shield building users from substantial temperature swings, ideally keeping variations imperceptible. An upper frequency limit, meaning the highest update rate for HVAC speed and power commands, is needed such that the following conditions are met: 1) HVAC drives are capable of responding, 2) undue wear and tear is not induced on drives or mechanical parts, and 3) update rates avoid discomforting audible pitch or amplitude changes. Approximate frequency bounds are discussed here. If the HVAC system can effectively filter power usage over a useful frequency band, the power grid would then be better able to provide and absorb slower changes power to balance the longer-term building energy flow. Beyond the upper frequency boundary, any more conventional onsite energy storage, such as batteries, could be used to balance the remainder where HVAC falls short. Water tanks, for example, could be used to absorb excess solar energy when HVAC starts to violate thermal comfort, i.e., beneath the lower frequency boundary. As a result, the power grid benefits from a much slower varied energy demand at the building's connection point, and conventional energy storage size is substantially reduced.

Data from three consecutive days in summer 2013 were used to illustrate the concept and simulated in the models. Figure 3 shows normalized maximum solar power in per unit for this subset. Data were collected from 4 a.m. until 8 p.m. (16 h) each day to capture all sunlight. A frequency domain analysis based on these three days is shown as a semilog plot in Figure 4. The lowest frequency components correspond to ideal diurnal solar power changes, which essentially form a "parabola" shape of daily solar profiles. Higher frequency components arise from dynamic cloud cover and similar changes. In particular, in Figure 4, frequencies lower than 1 mHz (~15 min) are associated with substantial fast Fourier transform (FFT) magnitudes. FFT magnitudes in the ~1 to ~20 mHz frequency range (~15 min to ~1 min) are likely to be suitable for dynamic regulation with the building's thermal storage and HVAC system, since internal environmental changes at this time scale are not likely to be perceptible. Note that the FFT magnitudes in this range are 0.1% to 1%. Frequency components above about 20 mHz are nearly absent, so update rates faster than about 30 s may be unnecessary.

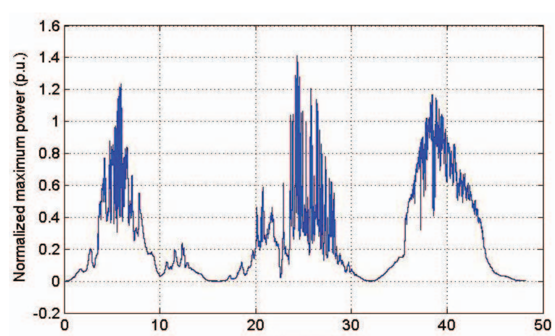

Figure 3. Solar power profile from three sampled days (4 a.m. to 8 p.m. per day).

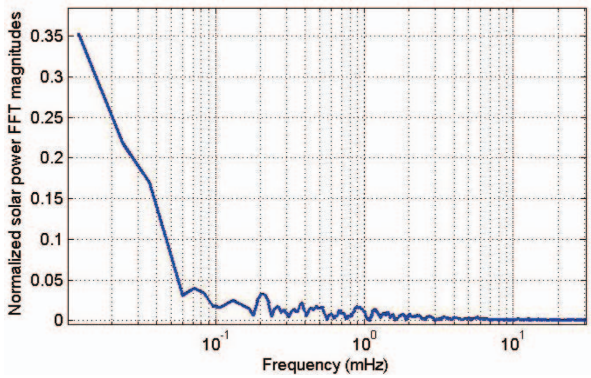

Figure 4. Day 1 solar power profile in frequency domain (semilog scale).

With the frequency domain analysis, the effects of an idealized HVAC system that offsets variations are modelled by passing the solar data through various low-pass filters, each with a different cut-off frequency. In reality, this means that solar energy variation faster than a defined frequency limit in effect is filtered by the HVAC system without being imposed on the power grid. In another words, dynamic filtering stores or releases building thermal energy via the HVAC system so that the grid sees a much smoother net energy resource, i.e., the low-pass filtered solar waveform. Consider Day One from Figure 3 as an example. Figure 5 shows low-pass filtered solar panel power from this day under filters with one-, five-, fifteen-, and thirty-minute cut-off time constants normalized to the daily maximum. Comparing Figure 3 and 5, it appears that the filtered data with a five-, and especially fifteen-minute cut-off intervals are of primary interest for thermal storage regulation as they effectively eliminate rapid power change. Filtered data with a one-minute cut-off interval appears nearly identical to the original waveform and therefore dynamic filtering may not effectively mitigate variation in solar energy if performed too quickly. Thirty-minute filtered data is likely to make building users uncomfortable owing to excessive thermal swings, as will be simulated via electrical-thermal models in MATLAB later.

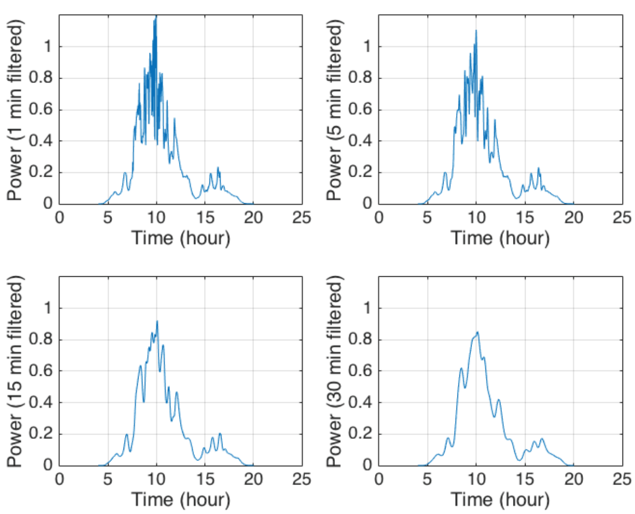

Figure 5. Solar power profile seen from the grid after HVAC filtering effect.

Figure 6 shows the amount of power filtered by the HVAC system for the filter configurations of Fig. 5. The graphs represent per-unit energy storage requirements when solar energy variation is mitigated via the building thermal energy and not by the grid. Even the one-minute cut-off interval invokes substantial energy ratings. As a result, a suitable objective is to create control mechanisms for an HVAC system that alleviate stochastic power up to the fifteen-minute range, or about 1 mHz. The band from 1 mHz to 33 mHz (1000 s to 30 s) appears to be of greatest interest for dynamic mitigation of solar resources. It trades off rapid variation in solar energy against limited changes in building comfort.

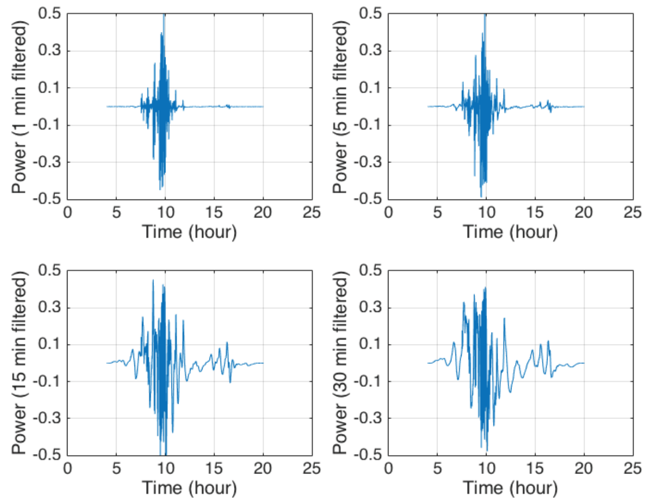

Figure 6. Solar power to be filtered by the HVAC systems.

Figure 7 summarizes to degree to which various cut-off intervals or frequencies help the grid reduce its requirements for regulation of stochastic solar energy, given that the thermal energy is able to absorb and release this varying solar energy. The results are expressed as a percentage, and shown this way must increase monotonically as the time interval increases. The range from about 5% (one-minute cut-off or 17 mHz) to about 25% (fifteen-minute cut-off or 1.1 mHz) reduction falls within the band of interest and reduces grid variability requirements substantially. The effect is that of offsetting real, and costly, energy storage or variability resources for an essentially "free" thermal resource. One point worth emphasizing is that the processes implied by this analysis do not alter average power or total energy demand from the grid since thermal control rates faster than 1 mHz are not altered. The grid-supplied total energy required for the facility stays the same although the grid supplies this energy much more smoothly rather than tracking rapid swings.

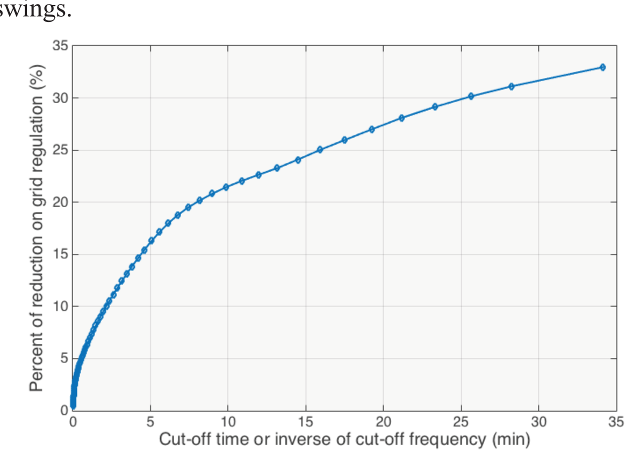

Figure 7. Percent of energy filtered for different cutoff intervals.

To demonstrate and validate the potential of dynamically controlled loads that implement filtering of stochastic energy content, possible control schemes are modelled for a scaled-down HVAC system. First, a small fan drive was characterized. A 1/3 HP, three-phase, four-pole, induction machine coupled with a squirrel-cage fan, which would be representative of typical blowers found in full-scale HVAC systems. For this experiment, the fan speed and its power are related by

$$P(\omega) = 1.659\times10^{-4}\omega^3 + 2.473\times10^{-3}\omega^2 + 1.788\times10^{-2}\omega + 7.446 \quad (1)$$

where the coefficients were identified by a least squares fit. This was necessary to match desired "filter" power to a motor drive operating on speed commands. There are limits on the available speeds and rates of change at any given moment, including available speed limitations of the motor as well as acoustic constraints. In a series of tests to be briefly described, these limitations were quantified and then used as parameters in a final model to determine the maximum feasible filtering potential that would preserve occupant comfort and respect drive capabilities. During testing, acoustic effects of the fan drive were recorded with a high-fidelity microphone as depicted in Figure 8 alongside the remainder of the experimental set up. A Yaskawa CIMR-F7U23P7 drive was used to control fan speed. The drive was externally programmed by a TI MSP430 microcontroller to adjust fan speed with a 20 ms update rate. The high update rate permitted close tracking of band-limited solar power profiles with high fidelity.

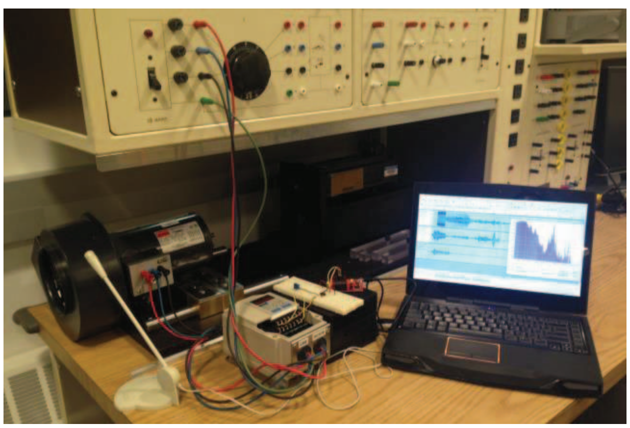

Figure 8. Experiment setup for acoustic effect from various fan speeds.

There are several inherent HVAC constraints that limit the potential energy can be filtered and stored. First, HVAC systems have maximum and minimum power capabilities. They neither generate power nor operate above a certain power or speed limit. A maximum of ~150% compared to baseline speed, or 86.3 Hz in this test case, was established. Second, acoustic bounds are subjective as noticeable changes can arise from the rates at various acoustic peaks occur. Dictated by these acoustic tests and subjective input, a maximum ramp rate of 9 Hz/sec was chosen. For perspective, this limit prevents the blower from ramping between minimum and maximum speed limits in less than 10 s. Further tests with various ramp rates and human subjects are necessary to confirm this result. Third, absolute changes in pitch or audible frequency content are inherent to speed changes and specific blower architectures. Therefore, while we analyzed the audible frequency spectrum for abnormal shifts, we turned our attention mostly to filtering limits imposed by amplitude changes. Ref. [9] describes in depth how we arrived at the final result. That is, we determined that a speed variation corresponding to 0 dB, or equivalently, a peak-to-peak change equal to the baseline magnitude ±16% seemed to be imperceptible. In real HVAC systems, motors and blowers are typically removed from the occupants, as opposed to a mere 0.5-meter away as in this experiment, and additional sound damping would be expected.

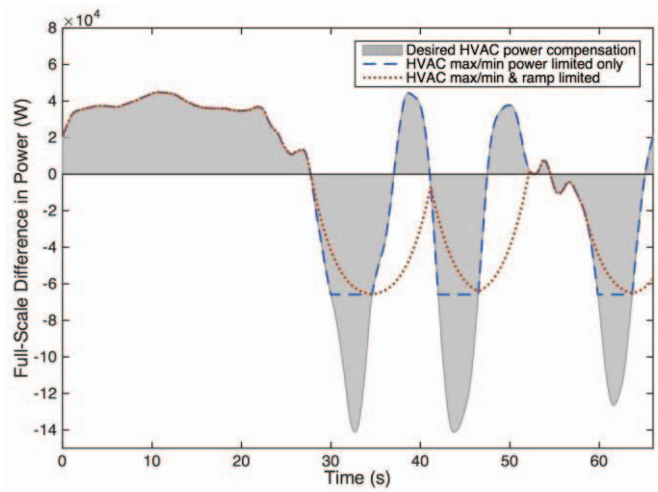

Figure 9. Desired power compensation requested from full-scale HVAC systems with and without speed clamps and ramp limiting.

After determining each of the three constraints using hardware, we used MATLAB to extrapolate to a full-scale implementation. A few parameters, such as solar capacity, had to be variable to encompass cases where this control implementation might be implemented. For example, net-zero buildings seek to have 100% of their average power from on-site renewable generation while more modest installations may seek only a fraction of average energy use from on-site renewables. Table I summarizes the capability of building types with solar installations of 25%, 50%, and 100% of average building load. Figure 9 depicts a one-minute sample of this power curve in gray. The maximum and minimum filtering capabilities in Table I were found by integrating the area under the gray region and under the dashed curve and then finding the ratio between the two. This was done in MATLAB by stepping through each time and determining the filtration desired and available based on solar fluctuations, fixed capacity limitations, and dynamic acoustic limitations. The ramp-limited case is more complicated because, as observed in Figure 9, the power consumption represented by the dotted curve is effectively time-delayed relative to the ideal filter. Thus during periods of rapid power fluctuation, there are times during which the HVAC filter is potentially counterproductive because of acoustic-based slew limits and should be calculated as negative filtration capability in MATLAB. Table I confirms this unfortunate side effect with ramp-limited filtering percentages that are strictly less than the capacity limited case. The general take-away from Table I is that while the ideal HVAC filter increases in effectiveness with narrower band filters, realistic implementations including ramp limiting controls better coincide with utility company aspirations of longer periods (30 or 15 minutes) of more constant power [23]. The missed or unfiltered energy, on the other hand, must rely on other energy storage devices or on the grid. The third constraint on overall HVAC filtering capability is illustrated in the far right column of Table I. The implication is that an HVAC system acting alone with full acoustic constraints will not be able to filter 100% of solar energy variation. As would be expected, the trend indicates that for a building of a given size, HVAC dynamic adjustment can manage an increasing share solar variability for decreased solar capacities.

Table I. Filtering capability percentage compared to ideal HVAC filter.

Solar Capacity (as % of Load)	**Upper Filter Limit (period in min)**	**Max/min limited filtering capability**	**Ramp-limited filtering capability**	**Acoustic amplitude & ramp-rate limited capability**
100	30	65.20%	62.90%	37.70%
	15	66.90%	63.90%	39.90%
	5	70.70%	65.40%	44.50%
	1	73.20%	57.90%	47.00%
50	30	83.50%	80.80%	54.40%
	15	84.70%	81.10%	56.00%
	5	85.80%	79.40%	61.00%
	1	89.50%	74.20%	62.20%
25	30	95.70%	93.40%	73.70%
	15	95.90%	93.00%	75.40%
	5	96.60%	91.70%	77.70%
	1	98.80%	92.30%	80.30%

III. Building Electrical and Thermal Energy Systems Modeling

A first-order physics-based thermal model [7], [21] of a commercial building is

$$C\frac{dT(t)}{dt} = -\frac{1}{R_w}[T(t)-T_o(t)] + c_p\dot{m}(t)[T_l - T(t)] + Q_o \tag{2}$$

where the variables and constants are described [7], [9]. The first term on the right hand side of the equation represents the heat loss due to heat conduction through the walls. The second term denotes the heat gain from the HVAC system. The third term is the heat gain from reheating, solar radiation, occupants, and lighting, etc., which varies depending on the time of day. The constants used in the model are estimated based on measurements obtained from a 4,000 m^2 university building [7], [9]. Outside temperature is extracted from historic data [22]. The HVAC air flow rate is determined from (1) based on the cube root of fan power. This fan power is linked with fluctuating solar power as discussed in previous sections. In this section, we assume all of the filtered solar power in Figure 6 is offset by the HVAC system. In summary, the following relationship holds:

$$\dot{m}(t) \propto \omega_{fan}(t) \propto P_{fan}^{1/3}(t) \tag{3}$$

In particular,

$$\dot{m}(t) = k_1\omega_{fan}(t) \text{ and } P_{fan}(t) = k_2\omega_{fan}^3(t) \tag{4}$$

where k_1 = 0.0964 kg/s and k_2 = 3.3×10^{-5} kW, and the nominal fan power is 35 kW [7].

We have previously, using frequency domain analysis, determined appropriate lower frequency bounds for the HVAC system to update the building's thermal storage based on stochastic solar resources. To demonstrate this further, a MATLAB/Simulink simulation based on the aforementioned thermal models and parameters is run for the four filtering scenarios from Figure 5. The initial condition is assumed that the room temperature is maintained at constant 25°C if a conventional HVAC system with only grid connection is used in the building. The room temperature is now measured as stochastic solar power in Figure 6 is offset by the building thermal mass via the HVAC system. In summer, a positive value in solar power means additional cooling power, thus lowering the room temperature, and vice versa. As a result, four temperature profiles are simulated and presented in Figure 10. It can be observed that there is only about ±0.5 °C and ±1.5 °C change throughout the day for the 1-minute and 5-minute cutoff filters, respectively. The ±3.0 °C change for the 15-minute cutoff filter may be pushing occupant comfort boundaries and is likely to be noticeable, while the ±8 °C for the 30-minute cutoff filter is considered too much for occupants to accept. Although results are unique for a given building, larger buildings with more thermal mass are likely to support 15-minute filters more readily, but the large changes for the 30-minute case may be almost insurmountable for conventional structures.

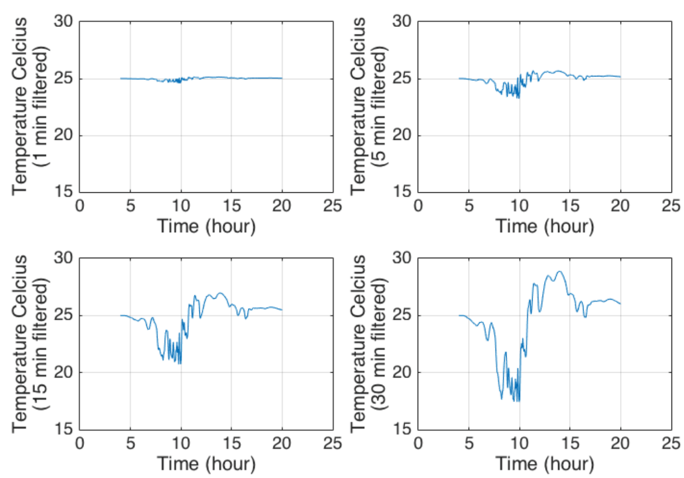

Figure 10. Room temperature profile for different filtering scenarios.

The lower frequency bound provides an opportunity for water tanks to store or compensate solar energy at slow rates, while the upper frequency bound requires batteries to react to fast solar radiation changes. An additional MATLAB simulation is performed when utilizing the batteries, HVAC, and water tanks all together as depicted in Figure 1, while imposing Day 1 solar profile from Figure 3 and selecting 1.1 mHz (15 min) and 0.1 Hz (10 s) as HVAC filtering lower and upper frequency bounds, respectively. This particular scenario assumes solar capacity as 100% of building loads and also takes into consideration the acoustic amplitude and ramp-rate limited capability as described in Table I. The results show reduction of approximately 75% and 55% in battery or in water-based storage, respectively, compared to a scenario without HVAC for dynamic energy regulation.

IV. Conclusion

This paper discusses various electrical and thermal energy system management in low-energy buildings to offset stochastic solar resources. In particular, the paper introduces a dynamic energy balancing and storage solution offered by HVAC systems that allow implementation of dynamic mitigation of rapid solar energy variations through an energy filtering concept. The lower HVAC update frequency limit appears to be about 1.1 mHz (15 minutes) and seems to limit temperature variations in occupied spaces while reducing long-term onsite thermal energy storage needs. The higher update frequency limit in the range of about 0.1 Hz (10 s), combined with ramp rate limits, lets a fan respond without generating annoying noise and reduces short-term onsite electrical energy storage needs, such as batteries. The process has been demonstrated by solar data frequency domain analysis and system-level electrical and thermal interaction modeling using MATLAB, as well as a small scaled fan drive experiment.

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