Modeling and Performance Evaluation of Grid-interactive Efficient Buildings (GEB) in a Microgrid Environment

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Abstract- A detailed analysis of how Grid-interactive Efficient Buildings (GEB) can participate as active elements in a microgrid through on-site PV electricity generation and energy efficiency applications is presented. A case study using three US Department of Energy (DoE)-developed prototype commercial building models are used. These represent a secondary school, a hospital and a large office building. Simulation results show that when schools, hospitals and office buildings are operated as GEBs, there are always electricity savings, but savings amounts vary depending on levels of HVAC and lighting controls within the limits of customer comfort levels. These comfort level ranges are determined through interactions with building occupants which resulted in ΔT of 2-5°F and dimming level range of 20% to 50%. Savings in the school building are so much higher for two reasons. One, because without GEB application these buildings are operated in a business-as-usual fashion throughout the year, even when the school is not in session. The second reason is – being a two-story building the roof area is comparatively much higher than the hospital or the multi-storied office buildings.

Index Terms— **Energy management, Grid-interactive efficient building, HVAC control, Lighting control, PV power systems.**

Nomenclature:

E_{pv}= Total PV generation
E_n= Energy consumption of GEB_n
E_{sys}= Total energy consumed by the microgrid
E_{fn}= GEB_n flexible load energy consumption
E_{sn} = GEB_n static load energy consumption
$E_{HVAC,GEB}$= *GEB* HVAC energy consumption
$E_{lighting,GEB}$ = *GEB* lighting energy consumption
$E_{other,GEB}$ =*GEB* other loads energy consumption
S_{GEB}= *GEB* HVAC setpoint
I_{GEB} = *GEB* brightness
S_{min}= Minimum allowed HVAC setpoint
S_{max}= Maximum allowed HVAC setpoint
I_{min}= Minimum allowed brightness
I_{max}= Maximum allowed brightness
E_{min}= Required minimum energy consumption
$E_{savings}$=GEB energy savings capability

I. INTRODUCTION

A. Background and motivation

For over a century, the structure of the electric utility business has been a supplier-driven model with consumers receiving and paying for electricity without any participation in the way how the electricity is produced, transmitted, or consumed. However, advances in renewable energy technologies such as PV panels, battery storage, smart devices, as well as financing models -and increasing concerns about greenhouse gas emissions - have given rise to prosumers, i.e., electricity consumers who produce energy from their rooftop PV panels while consuming electricity from the grid as needed. Prosumers are interested in monetizing the value of their PV investment/production while regular consumers desire cheaper electricity prices. On the other hand, buildings are becoming grid-interactive to take advantage of the energy efficiency programs offered by electric utilities. Grid-interactive efficient buildings (GEB) help to maximize building, community and grid efficiency using load flexibility, demand response (DR) and distributed energy resources (DERs), which interact with one another. Demand response is a process to reduce the system-wide electrical power consumption during peak demand periods, thus allowing an economic and stable operation of the electric power grid. The demand response process is also economically beneficial for the consumer since this helps to reduce their peak demand charges. These efficient buildings are called GEBs (grid-interactive efficient buildings), which can reduce electricity demand and utility costs while offering the customer electricity bill savings without compromising their safety and health. Furthermore, GEBs can help smooth the electrical demand curve by shifting consumptions from high to low-demand periods. Carrying this idea forward - a microgrid can be designed which includes a group of GEBs with diverse and flexible end-use equipment that collectively work to maximize building and grid efficiency without compromising occupant needs and comfort. Such buildings may have integrated PV panels and battery storage including electric vehicle charging stations. The GEB - in conjunction with solar PV and battery storage - may also be a building block of the non-wires alternative to provide electrical capacity in congested urban areas to serve new loads. For this scenario, a GEB is not just an electrical load, it is an electric power grid asset.

The majority of larger (100,000 sq. ft or above) modern buildings today have building energy management systems (BEMS) that are capable of continuously monitoring the status of the building energy consumption through IoT-enabled sensors and actuators connected to the HVAC, lighting, plug loads, ventilation and other auxiliaries in the building like the elevator. These ensure proper electrical and environmental control of the building operation. But GEB related features are not integral to such BEMS. With the growing installation of photovoltaics, building energy management platforms and demand response enabled smart devices, traditional energy operation is evolving from a unidirectional utility-to-consumer model into a more distributed bi-directional power flow paradigm. Photovoltaics and energy saving capabilities are two major resources of energy efficiency in microgrids involving grid-interactive efficient buildings (GEB).

B. Literature review

Relevant research regarding customer-owned PV electricity focuses on different algorithms, auction mechanisms and outlooks on distributed electricity trading within a microgrid. Such research present how PV electricity contributes to overall grid energy efficiency from the generation side. However, a detailed methodology to quantify the effectiveness of building-level PV electricity generation as demand side asset in grid energy efficiency needs to be further explored, as presented the paper. Authors in [1] review the current peer-to-peer PV electricity trading models and their practical applications in the real world. Authors in [2] present PV electricity trading structure through flexible load control in a microgrid. Authors in [3] present a three-dimensional four-layered architecture for electricity trading among prosumers and consumers. In a hierarchical system architecture, an energy trading platform called Elecbay is presented. An associated bidding system using game theory and the Nash Equilibrium for the P2P energy trading among consumers and prosumers is proposed. Case studies show that PV electricity trading can reduce the energy exchange between the microgrid and the utility grid and balance local generation and demand. Authors in [4] present a distributed framework that facilitates P2P electricity trading in a microgrid. Both microgrid control flows and power transaction flows are designed. Authors in [5] present a multiagent structure that combines smart contracts and distributed mechanisms to facilitate P2P electricity trading without human intervention. Authors in [6] present a framework to integrate DR resources in a day-ahead wholesale market. The framework utilizes flexibilities provided by DR resources for load curtailment and load shifting applications during high-demand periods. Authors in [7] present a distributed architecture-based platform for the solar electricity exchange. The implementation is based on the IoT smart devices deployed in buildings and the modeling of PV electricity trading participants, assets, transactions and transaction flows. How distributed platform tracks the transaction records of solar PV output exchanges is also described in detail. Authors in [8] and [9] present a multi-agent-based energy management system, BEMOSS- Building Energy Management Open Source Software. They present how building-level real-time energy consumption can be monitored through REST API based communications. The architecture can, furthermore, be extended to monitor PV electricity generation Authors in [10] present an optimal energy dispatch of distributed PVs for distribution management system. The dispatch strategy is optimized to provide grid services e.g. voltage regulation. Authors in [11] present a software-defined control architecture for microgrid. Their analysis show the approach improves the robustness and applicability of DER resources within a microgrid compared to hardware-only approach. Researches show PV electricity trading is beneficial for both the grid and the consumers.

On the other hand, to achieve energy efficiency, consumers can commit to certain electrical consumption reductions through optimizing their HVAC setpoints, brightness adjustments and controlling plug loads. Relevant research focuses on optimal operation of electrical loads to minimize electricity cost. However, a detailed methodology to quantify building-level load reduction capability coupled with on-site PV generation needs to further explored, as presented in the paper. Authors in [12] propose an economic load model that considers the price elasticity of the consumers to shape the electricity consumption during the high consumption periods through interruptible load control. Authors in [13] present a priority-based intelligent algorithm that can control the devices within a home energy management setup to cut down electricity consumption during demand response periods. Authors in [14] present a genetic algorithm (GA) optimized equipment scheduling technique during high consumption periods for an optimal operation. Authors in [15] propose a convex programming electricity consumption optimization framework for scheduling various household appliances in a smart home under the real-time pricing scenario. Authors in [16] present both a model based and a data driven HVAC control strategy for the residential demand response. The objective is to minimize electricity cost and utility level load violation while considering occupant comfort. Authors in [17] present game theory and reinforcement learning based multi-agent architecture to minimize energy cost through HVAC control. The case study presents how the methodology can reach the global optimal point under different weather conditions. Authors in [18] present a system-wide demand response management where reduction in the power consumption is achieved through ensuring the overall economic benefit of the participating customers. Authors in [19] present a reinforcement learning-based approach to energy efficiency. The algorithm presents how optimally shifting non-essential loads allows consumers to stay within a pre-set power consumption limit during the peak demand periods. Authors in [20] present a reinforcement learning (fitted Q-iteration) based approach to reduce energy consumption. Authors present how thermostatically controlled loads can be utilized to keep the electrical energy consumption to a minimum level during the high electricity price periods. Authors in [21] present a detailed survey on the lighting energy savings from the dimmable lighting control in The New York Times headquarters building. This analysis shows the light dimming capability is highly effective in reducing energy consumption both in and outside the demand response periods. Authors in [22] present how lighting loads can be optimally controlled through distributed wireless occupancy and illuminance sensors to reduce electrical load consumption. Authors in [23] present an interesting approach to demand response through HVAC control. Here authors propose a voting scheme to fix the HVAC setpoints in a multi-zone environment. The study utilizes data to train an ANN model to predict the optimal setpoints during a demand response period to reduce the overall power consumption without causing occupant discomfort. Authors in [24] consider energy efficiency capabilities as a market resource in different existing and evolving programs at different ISOs/RTOs. This includes auxiliary service benefits from demand response programs. In addition to on-site PV generation, research shows that energy efficiency capabilities in a building are beneficial to both consumers and the grid. However, a methodology to model and quantify the effectiveness of overall building-level energy saving potentials needs to be further explored, as presented in this paper.

C. Contributions of the paper

The paper presents a framework showing how a grid-interactive efficient building (GEB) with on-site PV electricity generation and energy efficiency applications can contribute to operating an efficient, safe, reliable and secure microgrid. Models developed allow the user to study the impact of PV output variability on building energy savings. In addition, models allow studying the impacts of building HVAC setpoint and lighting brightness controls on the microgrid load control objectives. This allows the building to be considered as an active grid asset not as passive consumer load.

Rest of the paper is organized as follows: section 2 describes the proposed framework of GEB within a microgrid, section 3 describes the methodologies to quantify building-level PV electricity generation and energy saving potentials and section 4 presents a case study to evaluate the performance of GEB within a microgrid.

II. PROPOSED FRAMEWORK OF THE GEB WITHIN A MICROGRID

Electric utilities in the U.S. have started to introduce decentralized models of electricity supply based on a Distribution System Operator (DSO) model. Under this model, the DSO is responsible for the overall management of distribution-side resources to mitigate distribution constraints. DSO has multiple sub-stations under its operation. A sub-station can directly supply electricity to consumers (GEB) or may have multiple microgrids (MG) under its operation which include GEBs, which can participate as active grid elements. Fig. 1 shows this architecture.

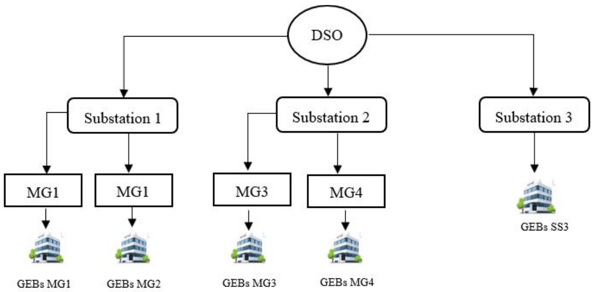


Fig. 1. GEB within an electrical power grid

During high electricity consumption periods, DSO places individual load reduction requirements in each sub-station. Sub-stations then distribute the reduction amount to individual microgrids or directly to the consumers. Under traditional demand response programs, buildings reduce their loads based on a pre-fixed operation modality to meet a power demand reduction target. However, GEBs (within or outside the microgrid) are capable of offering flexibility through PV electricity generation and dynamic load reduction capabilities. GEBs, therefore, function as active assets to improve the overall energy efficiency in microgrid operations. Fig. 2 shows the proposed architecture of GEBs contributing to the overall grid level energy efficiency. On the demand side, GEBs provide flexibility through dynamic load reduction potentials and on the supply side, through PV electricity generation.

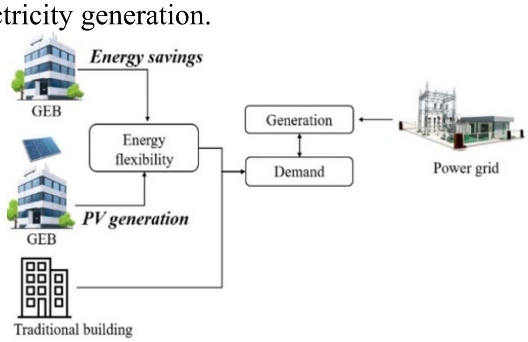


Fig. 2. The proposed architecture of GEB

III. OPERATION OF THE GEB

A. PV generation capability of the GEB

An accurate PV generation calculation is essential to quantify the capabilities of a GEB. PV electricity calculation helps the GEB operator determine the PV electricity that can be available over different periods of the day. Fig. 3 presents the methodology to calculate the PV electricity generation capability of a GEB. By using solar irradiance data along with PV module parameters, inverter parameters, site location, array configuration and other weather forecast information the available PV electricity is calculated. Therefore, PV electricity generation can be expressed as a function mentioned in eq. 1.

$$\boldsymbol{Epv} = \boldsymbol{f}(\boldsymbol{T}, \boldsymbol{Irr}, \boldsymbol{Loc}, \boldsymbol{Arr_{conf}}, \boldsymbol{Arr_{para}}, \boldsymbol{Inv\_para}, \boldsymbol{W}) \tag{1}$$

Where, E = PV generation, T = time, Irr = hourly solar irradiance on rooftop panels, Loc = location factor of building site, including site latitude, site longitude and site elevation, Arr_{conf} = array configuration parameters including tilt angle, facing side, array series and strings configuration, Arr_{para}= PV module's electrical and mechanical characteristics, Inv_para= inverter's electrical and mechanical characteristics and W= hourly weather forecast information including wind speed, pressure and air mass from the nearby weather station. The "PV_LIB Toolbox" of MATLAB is used to simulate the PV generation for the case study presented [25]. This analysis can further be used by the energy market operators to assess if a PV transaction bid is within the range in a PV trading scenario. If the bid is within the range it is allowed to proceed. If the bid is not within this range, it is flagged as an anomaly for further review. With the addition of this PV generator

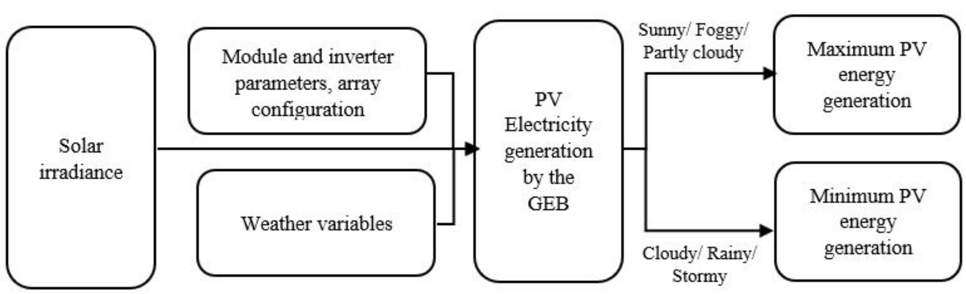


Fig. 3. PV electricity generation capability of a GEB

predictor, both the GEB and the energy market can better assess how much PV electricity is available in the next trading periods and can adjust microgrid market operations accordingly.

B.Energy savings capability of the GEB

Traditional building operations under the current demand response programs require shutting down some of the electrical equipment to reduce electricity consumption using a pre-fixed look-up chart, which is "reactive and static" in nature. Due to the user inconvenience presented by this approach, its uptake is limited. GEB operations, on the other hand, offer dynamic and diverse controls like HVAC setpoint and brightness adjustments in different timeframes based on the building operator preferences to achieve overall energy efficiency. This context-aware operation maximizes energy savings with no or minimal inconvenience to building occupants.

Total hourly energy consumption within the microgrid can be expressed in eq. 2.

$$E_{sys} = \sum_{i=1}^{n} (E_1 + E_2 + \ \dots\dots \ + E_n) \tag{2}$$

Where, E_n is the individual energy consumption of GEB_n and E_{sys} is the sum of energy consumed by the microgrid. Furthermore, type-wise i.e. heating/cooling, lighting, etc. energy consumption can be considered as well. This will provide information regarding energy reduction flexibility within each GEB. Eq.3 shows the total energy consumption of each GEB broken into flexible and static components.

$$E_{sys} = \sum_{i=1}^{n} \left(E_{f1} + E_{f2} + \ \dots\dots \ + E_{fn}\right) + \sum_{i=1}^{n} \left(E_{f1} + E_{f2} + \ \dots\dots \ + E_{fn}\right) \tag{2}$$

Where, E_{sys} is the total energy consumption, E_{fn} is the flexible load and E_{sn} is the static load of GEB_n.

The objective of the GEB is to reduce the overall energy consumption. Therefore, the objective function can be written as:

$$Minimize \ \ E_{GEB} = \sum (E_{HVAC,GEB} + \ E_{lighting,GEB}) + \ E_{other,GEB}$$

$$\textit{Subject to: } \ E_{HVAC,GEB}\ ,\ E_{lighting,GEB},\ E_{other,GEB} > 0$$
$$S_{min} < \ S_{GEB} < \ S_{max}$$
$$I_{min} < \ I_{GEB} < \ I_{max}$$
$$E_{min} < \ E_{GEB} < \ E_{sys}$$

Where, E_{GEB} is the total energy consumption by the GEB with a dynamic operation scheme and $E_{HVAC,GEB}$, $E_{lighting,GEB}$, $E_{other,GEB}$ are the energy consumptions due to HVAC, lighting and other loads respectively. $E_{other,GEB}$ includes energy consumed by the non-flexible loads and appliances with operational constraints. S_{GEB} and I_{GEB} are the setpoint and brightness of the GEB to achieve energy efficiency. S_{min} and S_{max} are the minimum and maximum allowed HVAC setpoints. I_{min} and I_{max} are the minimum and maximum allowed brightness. E_{min} is the required minimum amount of consumption fixed by the grid operator. E_{min} is introduced to ensure grid stability. These constraints are imposed to ensure customer comfort. Their values are fixed based on the feedback from occupants. Therefore, the energy savings potential of a GEB can be calculated using eq. 4.

$$E_{Savings} = \ E_{sys} - \ E_{GEB} \tag{4}$$

Where, $E_{Savings}$ is the energy saving capability of the GEB, E_{sys} is the baseline energy consumption and E_{GEB} is the energy consumption of the GEB. Fig. 4 shows the mechanism to quantify energy saving potentials of individual GEB.

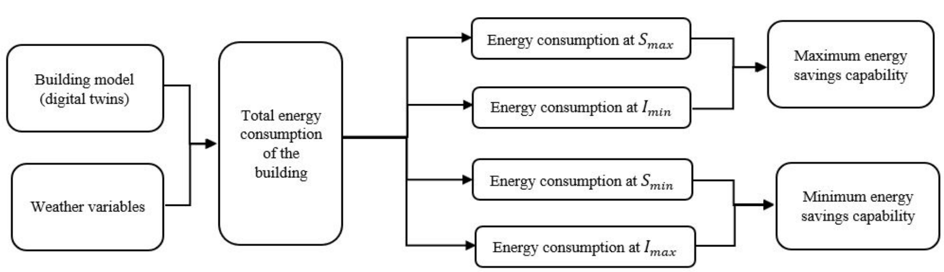


Fig. 4. Energy savings capability of a GEB

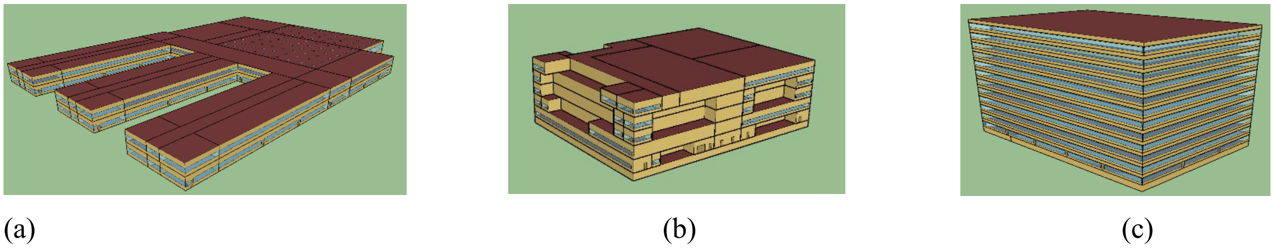


Fig. 5. DoE developed commercial prototype buildings (a) school (b) hospital (c) office

IV. CASE STUDY

A. Dataset

For the case study, three commercial prototype building models - a secondary school, a hospital and an office building developed by the US Department of Energy (DoE) are selected [26]. The buildings are assumed to be located in Denver, Colorado. Fig. 5 shows the building shapes and Table I shows the relevant prototype building specifications.

Table I: Prototype building specifications

	School	Hospital	Office
Floor size (sq. Ft)	210,900	241,410	498,600
No. of floors	2	5+base-ment	12+base-ment
HVAC (Cooling)	Electrical	Electrical	Electrical
HVAC (Heating)	Gas	Gas	Gas
HVAC set point (Cooling, °F)	75	75	75
HVAC set back (Cooling, °F)	85	N/A	85

B. PV generation by the GEB

PV electricity generated is simulated for all three prototype buildings. All three prototype rooftops are flat, and the available space panel deployments is calculated according to [27]. Generally speaking, 5% of the flat rooftop is covered by HVAC equipment and 30% of the area is shadowed by other rooftop elements and trees. Therefore, it is assumed that 65% of the flat rooftop area is available for use by PV panels. The school building has a skylight area of about 35,000 sq. Ft., which is also excluded from the available rooftop for PV utilization. For the case study, irradiance data for 2019 for the selected location (Denver, Colorado) from the NSRDB data viewer [28] is used. Canadian Solar CS5P-220M is chosen as the PV panel for all three prototype buildings. PV Powered inverter (PVP260kW) with a capacity of 260 kW is chosen for the school and the hospital. Power-One inverter (PVI-CENTRAL-300-US) with a capacity of 300 kW is chosen for the office building. Both inverters operate at an input voltage of 600 VDC and output voltage of 480 VAC. Table II specifies relevant information related to PV electricity calculation.

Table II: PV panel specifications

	School	Hospital	Office
Available rooftop for PV panel use (sq. ft)	61,270	23,630	24,930
Panel size (sq. ft)	18.31	18.31	18.31
No. of panels in series in an array	10	10	10
No. of arrays in parallel in a field	103	109	125
No. of fields	3	1	1
No. of inverters	3	1	1

From the available rooftop area for PV utilization, 5% of the space is set aside for maintenance purposes. Each PV field is connected to one inverter. For the school, each of the three fields has 1030 PV panels with a total field capacity of 226x3 = 678kW. For the hospital, the field has 1190 PV panels with a total field capacity of 261.8 kW. For the office building, the field has 1250 PV panels with a total field capacity of 275 kW.

Fig. 6 shows the available PV electricity from the school, hospital and office buildings. Table III shows the total PV electricity generated by these GEBs in 2019. Because of the availability of a much larger rooftop area, the school building generates the highest amount of PV electricity.

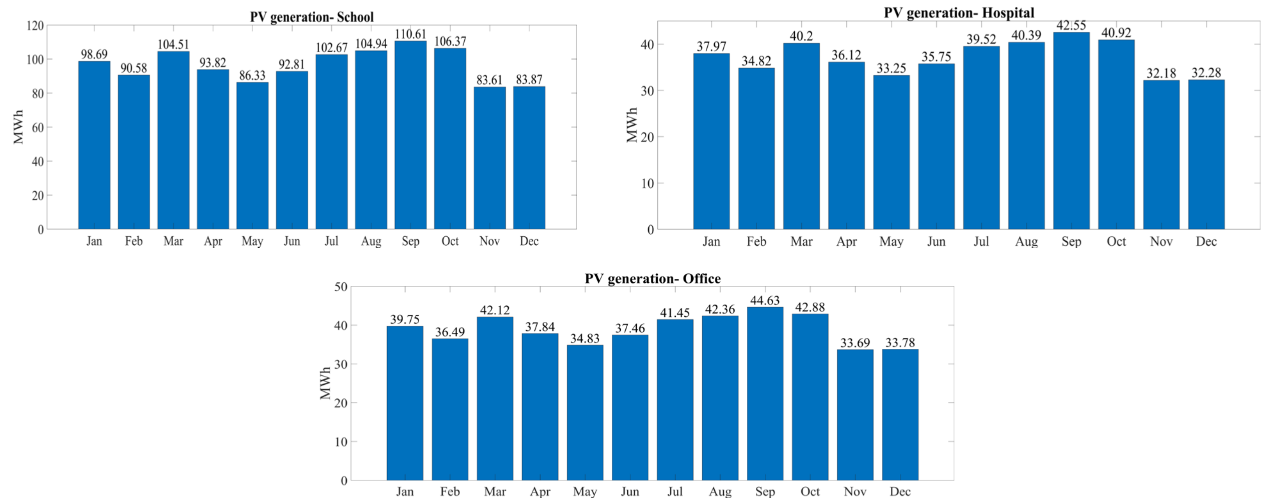


Fig. 6. PV generation of school, hospital and office

Table III: PV electricity generation by the GEBs

	Total PV electricity generation (MWh)
School	1158.80
Hospital	445.95
Office	467.27

C. Energy savings capability of the GEB

The energy savings capability of a GEB is calculated using the US DoE EnergyPlus software platform. It is assumed that the HVAC setpoints and the brightness levels are allowed to change within a specified range. All three buildings use gas for heating purposes. Therefore, only cooling setpoints are adjusted to show the impacts on electricity consumption. Adjustments are made from 7 AM to 11 PM. Table IV specifies the allowed temperature adjustment bands and dimming controls to reduce energy consumption.

Table IV: Allowed margin for energy savings

	Min allowed adjustment	Max allowed adjustment
HVAC cooling setpoint (°F)	77 (Base+2°F)	80 (Base+5°F)
Brightness	20% reduction	50% reduction

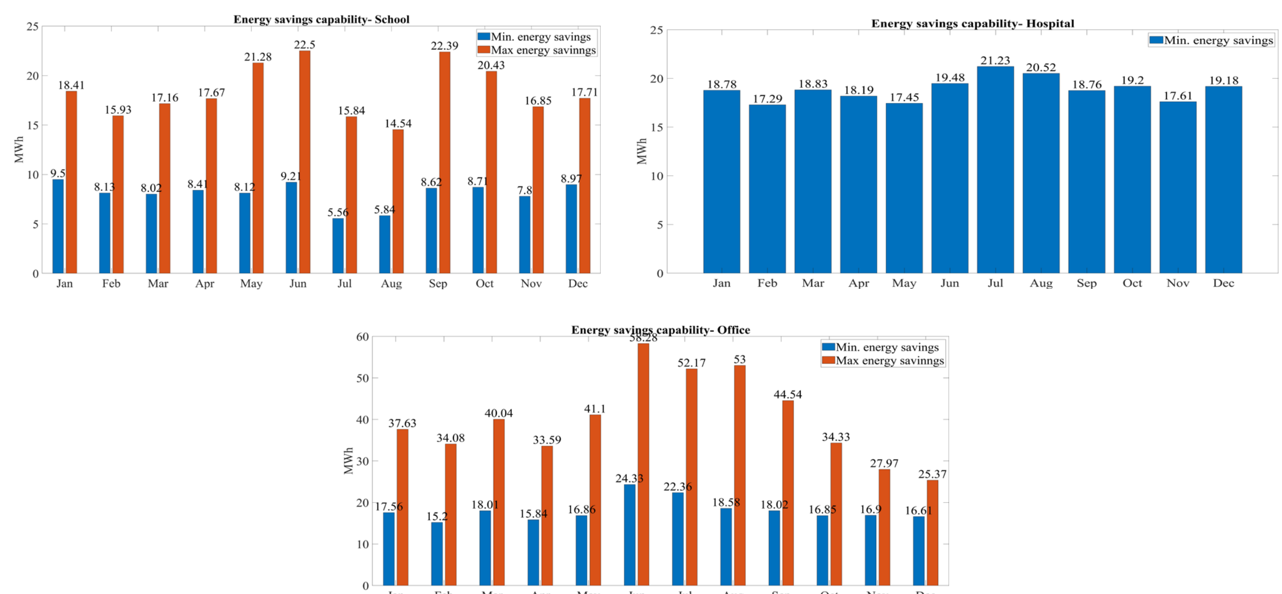


Fig. 7. Energy savings capability of school, hospital and office building

Maximum energy savings are achieved by raising the HVAC cooling setpoint to 80°F and reducing the brightness by 50% from the base case. For the hospital, only minimum allowed adjustments are made for the entire 24-hr considering its critical functions. Fig. 7 shows the monthly maximum and minimum energy savings capability of the three prototype buildings. Table V shows the yearly maximum and minimum energy saving potentials of the three GEBs. For the hospital, higher-end adjustment is not allowed. Therefore, it shows an energy savings capability with only the minimum level of adjustments.

Table V: GEB energy savings capability

	Yearly minimum savings (MWh)	Yearly maximum savings (MWh)
School	96.90	220.70
Hospital	226.52	226.52
Office	217.12	482.11

D. Performance evaluation of the GEB

The GEB through their PV electricity generation and energy saving capabilities work as an active microgrid element. This section will present how that impacts the overall energy efficiency of a microgrid. Table VI shows the total yearly energy savings through both the GEB capabilities i.e., PV electricity generation and energy reduction through cooling setpoint adjustments and brightness control. Baseline consumption is calculated when the building is operated under its regular operation mode as described in details in [26]. Table VI shows, the school building is capable of reducing its total energy consumption by almost 90% from the normal operation. Savings in the school building are so much higher for two reasons. One, because without GEB application these buildings are operated in a business-as-usual fashion throughout the year, even when the school is not in session. The second reason is – being a two-story building the roof area is comparatively much higher than the hospital or the multi-storied office buildings. However, results show that a typical hospital and office building is capable of reducing a significant amount of electricity consumption through GEB functionalities as well.

Table VI: GEB performance evaluation

	Yearly baseline energy consumption (MWh)	Yearly maximum energy savings (MWh)	Yearly maximum energy savings (% of base)
School	1534.84	1379.50	89.87%
Hospital	5545.66	672.47	12.14%
Office	7649.44	949.38	12.42%

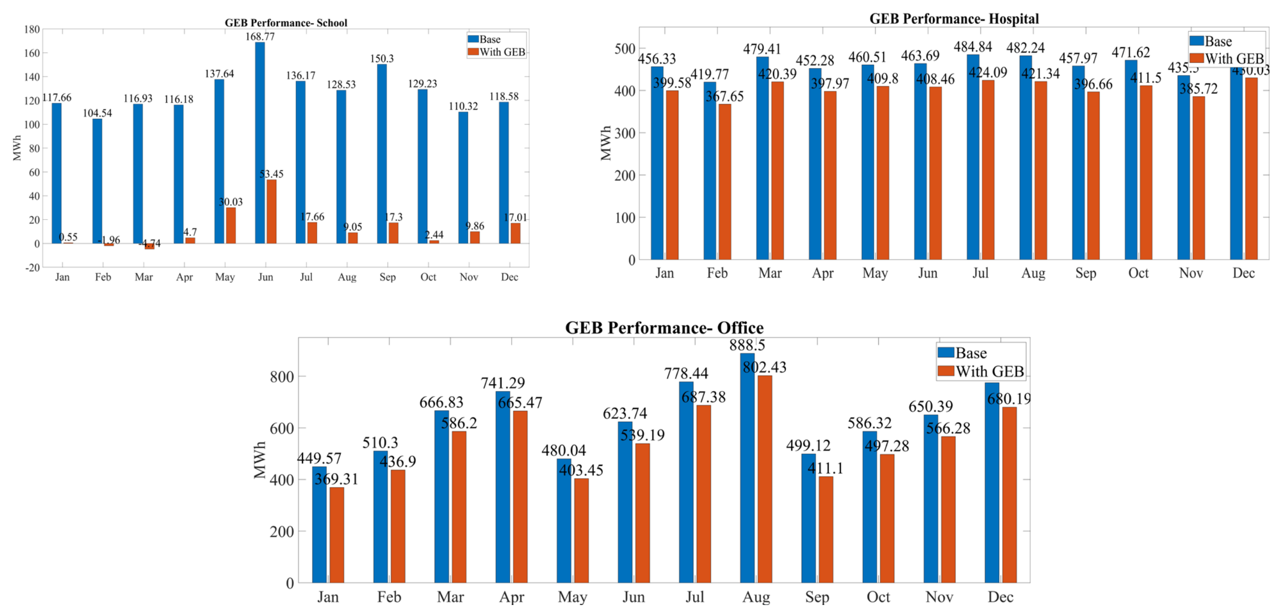


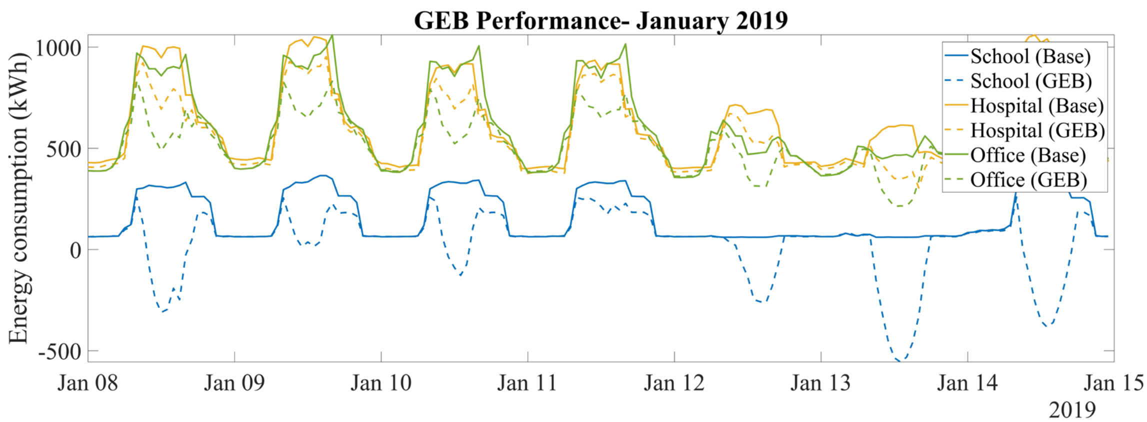
Fig. 8. GEB performance of school, hospital and office building

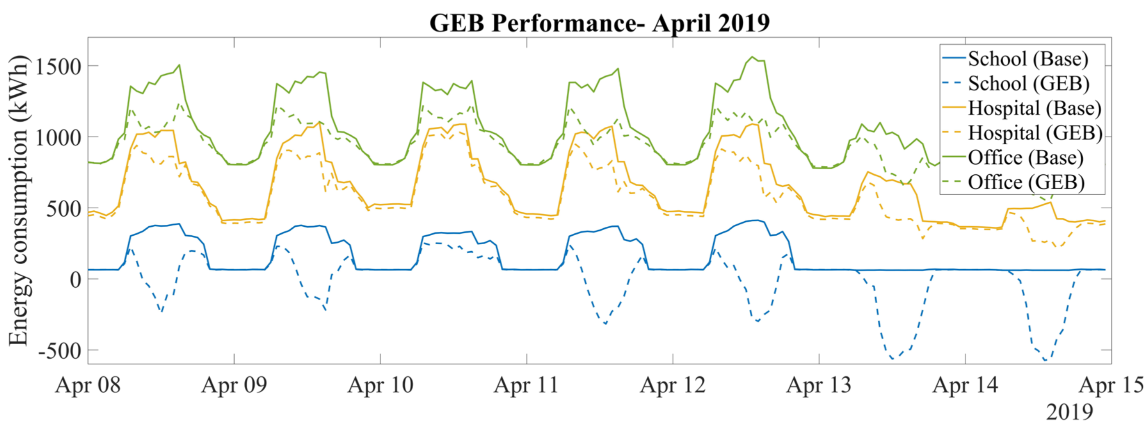
Fig. 8 shows how GEBs (including the PV contribution) can reduce energy consumption when both the minimum and maximum GEB capabilities are utilized. If operated as a GEB, the school building achieves a good amount of energy savings because of its higher total floor size to available rooftop ratio and the energy savings during 7 AM to 11 PM that covers the full operation period. The hospital operates at the same operating condition throughout the year and only minimum energy-saving settings are implemented due to its critical function. Therefore, almost similar energy savings is observed throughout the year. The office building uses gas for heating purposes. Therefore, shows slightly higher energy savings capability during the summer periods.

Fig. 9 shows an in-depth granular look at the energy savings from the GEB buildings for the 2nd weeks of January, April, July and October of 2019. These months represent four different seasons in North America. Figures show, when operated as a GEB, the school building is even capable of supplying electricity to the microgrid in addition to reducing overall energy consumption. The hospital building shows almost constant energy savings capability across all four months due to its operational settings. The office building uses gas for heating purposes and operates at setback condition outside its operation period. Therefore, higher savings capability is observed during its operational period and summer months. Table VII summarizes the energy efficiency potential of the GEBs for the 2nd week of January, April, July and October of 2019 in detail. The negative energy consumption of the school shows that it is capable of supplying electricity to the microgrid after meeting its full requirements.

Table VII: Energy consumption analysis for the 2nd week of January, April, July and October of 2019

	School		Hospital		Office	
	Base MWh	GEB MWh	Base MWh	GEB MWh	Base MWh	GEB MWh
Jan-Wk2	27	6	104	96	103	87
April-Wk2	28	2	110	95	175	157
July-Wk2	31	4	108	92	180	159
Oct-Wk2	29	-2	105	98	132	113





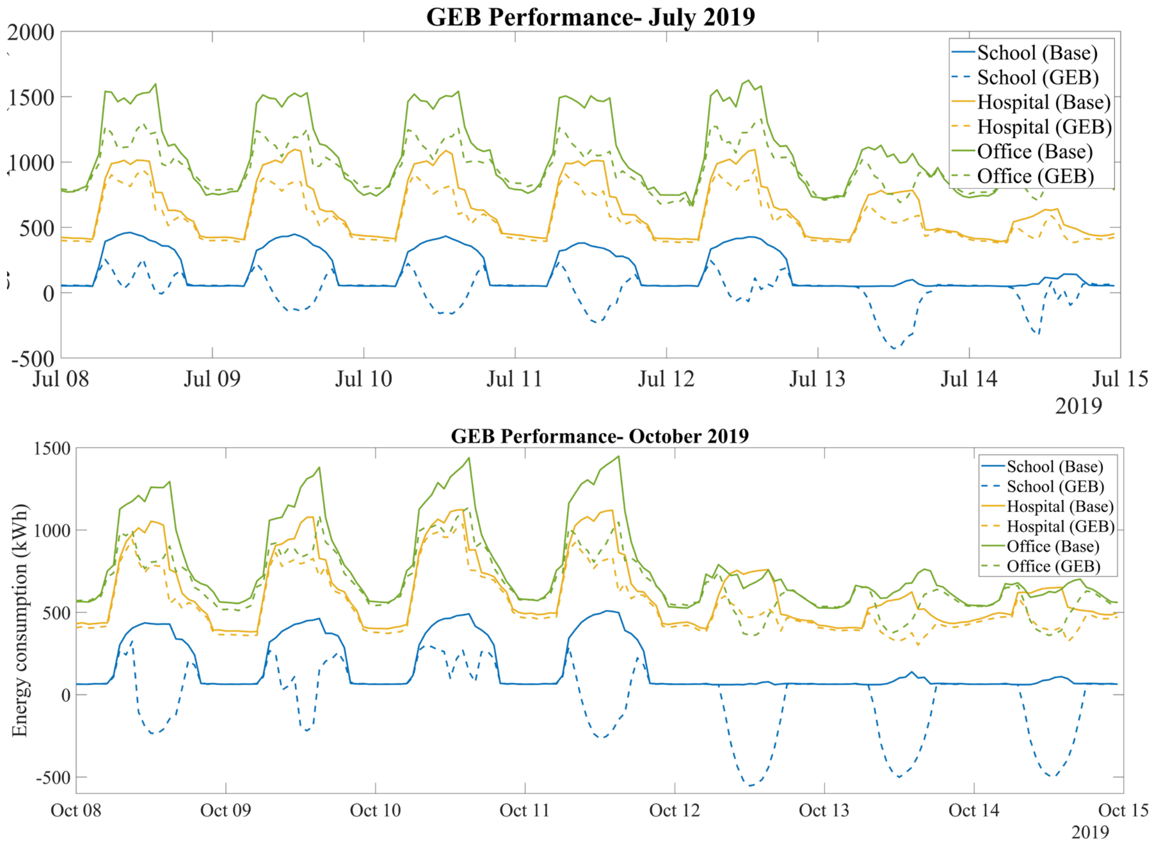


Fig. 9. GEB performance of school, hospital and office for the 2nd week of January, April, July and October of 2019

V. CONCLUSION

Grid-interactive efficient buildings (GEB) are capable of providing energy efficiency through offering electrical load flexibility and PV electricity generation. With proper planning and applications of modern IoT technologies, buildings like these have the potential to be the backbone of a power grid's cyber-physical ecosystem. However, the lack of standards regarding communication protocols, security measures, data granularity and data exchange protocol specific to the GEB operation, are major challenges towards realizing their full potential. Future research can involve addressing these challenges along with exploring applications of advanced deep learning algorithms to forecast GEB's demand flexibility with acceptable error margins.

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