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Accuracy of Peak Demand Estimates for Office Buildings Using eQUEST

Mahdiyeh Zafaranchi, Ethan S. Cantor, William T. Riddell, Jess W. Everett

***Abstract*—**The New Jersey Department of Military and Veteran's Affairs (NJ DMAVA) operates over 50 facilities throughout the state of New Jersey, US. NJ DMAVA is under a mandate to move toward decarbonization, which will eventually include eliminating the use of natural gas and other fossil fuels for heating. At the same time, the organization requires increased resiliency regarding electric grid disruption. These competing goals necessitate adopting the use of on-site renewables such as photovoltaic and geothermal power, as well as implementing power control strategies through microgrids. Planning for these changes requires a detailed understanding of current and future electricity use on yearly, monthly, and shorter time scales, as well as a breakdown of consumption by heating, ventilation, and air conditioning (HVAC) equipment. This paper discusses case studies of two buildings that were simulated using the QUick Energy Simulation Tool (eQUEST). Both buildings use electricity from the grid and photovoltaics. One building also uses natural gas. While electricity use data are available in hourly intervals and natural gas data are available in monthly intervals, the simulations were developed using monthly and yearly totals. This approach was chosen to reflect the information available for most NJ DMAVA facilities. Once completed, simulation results are compared to metrics recommended by several organizations to validate energy use simulations. In addition to yearly and monthly totals, the simulated peak demands are compared to actual monthly peak demand values. The simulations resulted in monthly peak demand values that were within 30% of the measured values. These benchmarks will help to assess future energy planning efforts for NJ DMAVA.

***Keywords*—**Building Energy Modeling, eQUEST, peak demand, smart meters.

I. Introduction

POPULATION expansion and environmental and technological issues related to resource depletion, such as energy shortages and increased greenhouse gas (GHG) emissions, have created concerns about energy consumption across the world. The building sector is responsible for more than 40% of global energy use, and by 2030, consumption related to the building sector is predicted to have increased by 50% [1]. Moreover, the building sector accounts for approximately 18% of total world GHG emissions [2]. The NJ DMAVA operates over 50 facilities throughout the state. Ongoing efforts to decarbonize have led to increased renewable generation at NJ DMAVA facilities and could eventually dictate the eliminating natural gas and oil use in these facilities. The combustion-driven heating systems that are currently in operation are likely to be replaced by electric-powered heat pumps. Resiliency requirements in the face of grid downtime compete with and complicate goals of electrification. Energy solutions for these facilities will involve smart microgrids that manage input and output power to the grid, as well as renewable generation and storage. Accurate modeling of building energy consumption is the foundation for developing strategies for improving and managing the energy performance of buildings [3]-[8]. This will be especially true for the energy management challenges faced by NJ DMAVA.

Simulation tools, such as EnergyPlus, eQUEST, IESVE, and TRNSYS, are based on models that incorporate first-principle physical and thermodynamic concepts. These tools have been used in a variety of buildings energy simulations [9], [10]. Models might depend on static equations or, more typically, dynamic equations that describe the time development of the heat balance [11]. Simulation with these tools is informed by characteristics of the building, and assume complete physical knowledge of the building design (e.g., the thermal conductivity of building exterior walls and HVAC configuration information) and operation (e.g., duration of workday and HVAC setbacks). However, such detailed information is often not available, and incorrect input parameters can lead to poor predictions [11], [12]. Another method for the estimation of the energy demand of buildings is the direct use of values obtained from smart meters or utility bills. Smart meters, when available, require a full year of data collection to account for seasonal variation in energy use. Utility bills will often only include monthly use totals. Neither of these approaches allow for the prediction of energy consumption after changes to building envelope, HVAC systems, or controls.

The accuracy of energy simulations remains a concern [13]-[15], so efforts to improve the precision of building energy consumption estimates are critical. Several organizations have published accuracy goals for yearly, monthly, and hourly consumption, based upon different statistical parameters [5], [16]-[23]. However, peak demand is also an important aspect of building energy use. For example, many large consumers in the US are billed based upon peak demand in a month, as well as total consumption. Demand is an important parameter when considering implementing renewables [24]. It is also a potentially limiting factor if electric-powered heat pumps are to replace combustion-driven boilers or furnaces. Models of building components, systems, and sub-systems are essential to anticipate the overall building and sub-system behavior, such as their energy consumption [10]. Although analyses on a daily or hourly scale are required for some applications, results are often only evaluated on a yearly scale.

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In this study, the energy consumption of two buildings were measured with smart meters in hourly increments and simulated using eQuest software. These simulations were informed by monthly and yearly totals. Despite the availability, hourly data were not consulted during the simulation process to reflect the information that will be available for most NJ DMAVA facilities. Many NJ DMAVA facilities only have monthly utility consumption data available. Some, but not all, of these facilities will also have peak monthly demand data available. However, a complicating issue for these analyses is that the many of these facilities have photovoltaic (PV) generation. At any given time, electricity might be generated from the PV system, and could flow to or from the grid. As a result, peak monthly demand from the utility might not coincide with the actual peak demand of the building.

Once the simulations were competed, measured and simulated peak hourly demand for each month were compared. As future planning and design efforts will require the extraction of peak demand values for buildings that do not necessarily have hourly data available, it is important to develop confidence that simulations tuned to yearly- and monthly-totals can predict electric use on shorter time scales, characterized by demand values, without *a priori* knowledge of these values. The goal of this paper is to evaluate the accuracy of buildings simulations developed with monthly data in terms of peak demand predictions. These results will be used to inform the approach toward simulations for future efforts.

II. Background

Building energy consumption estimation is critical in building energy management and energy policy. There are various methods to estimate the amount of energy consumption in buildings. eQUEST [25] and EnergyPlus [26] are two of the most widely used open-source applications. There have been several studies comparing the accuracy and other capabilities of the software. EnergyPlus benefits from sub-hourly time increments, independent radiation modeling, customized HVAC systems, and integrated simulations for reliable findings. eQUEST, is user-friendly and quick (results are available in minutes), but it is restricted to hourly time steps [27]. A performance comparison revealed that eQUEST energy consumption projections were more accurate than EnergyPlus findings [27]. Another study [28] found that eQUEST is easier to use than EnergyPlus and discovered that eQUEST forecasts were substantially more accurate than EnergyPlus projections. A study compared the performance characteristics of EnergyPlus, DeST, and DOE-2.1E and discovered that DOE-2.1E can provide relatively inaccurate results in double zone models (conditioned zone and adjacent non-conditioned zone) because DOE-2.1E uses the previous hour's adjacent space temperature values for current calculations [29].

Mostafavi et al. used a case study to examine the yearly accuracy of three techniques for building energy estimation: eQUEST, IESVE Revit Plug-in, and Green Building Studio [20]. According to the final comparison, eQUEST has a 98% accuracy in electricity and a 97% accuracy in gas usage annually, IESVE has a 72% accuracy in electricity and a 99.8% accuracy in gas consumption, and Green Building Studio has a 96% accuracy in both gas and electric usage. However, the study did not consider the accuracy for shorter time scales, such as monthly or hourly. In another study [16], the energy simulation of a building using eQUEST predicted that annual electricity consumption would be 1.5% lower, and gas consumption would be 7% lower compared to the measured annual consumption. The authors concluded that accuracy might be improved by on-site weather measurement, hourly energy consumption collection, and occupancy data.

III. Methodology

Two office buildings in New Jersey were selected as case studies. Both of these buildings have on-site PV generation that is net-metered through the utility meter. As a result, electric use is reported with both in and out values. In addition, PV generation is recorded. The total electricity used by a building for any time increment, E_t, is given by:

$$E_t = In_t - Out_t + PV_t \tag{1}$$

where PV_t is energy generation by PV, and In_t is net energy into the utility meter, and Out_t is the net energy out of the utility meter. These values are available for both buildings in hourly increments over a three-year period. For this study, monthly and yearly totals are compiled, so the increments can refer to consumption for months or years as well as hours. In addition, monthly natural gas use totals are available for one building.

In the first step of the study, the values of hourly electric use were totaled for each building to develop monthly and yearly totals. Likewise, monthly utility bills for natural gas use were totaled to obtain yearly totals. Then, the monthly and yearly totals for electric and gas were used to develop simulations for each building, which provide information about consumption on an hourly increment, as well as consumption by building system. Hourly measured consumption data were not consulted during the simulation process. Finally, the accuracy of the simulations was compared to measured data, comparing yearly, monthly and monthly peak-demand values. For the purposes of the study, the monthly peak-demand values were taken as the maximum consumption during any hour in the month. The flow chart of the methodology for this study is displayed in Fig. 1.

eQUEST was selected as a simulation method and used to estimate the electric and gas consumption of each consumer parameter and the total demand. As shown in Fig. 2, eQUEST is a combination of a building development wizard, an energy efficiency measure wizard, and graphical reporting with a simulation "engine" [30]. eQUEST calculates hour-by-hour building energy use over a complete year (8760 hours) using hourly weather data for a specified region. An average of 10 years' worth of weather data are used as input in this study [31]. Average weather data were used rather than specific yearly weather data to reflect the intended use of the simulations to predict future use, rather than reproduce known events. The program's input data include occupant hourly scheduling, lighting equipment, thermostat settings, shading devices, details about the building envelope, and thermal mass.

Additionally, building features such as shading, and dynamic responses to heating and cooling systems are considered, and a dynamic lighting model is used to assess the influence of natural lighting on thermal and lighting demand. eQUEST calculates metrics such as overall electric and gas usage based on the specifications input by the user [32].

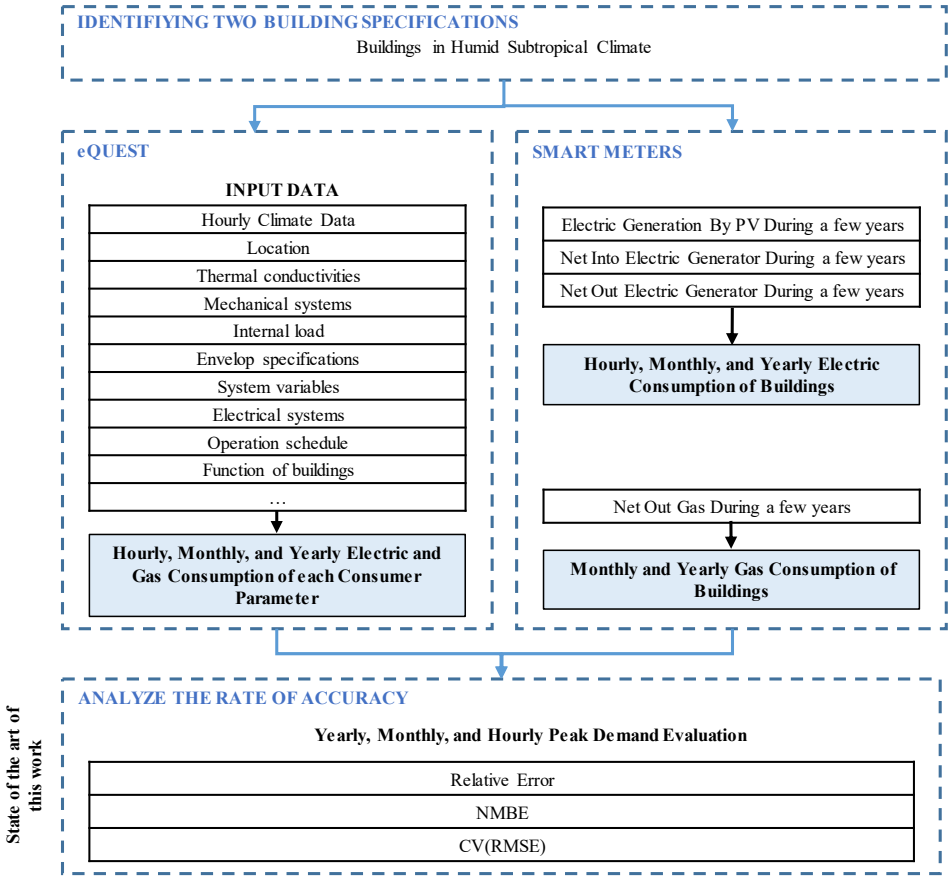

Fig. 1 Flowchart of methodology

IV. Buildings Description

This study was developed for two NJ DMAVA office buildings, denoted Building 1 and Building 2, which were constructed in the 1970s. Both buildings are located in parts of New Jersey that are considered to have a humid, subtropical climate. The warmest month in New Jersey is July, with an average temperature of 24.5 °C, and the coldest month is January with an average temperature of -1 °C [34]. The average monthly temperature for 10 years considered in this study is represented in Fig. 3 [33]. Key information for these buildings is summarized in Table I. Some identifying information regarding these buildings has been obscured to satisfy security policies of the sponsor [35].

Building 1 has a floor above ground where employees work Monday through Friday from 7:00 a.m. to 6:00 p.m. The building has a central HVAC system with a 22–23 °C setpoint. The dominant materials of the building envelope are brick and concrete masonry units with double-pane windows. The ratio of window to wall area is approximately 17%.

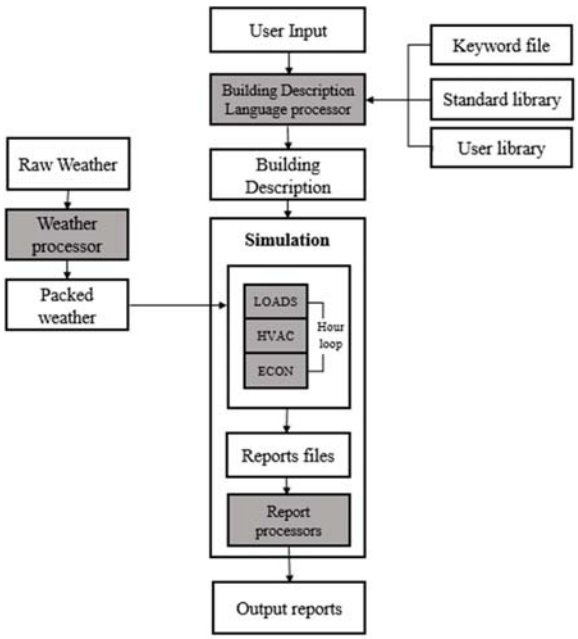

Fig. 2 DOE-2.2 program flow adapted based on eQUEST manual (shaded boxes are programs) [30]

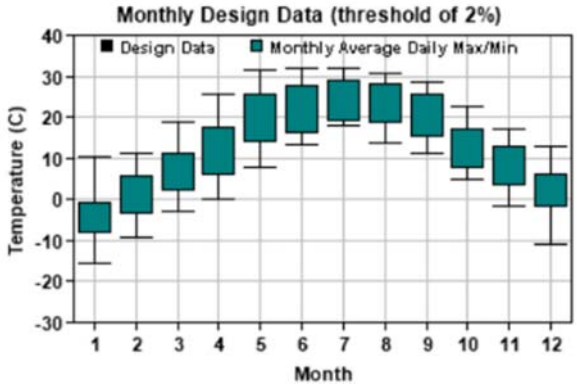

Fig. 3 An average of 10 years of temperature was used as input data for the eQuest simulation [33]

TABLE I
SUMMARY OF THE BUILDINGS

	Building 1	Building 2
Operation Area	6,000 to 7,000 m²	3,000 to 4,000 m²
Building Operation Schedule	7:00 AM – 6:00 PM during workdays	7:00 AM – 5:00 PM during workdays
Energy Source	Electricity and Natural Gas	Electricity
Building envelope	Brick and concrete masonry units 17% double pane window to wall ratio	Brick and concrete masonry units 27% double pane window to wall ratio
HVAC	Boiler, Space Heaters, Window A/C, and Central A/C	Condenser, DX, Air Cooled - Direct Drive, Indoor Modular - Central AHU
Setpoints	HVAC (22 – 23 °C)	HVAC (20 – 21 °C)

Building 2 has two floors above ground and a basement where employees work Monday through Friday from 7:00 a.m. to 5:00 p.m. The building has a central HVAC system with a 20–21 °C setpoint. The dominant materials of the building are brick and concrete masonry units with double-pane windows. The ratio of windows to wall area is approximately 27%. Most energy-consuming equipment in both buildings is only powered on and off according to the workday hours, except for HVAC systems that work constantly.

V. SIMULATION OF ENERGY USE

The gas and electric consumption of the two buildings were determined by combining smart meter and PV data for electric consumption using (1) and monthly utility bills for natural gas use (converted from therms to kWh for constituency across comparisons). Equation (2) indicates the error, e_t, between the simulated and the measured values at the increment t:

$$e_t = E_t - P_t \quad [kWh] \tag{2}$$

where E_t is the measured use and P_t is the simulated use. Relative error for an increment can be found as a percentage of the true value by

$$RE = \frac{e_t}{E_t} \times 100 \tag{3}$$

The measured electricity consumption for Building 1 was 108.70 kWh/m² in 2020, 104.80 kWh/m² in 2021, and 108.20 kWh/m² in 2022, with an average of 107.23 kWh/m² of electricity per year during the three years. The eQuest simulation resulted in 104.10 kWh/m² of electricity per year, which is approximately a 3% relative error. The measured gas consumption was 98.30 kWh/m² in 2019, 98.19 kWh/m² in 2020, and 104.94 kWh/m² in 2021, resulting in an average of 100.48 kWh/m² of natural gas per year. The simulation resulted in 92.26 kWh/m² of gas per year which is approximately an 8% relative error. The measured electric consumption for Building 2 was 402.50 kWh/m² in 2020, 431.65 kWh/m² in 2021, and 455.95 kWh/m² in 2022, with an average of 430.03 kWh/m² of electricity per year during those three years. The annual simulated result showed 418.28 kWh/m² of electricity per year, which is less than a 3% relative error. The yearly simulated values are good approximations of the measured values.

One of the main advantages of eQUEST simulation software is estimating the energy consumption of each consumer parameter separately, which can be useful in designing energy-efficient strategies such as heat pumps to satisfy heating and cooling demand. Based on the simulation results, the dominant energy consumption of consumer parameters is space heating at 51% in Building 1 and 38% in Building 2; more specific information about annual energy consumer parameters is presented in Table. II. Note that this table includes both electric and natural gas consumption for Building 2, and that there is no natural gas consumption for Building 1. The energy intensity for Building 2 is noticeably higher than that for Building 1. This is attributed to a considerable number of computer servers that operate in Building 2, as well as the relatively inefficient electric heating system.

Figs. 4 and 5 present comparisons of monthly measured and simulated electric use for individual years as well as the three-year average values for Building 1 and Building 2, respectively. The monthly measured and simulated natural gas use for Building 1 is shown in Fig. 6 (recall that Building 2 does not use any natural gas). Based on the monthly investigations, the simulation values generally agree with the actual measured values, but in some cases the same month can be overestimated one year and underestimated another year. These differences can be attributed to both changes in weather from year to year as well as simulation errors. These errors are quantified and compared to published recommendations in the following section.

VI. VALIDATION OF SIMULATION MODELS

Building simulation models are dependent on various independent interacting variables and the complexity of base building information; therefore, accurate simulation model representation of the actual building is difficult. To obtain accurate and useable results, calibration of model output with measured data is critical to any modeling simulation study [36], [37]. To validate the simulation model, some researchers applied statistical analysis to compare the measured and simulated data [38], [39].

An accepted criterion to evaluate the calibration of a building simulation involves the normalized mean bias error (NMBE),

which is the mean difference between actual and simulated energy consumption values, normalized by the actual energy consumption mean value [40].

The NMBE is stated as a percentage and is calculated as the negative total sum of the errors, e_t, in the time intervals divided by the sum of the measured energy consumption, E_t, as given in (4):

$$NMBE = -\frac{\sum_{i=1}^{n} e_i}{\sum_{i=1}^{n} E_i} \times 100 \quad (4)$$

TABLE II
ENERGY CONSUMPTION OF CONSUMER PARAMETERS ESTIMATED BY eQUEST (kWh/year-m^2)

Name of Building	Space Cool	Space Heat	Hot Water	Vent. Fans	Pumps & Aux	Misc. Equip.	Area Lights	Total Consumption
Building 1	16.17	100.55	6.13	16.68	0.74	18.36	37.73	196.37
Building 2	31.77	158.20	12.10	30.33	0.27	118.32	67.29	418.28

NMBE could be used to determine how well simulated or expected demand matches real energy usage. However, one significant disadvantage of this index is the offsetting of mistakes when positive and negative errors cancel each other out. Bou-Saada and Haberl [41] demonstrate that Root Mean Square Error (RMSE) is a good metric to determine model validation. The RMSE is calculated by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n}} \text{ [kW]} \quad (5)$$

The normalized measure of the RMSE is the Coefficient of Variation of Root Mean Squared Error (CV (RMSE)) (7). It is based on RMSE (6), but scaled by A (6), which indicates the measured average energy consumption. A lower CV (RMSE) value indicates a better calibrated model [42].

$$A = \frac{\sum_{i=1}^{n} E_i}{n} \quad [kWh] \quad (6)$$

$$CV(RMSE) = \frac{RMSE}{A} \times 100 \quad (7)$$

Both CV (RMSE) and RMSE assess the total error without offsetting positive and negative errors. However, CV (RMSE) has the additional advantage in that the error is normalized, which allows errors to be compared between simulations without bias for the magnitude of the results.

The accuracy of the simulations in this study were evaluated using Relative Error, NMBE, and CV (RMSE). The measured annual, monthly, and peak hourly values, denoted by E_t, and values obtained by eQUEST simulations, denoted with P_t, were compared. These indices are assessed for each type of energy used in a building for both yearly and monthly intervals. ASHRAE Guideline 14 (2002) specifies acceptable limits for the indices [43], International Performance Measurements and Verification Protocol (IPMVP) [44], Federal Energy Management Program (FEMP) Measurements and Verification (M&V) guidelines [45]. To validate the method's reliability, the values obtained by (3) and (6) should be under a specified threshold, as shown in Table III.

TABLE III
COMMONLY USED CALIBRATION CRITERIA [47]-[50]

Index	ASHRAE	IPMVP	FEMP
NMBE month	± 5%	± 20%	± 5%
CV (RMSE) month	± 15%		± 15%
NMBE hourly	± 10%	± 5%	± 10%
CV (RMSE) hourly	± 30%	± 20%	± 30%

Simulation results that fall within these parameters are deemed to be sufficiently near to the physical world that the simulation is meant to replicate [46]. While criteria for hourly data are published, results for this study were not evaluated for hourly increments. To achieve good results on an hourly basis, a simulation would need to use actual weather data for the simulated time period and have the dates of the study correspond to the actual dates of the simulation so that weekends align in the simulation and actual time period. This study used 10-year average weather data and did not align the workweeks for specific dates, so it was not reasonable to expect accurate simulation results on an hourly basis.

VII. RESULTS

NMBE and CV (RMSE) values for both buildings during three individual years of monthly and peak hourly data were calculated. Table IV shows the monthly validation analysis. The NMBE for monthly values ranges between -12.07% and 3.92%, with an average of -4.39%. The CV (RMSE) for monthly values ranges between 5.09% and 27.33%, with an average of 14.34%. Based on the results, the monthly electric consumption predictions are satisfactory when considering a -2.68% average NMBE (about 2.5% underestimated) and a 12.92% average CV (RMSE). But the average NMBE for monthly gas consumption is -8.08% and the average CV (RMSE) is 21.41%. Gas consumption, which is used for heating, is highly dependent on outside weather temperatures, which increases the range of prediction error and variation from year to year. Results from simulations of gas were less accurate than those of electricity.

Peak demand is the largest instantaneous power demand during a given time interval. Peak demand is an important parameter for developing energy management strategies. In this study, the maximum simulated and measured hourly value in a month was taken as a peak demand of each month for three individual years. The resulting monthly peak demands are plotted in Figs. 7 and 8 for Building 1 and Building 2, respectively. The errors for these values are summarized in Table V. The overall shapes of the simulated peak demands resemble the measured peak demand in both buildings. The simulated peak demand values tend to be higher than the measured peak demand values. The simulation of Building 1 results in a 30% overestimated on average and the simulation of Building 2 results in a 1.93% overestimation, according to NMBE. The average CV (RMSE) of Building 1 is 32.98% and

that of Building 2 is 15.63%. The simulated peak hourly demand value for each month is considered reasonable compared to measured values despite the simulations not accounting for specific weather and workweek schedules.

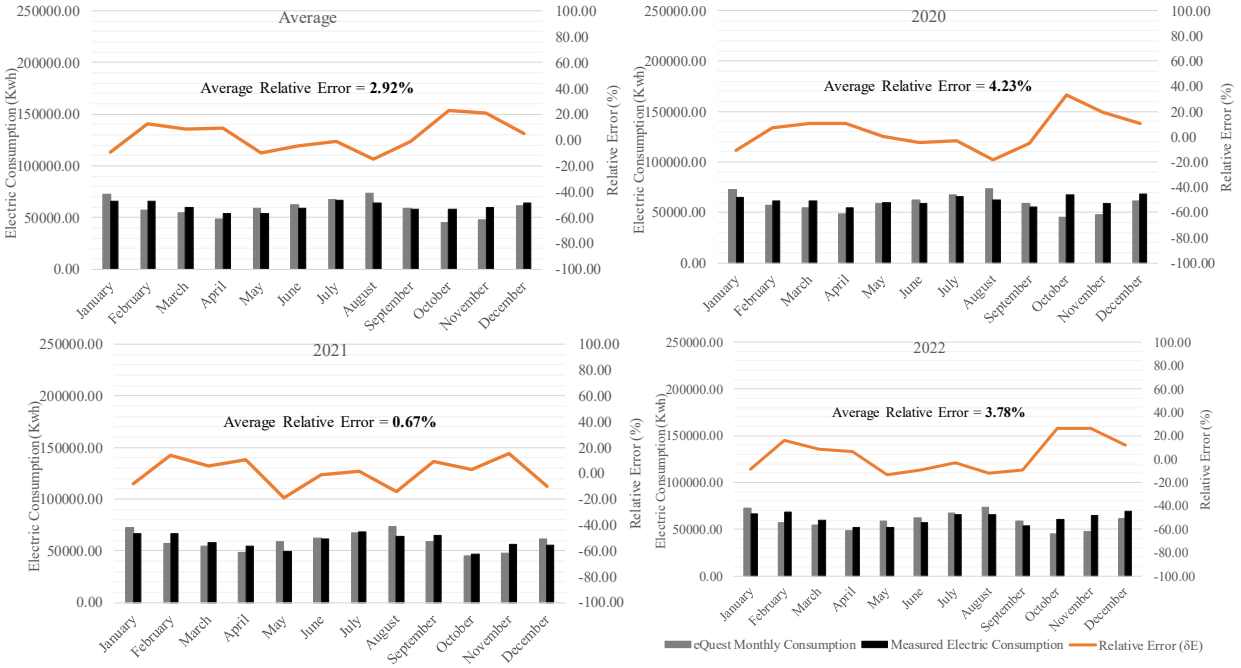

Fig. 4 Monthly electric consumption of Building 1

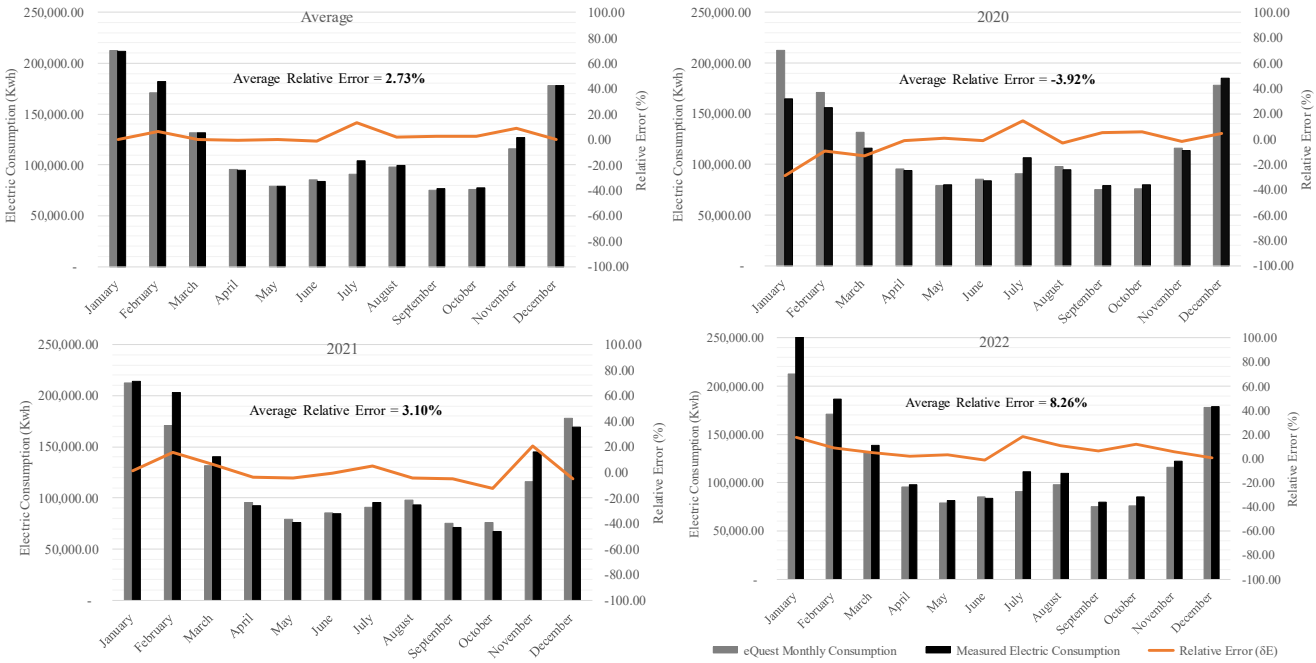

Fig. 5 Monthly electric consumption of Building 2

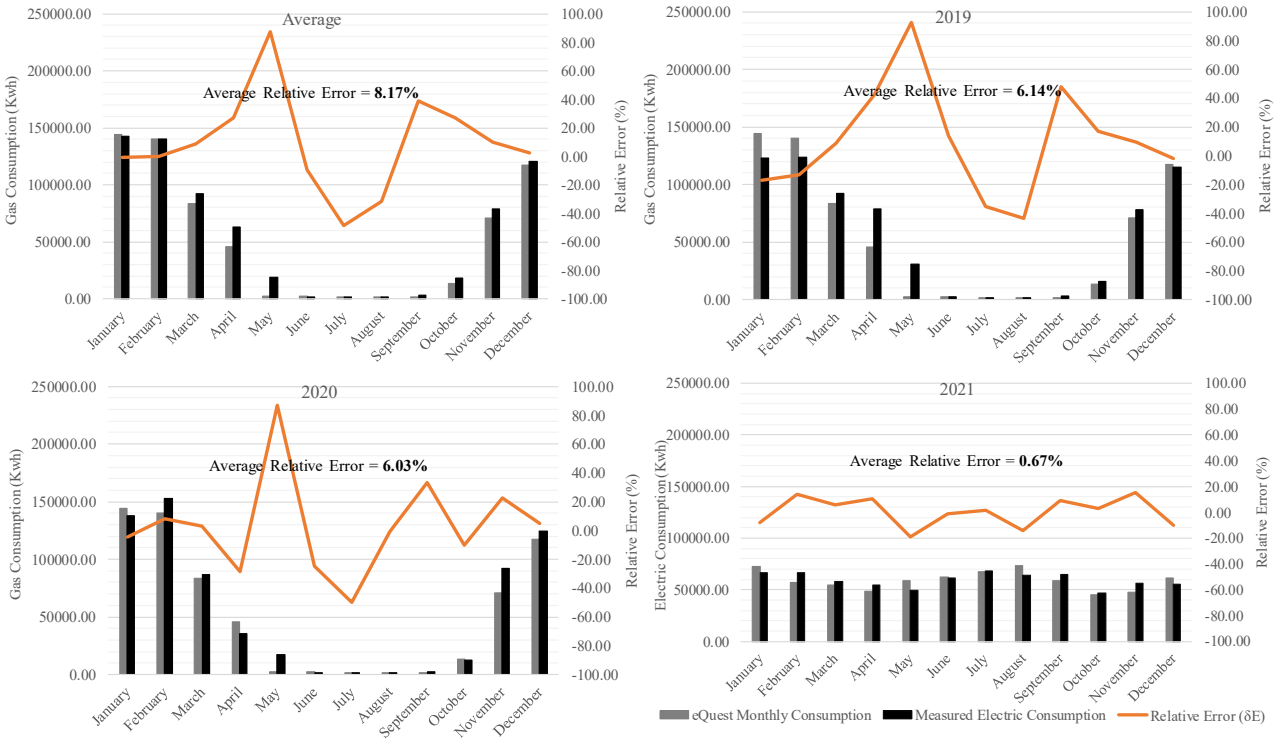

Fig. 6 Monthly gas consumption of Building 1

TABLE IV
THE MONTHLY VALIDATION ANALYSIS FOR SIMULATED VS. MEASURED VALUES DURING THE THREE YEARS

		2020 Monthly		2021 Monthly		2022 Monthly		Average Monthly	
		NMBE	CV (RMSE)	NMBE	CV (RMSE)	NMBE	CV (RMSE)	NMBE	CV (RMSE)
Building 1	Electric	-4.22	14.59	-0.66	10.58	-3.78	14.67	-2.91	11.83
	Gas	-6.14	27.33	-6.03	16.52	-12.07	20.4	-6.75	13.11
Building 2	Electric	3.92	14.25	-3.09	11.26	-8.26	12.4	-2.73	5.09

TABLE V
EVALUATION OF THE MONTHLY PEAK DEMAND FOR ELECTRIC CONSUMPTION OF TWO BUILDINGS FOR SIMULATED VS. MEASURED VALUES DURING THE THREE YEARS

Building	Year	NMBE (%)	CV(RMSE) (%)
Building 1	2020	32.87	34.89
	2021	26.93	30.58
	2022	30.25	33.47
Building 2	2020	7.68	23.47
	2021	3.11	10.16
	2022	-4.98	13.28

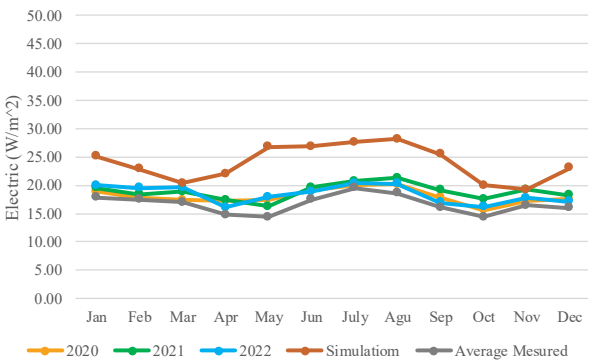

Fig. 7 Monthly electric peak demand Building 1

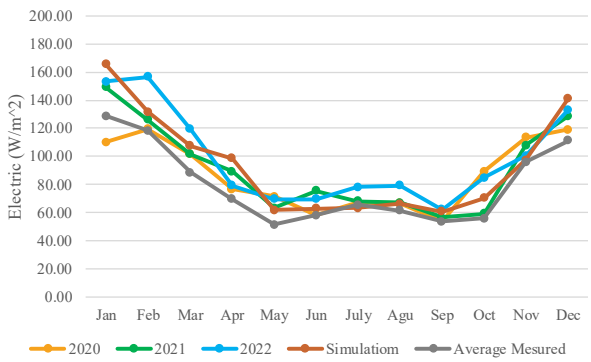

Fig. 8 Monthly electric peak demand of Building 2

VIII. CONCLUSION

In this paper, two existing buildings located in New Jersey, US, are selected as case studies. The energy demand of buildings is estimated by eQUEST software and measured over three years by smart meters. In the next step, the yearly, monthly, and hourly peak energy demands of buildings are analyzed and compared with each other. The innovation of this paper lies in evaluating the accuracy simulated peak demand values for simulations that were developed only with yearly and monthly use data.

Relative error, NMBE, and CV (RMSE) were considered to quantify accuracy. Results for yearly and monthly use were compared to acceptable ranges that have been published in the literature. The findings show that the annual simulated values are significantly close to the measured values. As anticipated, as the time scale under consideration becomes smaller, the error increases. The monthly electric demand estimation is satisfactory with a -2.68% average NBME and a 12.92% average CV (RMSE). However, natural gas use simulations are impacted by outside temperatures, resulting in greater errors for some months during the time period of study. For monthly gas consumption, the average NMBE is -8.08%, while the average CV (RMSE) is 21.41%. According to NMBE, the simulated hourly peak demand for Building 1 is 30% and the Building 2 is 1.93% greater than the measured peak demand. Building 1's average CV (RMSE) is 32.98%, whereas Building 2's is 15.63%.

The development of energy management strategies will require efficient modeling with well understood accuracy. The results of this study can serve as a benchmark for future simulations of NJ DMAVA facilities. Additional areas of study that are needed include the simulation of NJ DMAVA buildings that have significantly different missions from the buildings chosen for this study, for example, readiness centers, as well as comparison of results from other modeling tools.

Acknowledgments

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