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Generative Smart Energy Management in Buildings Using IoT Sensors: An Optimization-Based Approach

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ABSTRACT:
Artificial Commercial and institutional buildings use a significant amount of electricity, much of which is wasted because heating, ventilating and air-conditioning (HVAC) and lighting systems are set on fixed schedules instead of according to need. The study aims to explore the effectiveness of IoT-based energy management in buildings based on experiments and optimization methods. An electricity sensor network was installed in a simulated three-zone building model (1200 m², offices, meeting rooms and a laboratory/classroom space) and measured the electricity consumption, indoor temperature, humidity, occupancy, status of HVAC systems, illuminance and other sensor readings every 15 minutes over a period of 28 days. The observations were summarized in time series, abnormal and incomplete readings were filtered and analyzed to describe the consumption patterns. A rolling-horizon linear optimization model was then formulated to determine the cooling power, fan speed, lighting dimming levels under the constraints of comfort, ventilation, and capacity with a penalty for peak demand. The five different operation scenarios under consideration were compared with a baseline based on a schedule: Occupancy rules, Optimized HVAC, Optimized lighting and Integrated optimization. The integrated approach resulted in an overall reduction in electricity consumption of 26.4%, and a reduction of 35.4% in controllable-load electricity consumption, a 36.4% reduction in peak demand, and a 98.5% compliance with the 22–26 °C comfort band as measured by the occupant weighted time index. There was a statistically significant amount of savings on each day (paired $t(27) = 6.57$, $p < .001$). A sensitivity analysis indicated that there was a definite relationship between the energy savings and reduction of peak. The results are an upper bound, as the study was performed with simulated sensors and an optimizer with a complete knowledge of the building model, and will be validated during a physical deployment.

Keywords: smart buildings; Internet of Things; energy management; optimization; model predictive control; HVAC; peak demand

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INTRODUCTION

The contribution of buildings to final energy consumption is significant in the global context, and the contribution of HVAC and lighting is usually the largest controllable loads (Pérez-Lombard et al., 2008) for commercial buildings. There are still many buildings, however, that are on a fixed schedule and have constant setpoints; cooling plants are still turning on early, fans are still operating at full speed, and lights are still on when rooms aren't in use and daylight is available. This results in energy loss that

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is not visible to facility managers who don't have the granular data needed to understand how spaces are used.

The Internet of Things (IoT) is one solution to this information problem. Low-cost wireless sensors, meters can report power, temperature, humidity, occupancy, illuminance continuously and edge gateways, cloud platforms can store, process and respond to these data (Al-Fuqaha et al., 2015). Analyses of the building energy and environment sensing infrastructure reveal its maturity but also the importance of the sensed data for its use in control, which depends on the control algorithm (Ahmad et al., 2016; Dong et al., 2019). Smart buildings architectures have been suggested, which integrate the IoT sensing system with next generation building management systems, for the optimization of energy consumption (Minoli et al., 2017).

Energy saving comes not when you sense it, but when you decide to save it. But there are simple rule-based strategies that can yield substantial savings with minimal complexity, like turning lights and other equipment off when a room is empty. Studies have demonstrated that HVAC and lighting energy can be saved by occupancy-driven control in operating buildings (Agarwal et al., 2010), and reviews of activity-aware control have confirmed the potential energy savings from incorporation of occupant information in building systems (Nguyen & Aiello, 2013). But rules act in the present and not the future. Buildings have thermal inertia and so can be cooled during less critical and/or more cost-effective periods of the day, and electricity consumption by a large number of such systems can be combined to yield the maximum demand for utilities and maximum cost for the customer.

Optimization-based control, in particular, model predictive control (MPC), enables this by considering a model of the building, as well as making forecasts of weather and occupancy, and then planning the operation in a future time horizon while taking the comfort limits into account (Afram & Janabi-Sharifi, 2014). The studies in the field and in simulation pointed to the potential to save energy with MPC when using the weather forecast and maintaining comfort (Oldewurtel et al., 2012). In the context of control systems for energy and comfort management, or optimized control for smart buildings, reviews indicate that optimization is one of the most promising approaches while the integrated treatment of several systems (e.g. HVAC, ventilation, lighting), along with the quality of the sensor data, remains under-explored in practice (Dounis & Caraiscos, 2009; Shaikh et al., 2014). Later studies on building energy management emphasize the integration of data-driven sensing, optimization and demand-side factors (Kathirgamanathan et al., 2021; Mariano-Hernández et al., 2021).

This study meets that need by proposing and testing a smart energy management strategy for the IoT utilizing a rolling-horizon optimization model. It makes three contributions. It presents a comprehensive system workflow from raw streams of IoT sensor data to cleaning and characterization of time-series data, all the way to optimization-based control. Second, it creates a single linear program representing the simultaneous optimization of cooling power, ventilation fan speed, and lighting dimming – including a peak-demand term – to account for interactions between lighting heat and cooling load. Thirdly, it compares five operating scenarios with an energy, peak demand, and occupant-condition indicator, and it examines how results are sensitive to the comfort limit and how much weight to put on the peak demand.

LITERATURE REVIEW

Energy Use and Sensing in Buildings

Climate, envelope, systems and most importantly their operation and use drive building energy consumption (Pérez-Lombard et al., 2008). This operation is understood from the data gathered through metering and environmental monitoring and reviews, and sub-metering of major end uses, along with indoor environmental and occupancy sensing, is the foundation for any analysis of efficiency (Ahmad et al., 2016). Smart building sensing systems have been reviewed, and it has been found that the costs of the sensors are now low, and that they can be wirelessly connected in a network, but their accuracy,

calibration and reliability issues continue to be challenges for control applications (Dong et al., 2019). These sensors are complemented by the standardized connectivity, edge processing and cloud analytics for the IoT paradigm (Al-Fuqaha et al., 2015), and smart-building architectures have been proposed that integrate these layers with building management systems (Minoli et al., 2017).

Occupancy and Comfort-Driven Control

Occupancy is the variable that is most directly related to building operation and need. Occupancy-driven strategies are based on changes to HVAC operation and lighting based on the presence detected, and operating-building studies have documented savings due to reducing HVAC conditioning of vacant spaces (Agarwal et al., 2010). The surveys on energy-intelligent buildings, which rely on user activity, categorize the ways in which energy savings can be achieved using activity data and highlight the tradeoff between energy savings and comfort when the control is too aggressive (Nguyen & Aiello, 2013). Thermal comfort limits are typically put forward by standards that define acceptable ranges for the operative temperature and humidity within an occupied room (American Society of Heating, Refrigerating and Air-Conditioning Engineers [ASHRAE], 2020), while lighting standards set the maintained illumination levels of various visual tasks in the workplace (European Committee for Standardization [CEN], 2021). The energy management strategy needs to be assessed based on comfort, visual condition and also on energy.

Optimization-Based and Predictive Control

At every decision step, MPC solves an optimization problem over a prediction horizon, and only implements the first of these actions before solving with new measurements (Afram & Janabi-Sharifi, 2014). In buildings, this enables pre-cooling, load shifting and system coordination. The benefits of MPC with weather forecasting for building climate control were demonstrated by Oldewurtel et al. (2012) and the reviews for energy and comfort optimized control of smart buildings listed the algorithms used for energy and comfort management (Dounis & Caraiscos, 2009; Shaikh et al., 2014). Recent reviews focus on predictive control, data-driven or model-based, for the exploitation of building energy flexibility (Kathirgamanathan et al., 2021) and on the combination of model-based predictive control and demand-side management and fault detection in building energy management systems (Mariano-Hernández et al., 2021). Peak demand is relevant because the desire to reduce and shift loads is inherent in demand side management for the purpose of improving the efficiency and reliability of the system for which it is designed, and intelligent control is a enabler for net zero oriented roadmaps for buildings (Palensky & Dietrich, 2011; Kolokotsa et al., 2011).

Data quality

The more reliable decisions that can be made are dependent on the accuracy of the data they rely on. Sensor streams in the real world are subject to spikes, drift, and gaps due to faults, communication problems and maintenance, and the treatment of these contaminations can affect the conclusions that can be made from the data (Pearson, 2005). Screening of unrealistic values, detection of outliers in a robust manner and filling in brief gaps are therefore part of the practical building analytics, which were also studied.

Research gap

Current research largely focuses on the separate components of sensing, data processing and control, on HVAC systems only, or on energy savings only and without other measures that reflect peak demand and occupant conditions. This study integrates all these in one workflow and test scenarios, focusing on the effect of individual systems and on their combination.

MODEL OF SYSTEM ARCHITECTURE AND OPTIMIZATION

Architecture

The proposed system consists of 5 layers as presented in Figure 1. The sensing layer consists of power meter, temperature and humidity sensors, occupancy sensors, illuminance sensors and HVAC sensors. The readings are time-stamped and buffered in the IoT gateway before being sent to a data platform that stores them as time series, preprocesses them and generates short-term forecasts of weather and occupancy. The optimization engine then calculates operating plans based on the cleaned measurements and forecasts, while the actuation layer executes the first half of each plan via HVAC setpoints and fan speeds, and lighting dimming levels. A monitoring module serves to compare optimized and baseline performance. The loop is closed, as new measurements are used for re-optimization every hour.

Figure 1. Architecture of the IoT-based smart energy management system

Thermal and electrical model

Each zone z was represented by a first-order resistance–capacitance thermal model. With a time step Δt of 0.25 h, the indoor temperature evolves as

$$T_{z,k+1} = T_{z,k} + \frac{\Delta t}{C_z}\left(UA_z\left(T_k^o - T_{z,k}\right) + Q_{z,k}^{occ} + Q_{z,k}^{eq} + Q_{z,k}^{sol} + P_z^L\, d_{z,k} - Q_{z,k}^c\right) \qquad (1)$$

where Cz is the thermal capacitance (kWh/K), UAz the envelope conductance (kW/K), To the outdoor temperature, Qocc the heat gain from occupants (kW), Qplug the plug heat gain (kW), Qsol the solar heat gain (kW), PLz the installed lighting power (kW), and dz,k is the lighting dimming level (0–1),dz,k the cooling delivered to the zone (kW thermal). 100% of the light power was assumed as heat in the zone. The electric power of the building at step k was

$$P_k = \sum_z \left(\frac{Q_{z,k}^c}{COP_k} + P_z^F\, v_{z,k} + P_z^L\, d_{z,k} + P_{z,k}^{eq}\right) \qquad (2)$$

where vz,k is the fraction of fan speed (between 0 and 1), PFz the fan power measured at full speed, and Peq the plug-load power, which is not controllable. A model of the coefficient of performance of the cooling plant was designed: COPk = min(4.8, max(2.2, 4.6 − 0.09(Tok − 20))).

Optimization problem

The optimizer was running linear programs with 96 steps K = 96 for 24 hours at each decision time. The goal was to reduce electricity consumption and peak demand and comfort violation penalties:

$$\min \sum_{k=0}^{K-1} \Delta t \sum_z \left(\frac{Q_{z,k}^c}{COP_k} + P_z^F v_{z,k} + P_z^L d_{z,k}\right) + \lambda\, P^{peak} + \rho \sum_{z,k} s_{z,k} \qquad (3)$$

subject to the thermal dynamics in Equation 1 and the following constraints:

$$T_{z,k+1} \le T^{max} + s_{z,k} \ \text{(occupied steps)}, \qquad T_{z,k+1} \le 30 \ \text{(unoccupied steps)} \qquad (4)$$

$$d_{z,k} \geq \max\left\{0, \frac{E^{req} - E_{z,k}^{day}}{E^{max}}\right\} \text{ (occupied steps)} \qquad (5)$$

$$v_{z,k} \geq 0.2 + 0.8\,\frac{n_{z,k}}{n_z^{max}} \text{ (occupied steps)}, \qquad 0 \leq Q_{z,k}^{c} \leq Q_z^{max}\, v_{z,k} \qquad (6)$$

$$\sum_z \left(\frac{Q_{z,k}^{c}}{COP_k} + P_z^F v_{z,k} + P_z^L d_{z,k} + P_{z,k}^{eq}\right) \leq P^{peak}, \qquad T_{z,K} \leq T^{max} - 0.5 \qquad (7)$$

The comfort slack s is a nonnegative value with a penalty value of ρ = 50 kWh/K as well as the required work plane illuminance Ereq = 400 lux are set in the base case. The illuminance generated by the lights at full output is denoted as Emax = 500 lux; the number of occupants is denoted as n and the cooling capacity is denoted as Qmax. The comfort and setback rule (Equation 4), daylight harvesting and dimming (Equation 5), demand controlled ventilation (Equation 6) and the final dumping of stored heat (Equation 7) are given.The following equations are given: the comfort and setback rule (Equation 4); daylight harvesting and dimming (Equation 5); the demand controlled ventilation (Equation 6) and the final dumping of the stored heat (Equation 7). In the base case, the weight λ was 3kWh/kW. All relationships are linear and the problem is therefore a linear program which can be solved reliably and quickly in a fraction of a second. The plan was re-optimized every hour and only the first four steps (one hour) of the plan was executed — this is the rolling-horizon idea of MPC.

METHODOLOGY

Research design

This research assumed an experimental and optimization-based research design to explore the energy saving efficiency of buildings' energy management using IoT. The experiment involved four different operating strategies, all tested in the same building for 28 days, with the same occupancy and weather conditions. In a paired comparison, the conditions are the same for each scenario, eradicating weather and occupancy variance as a confounder, which was not possible in a physical building in a before and after comparison where conditions were different between the two time periods. The performance of the proposed strategy was evaluated by comparing the optimized energy consumption with the pre-optimized energy consumption.

A virtual sensor network was installed in a 1200 m2 commercial building with three zones to produce data. The first zone (A) was an open plan office of 600 m² accommodating up to 60 occupants, the second (B) was a 200 m² meeting-room zone which was used intermittently by up to 25 people and the third (C) was a 400 m² laboratory/classroom zone with scheduled use by up to 40 occupants. The zone parameters are provided in Table 1. It started on a Monday and the weather was cooling-dominated with temperatures ranging between 20.4 and 35.5 °C with an average temperature of 27.9 °C. Occupancy followed weekday arrival, lunch and departure patterns with randomness from day to day, half use on Saturday and almost no use on Sunday, and meeting and class blocks were generated randomly in zones B and C, with solar gains and daylight determined by a clear sky profile adjusted for the daily amount of cloudiness. The formulation also applies to heating, which was not used in this test period, but is available for heating with signed thermal power.

Table 1. Parameters of the simulated building zones

Zone	Use	Area (m²)	C (kWh/K)	UA (kW/K)	Lighting (kW)	Plug load, max (kW)	Fan, max (kW)	Cooling capacity (kW)	Max occupants
A	Open office	600	60	0.60	7.2	6.0	4.0	35	60
B	Meeting rooms	200	18	0.20	2.4	1.5	1.2	15	25
C	Laboratory/classroom	400	40	0.40	4.8	8.0	2.5	25	40

IoT sensing and data acquisition

A total of 18 data channels were recorded at 15-minute intervals, for a total of 2,688 channels and 48,384 readings. Chosen channels included whole-building electricity consumption, HVAC power (including fan power), and lighting power, as well as indoor temperature, relative humidity, number of occupants, illuminance, and HVAC operating status for each zone. The models of noise and error, which were the same as those used in commercial devices, were used to represent the behavior of the sensors (Table 2). The weather-station inputs to the outdoor temperature and solar radiation were treated as such, and the errors in their forecasts were increased in relation to the forecast lead time (error of about 0.8 °C for outdoor temperature and of about 8% for solar radiation for short lead times). The forecasts of occupancy were based on the average occupancy schedules instead of the actual randomized occupancy, and the measured occupancy for the first two steps of each horizon.

Table 2. Virtual sensor channels and error models

Measured variable	Device type	Unit	Sampling	Error model
Building electricity	Smart meter	kW	15 min	±1% (Gaussian)
HVAC and lighting power	Sub-meters	kW	15 min	±1% (Gaussian)
Indoor temperature (3 zones)	Digital sensor	°C	15 min	SD 0.2 °C
Relative humidity (3 zones)	Digital sensor	%	15 min	SD 1% RH
Occupancy (3 zones)	PIR/people counter	persons	15 min	±1 person
Illuminance (3 zones)	Lux sensor	lux	15 min	SD 5%
HVAC status (3 zones)	Current transformer	on/off	15 min	none

Data preprocessing

All these observations were arranged in the form of time series and preprocessed by discarding the abnormal readings and missing observations. To simulate the preprocessing pipeline in realistic condition, 1% of the continuous ones were randomly damaged by spikes and 2.1% of readings were corrupted in intervals of 15 minutes to 2.5 hours to simulate the loss of communication. The cleaning process was done in four stages. First, the range checks eliminated physically implausible values, based on variable and zone capacity limits. Second, isolated outliers were identified using a Hampel filter that looks for data points that are 7 or more robust standard deviations (or median absolute deviations) away from the 13-point rolling median. Thirdly, gaps up to 1 hour were linearly interpolated. Fourth, longer gaps were filled in with the same hourly mean of the week. The filter approach is based on standard advice regarding contaminated and incomplete records (Pearson, 2005).

Descriptive and time-series analysis.

The cleaned baseline data were first analyzed using descriptive and time-series analyses to gain insights into energy consumption behaviour. Each of the key variables was summarized using descriptive statistics (mean, standard deviation, minimum, and maximum values). Two autocorrelation functions (one for 15 minutes and one for 24 hours) were calculated for the total building load over a one-week period, as well as the proportion of the load variance that could be explained by a mean-hour-of-week profile. Pearson correlation was calculated between daily consumption, occupied-hour consumption, outdoor temperature, and building occupancy.

Operating scenarios

Five scenarios were contrasted. The baseline (S0) was schedule-based operation with HVAC-S ON 06:00–20:00 and lighting-S ON 07:00–19:00, Monday through Saturday as well as fixed cooling setpoint of 22 °C with proportional control over a 1 K band, and full-speed fans when HVAC-S was scheduled. Occupancy control in scenario S1 was based on a 24.5 °C setpoint; HVAC and lighting switched off after a zone went to waste for 30 minutes and pre-cooling was applied from 06:30 until 08:00 on weekday mornings; ventilation proportional to occupancy. The optimization model was used for HVAC and ventilation in scenario S2, but was not used for lighting. Occupancy-based dimming with daylight harvesting was added to lighting in Scenario S3 and HVAC controls were not modified. In Scenario S4, the full integrated optimization of HVAC, vent and lighting and the peak demand term were applied. If measured temperature change was more than 0.3 K above the comfort limit during the measured occupancy period (S2S4), local safeguards could override the plan, and if measured occupancy had a higher ventilation or light requirement than planned, then local safeguards could override the plan.

Implementation

The simulation and optimization were done using Python. The linear programs were numerically solved using SciPy's HiGHS solver and had approximately 1,440 decision variables, and were solved in about 0.02–0.03 s per solve. For each optimized scenario, 672 optimizations (one for each hour) were solved for. The same random seed was used for sensor-noise in all scenarios to facilitate comparability.

Evaluation metrics and statistical analysis

The total Electricity Consumption (kWh), controllable-load Electricity Consumption (HVAC, fans, and lighting), and estimated percentage savings compared to baseline, peak demand (maximum 15 minute load, kW), and Mean Daily Peak (MDP) were compared across scenarios. The percentage of occupant weighted time spent in the 22–26 °C band, the mean temperature experienced by occupants, the degree hours above 26 °C for the occupied zones, and the percentage of occupied zone-intervals with an illuminance of at least 400 lux were used to assess the conditions for the occupants. Mean differences (baseline and integrated scenarios) between the daily energy consumption values were tested using a paired t-test and Wilcoxon signed-rank test over the 28 daily values and the effect size calculated as

Cohen's dz. In the integrated scenario, sensitivity analysis was conducted by changing the upper comfort limit (25 °C, 26 °C and 27 °C) and the peak demand weight (λ) (0 kWh/kW, 3 kWh/kW and 10 kWh/kW).

RESULTS

Data quality and preprocessing

The preprocessing results are presented in a summary in Table 3. Of the 48,384 readings, 1,012 (2.09%) were missing and 480 (0.99%) were contaminated with injected spikes. There were 777 flagged data points, with 364 of the points being injected spikes, for 75.8% detection of contaminated readings. The remaining 413 flagged were mostly actual rapid transitions from HVAC start-up and light switching, with only 46.8% of the flags being for actual spikes, and only small spikes were undetected when there were no spikes injected. Flagged and missing values were considered gaps and filled by interpolation (1,176 values) and hour-of-week substitution (613 values) without leaving any missing values. In total, 3.7% of the values were considered as gaps without excluding any day or channel.

Table 3. Summary of data preprocessing

Item	Count	Share of readings
Total readings (18 channels × 2,688 intervals)	48,384	100%
Missing readings (communication loss)	1,012	2.09%
Injected spikes	480	0.99%
Values flagged by range and Hampel checks	777	1.61%
Injected spikes correctly flagged	364	75.8% of spikes
Gaps of 1 hour or less filled by interpolation	1,176	2.43%
Gaps filled by hour-of-week substitution	613	1.27%
Missing values after preprocessing	0	0%

Baseline consumption patterns

Table 4 gives descriptive statistics for the cleaned baseline data. The mean building load was 22.9 kW with a standard deviation of 20.5 kW, a night-time base load of approximately 3.9 kW and a maximum load of 58.1 kW. The average of HVAC and fan power was 11.0 kW, and the average light power was 6.1 kW. The average temperature during occupied periods was 23.0 °C, a value very close to the setpoint temperature of 22 °C, and the average relative humidity was 52.7% which was much lower than required by the 22–26 °C comfort zone.

Table 4. Descriptive statistics of cleaned baseline data (S0, 2,688 intervals)

Variable	Mean	SD	Minimum	Maximum
Total building load (kW)	22.94	20.51	3.75	58.13
HVAC and fan power (kW)	10.98	11.43	0.00	30.47

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Variable	Mean	SD	Minimum	Maximum
Lighting power (kW)	6.11	7.06	0.00	14.83
Outdoor temperature (°C)	27.87	4.29	20.42	35.50
Indoor temperature, occupied intervals (°C)	23.01	0.56	22.31	25.08
Indoor relative humidity (%)	52.71	8.07	27.93	81.22
Total occupancy (persons)	21.42	33.05	0.00	110.00
Mean illuminance (lux)	243.84	274.43	0.00	663.72

The time-series analysis revealed high structure in consumption. The 15-minute lag autocorrelation of total load was 0.985, the 24-hour lag was 0.691 and the one-week lag was 0.739. The mean hour of week profile accounted for 98.8% of the load variance, suggesting that the fixed load was the most important component of baseline consumption. Daily consumption was significantly correlated with daily occupied person-hours ($r = .84$, $p < .001$), but only moderately with daily mean outdoor temperature on weekdays ($r = .22$, $p = .34$), while HVAC power during the scheduled hours was positively correlated with the outdoor temperature ($r = .64$, $p < .001$). In this case consumption was more a function of the schedule than of occupancy or weather (the inefficiency sought to be minimized by the optimization strategies). The mean baseline load increased significantly at 06:00 when HVAC was turned on, as seen on the weekdays of the week, and was high even when the building was unoccupied throughout the rest of the day until 19:00, when it reached 54.3 kW at 15:00 (Figure 2).

Scenario comparison

Table 5 is a comparison of the five scenarios. The baseline utilized 15,513 kWh in 28 days, with 11,576 kWh of controllable loads. Occupancy rules (S1) achieved a saving of 20.1% of the total electricity use, but at the cost of comfort, with only 81.7% of the mean occupied temperature (TOT) within the comfort band, and no reduction in peak demand. Then, when HVAC is optimized alone (S2), the total electricity savings are 8.3% while the peak demand is reduced by 23.7% due to pre-cooling and load spreading, with comfort compliance of 97.0%. Lighting control alone (S3) resulted in the largest savings of 19.1%, due to the large portion of lighting (also the heat load is also a part of the cooling load) in the lightly used zones and to reduce peak demand by 10.1%. The integrated strategy (S4) resulted in the highest savings with the total electricity consumption reduced by 26.4% (to 11,416 kWh); the controllable load energy consumption was reduced by 35.4% (to 11,326 kWh); the peak demand reduced by 36.4% (to 36.8 kW); 98.5% of the occupant-weighted time was within the comfort band and 98.9% of the occupied intervals met the illuminance requirement. The baseline exceeded the temperature range goal 100% of the time, but only by overcooling; and failed the illuminance goal in 7.8% of occupied intervals due to lights being off outside of scheduled hours (e.g. Sunday and/or in the evening).

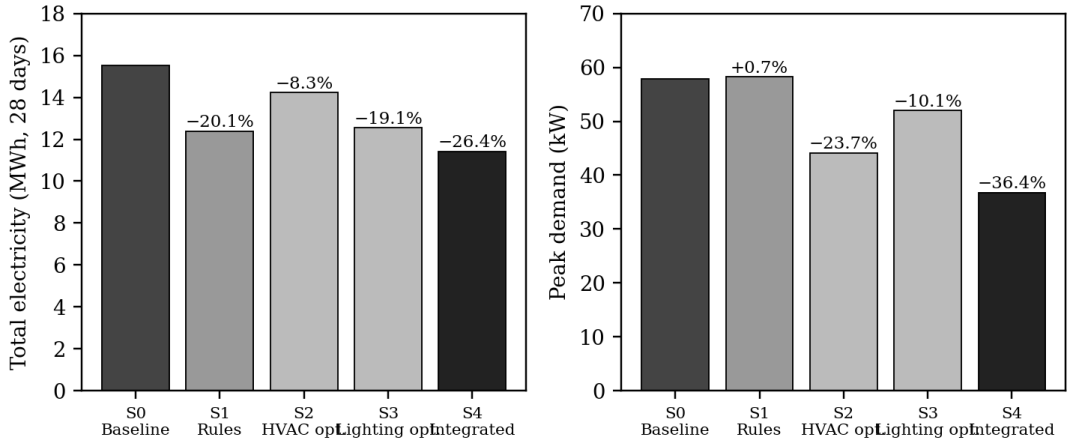
Table 5. Comparison of operating scenarios over 28 days

Indicator	S0 Baseline	S1 Occupancy rules	S2 Optimized HVAC	S3 Optimized lighting	S4 Integrated
Total electricity (kWh)	15,513	12,389	14,227	12,549	11,416

Indicator	S0 Baseline	S1 Occupancy rules	S2 Optimized HVAC	S3 Optimized lighting	S4 Integrated
Controllable load (kWh)	11,576	8,452	10,290	8,612	7,479
Total savings (%)	–	20.1	8.3	19.1	26.4
Controllable-load savings (%)	–	27.0	11.1	25.6	35.4
Peak demand (kW)	57.8	58.2	44.1	52.0	36.8
Peak reduction (%)	–	−0.7	23.7	10.1	36.4
Mean daily peak (kW)	47.4	49.9	34.4	41.9	29.5
Occupants in 22–26 °C band (%)	100.0	81.7	97.0	100.0	98.5
Mean temperature of occupants (°C)	22.9	25.6	24.5	22.8	24.7
Degree-hours above 26 °C (K·h/day)	0.00	3.38	0.08	0.00	0.05
Occupied intervals with ≥ 400 lux (%)	92.2	99.5	92.2	98.7	98.9

Total consumption and peak demand by scenario is displayed in Figure 3. The separate savings from HVAC optimization (S2) and lighting optimization (S3) (27.4%) was near S4 (26.4%) which suggests that the HVAC- and lighting-optimalizations were largely additive with some overlap because both heat reduction and cooling load reduction occur when doing HVAC optimization.

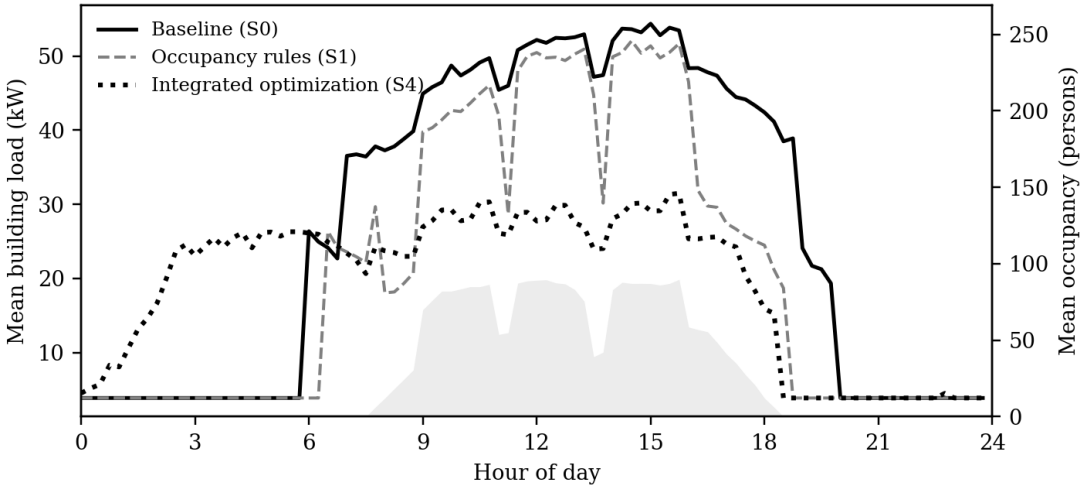
Figure 3. Total electricity consumption and peak demand by operating scenario



Load profile and indoor conditions

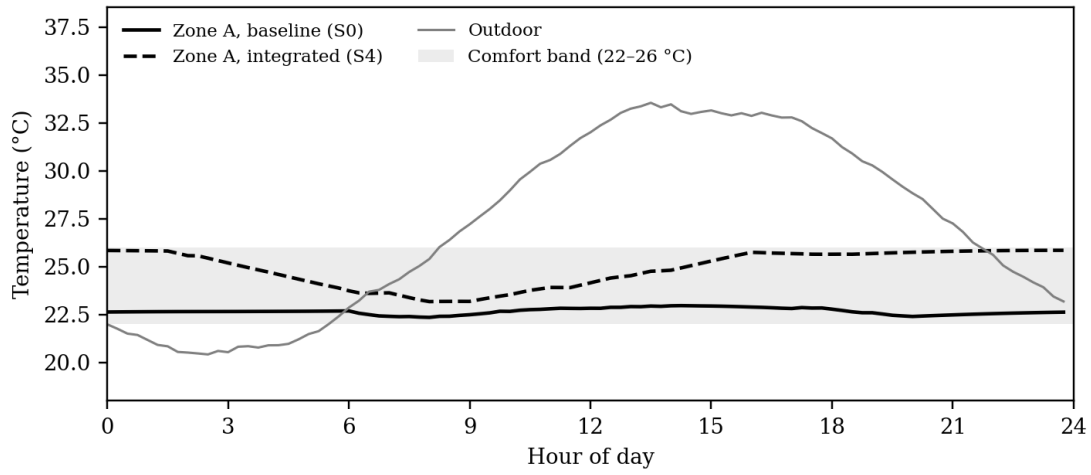
The mean daily weekday load profile is depicted in figure 2. The baseline was characterized by high load during the day, after systems were initiated during the morning. The profile under the integrated strategy had a higher cooling level during the morning, while the building's thermal mass was pre-cooled (between 06:00 and 09:00, the HVAC and fan power averaged 12.1 kW, as compared to 11.5 kW in the baseline); it was significantly lower during the hottest hours (between 13:00 and 17:00, the HVAC and fan power averaged 3.4 kW, compared with 18.6 kW in the baseline). The weekday afternoon peak fell from 54.3 kW at 15:00 to 31.5 kW at 15:45. The mean weekday load between 17:00 and 20:00 was 11.8 kW under S4, compared to 35.4 kW under the baseline, which continued systems until the end of the schedule. Under the rule-based scenario, there was a reduction in consumption during low occupancy, but still a high peak.

Figure 2. Mean weekday building load under baseline, rule-based, and integrated optimization scenarios



The graph in Figure 4 shows indoor temperature for a typical Wednesday in the open office area. The zone temperature was essentially held at 22 °C during the occupied hours for the whole working day with the optimized strategy, with the temperature floated higher during the unoccupied hours, but not exceeding the 22-26 °C comfort band for more than a few intervals, thus minimizing cooling energy usage. The mean temperature experienced by occupants for S4 was 24.7 °C while for the baseline it was 22.9 °C.

Figure 4. Indoor temperature in zone A on a typical weekday under baseline and integrated optimization



Savings by end use

Table 6 breaks down consumption by end use for the baseline and the integrated scenario. The greatest relative reductions were in lighting (50.4%), cooling electricity (32.8%) and fan (16.2%). Plug loads that were not controllable stayed the same and accounted for 25.4% of baseline consumption, thus reducing the amount of savings that can be achieved on total consumption compared to the amount of savings that can be achieved for controllable consumption. Fan savings were less than cooling savings, as the airflow needed to be correlated to occupancy and to cooling delivered.

Table 6. Electricity consumption by end use, baseline versus integrated optimization (kWh over 28 days)

End use	S0 Baseline	Share of baseline (%)	S4 Integrated	Reduction (%)
Cooling (compressor)	4,841	31.2	3,253	32.8
Fans (ventilation)	2,587	16.7	2,168	16.2
Lighting	4,147	26.7	2,059	50.4
Plug loads (uncontrollable)	3,937	25.4	3,937	0.0
Total	15,513	100.0	11,416	26.4

Statistical significance

The median daily savings on the 24 days the daily electricity consumption was lower under the integrated strategy than under the baseline were 172.4 kWh per day. The mean daily saving was 146.3 kWh (95% CI [100.6, 192.0]), and the difference was statistically significant, paired $t(27) = 6.57$, $p < .001$, with a Wilcoxon signed-rank test confirming the result ($p < .001$) and a large effect size ($dz = 1.24$). Savings were greater during weekdays (28.5% of baseline weekdays consumption) than on Saturday and Sunday (16.1%). The four exceptions were all Sundays when the baseline systems were off and the integrated strategy used between 117-140 kWh more than the baseline. During those days only a few staff members were present who were able to cool their zones after zones had been allowed to drift towards the 30 °C unoccupied ceiling, which took a large recovery load. This is actually a real failing of aggressive setback for unforecast occupancy, and is discussed in Section 6.

Sensitivity analysis

How the integrated strategy reacted to the comfort limit and peak-demand weight is displayed in Table 7. An increase in the upper comfort limit led to an increase in energy savings, from 24.6% at 25 °C to 28.2% at 27 °C, with a 22–26 °C exposure level of 4.58 K•h per day at 27 °C leading to only 58.7% of the occupant-weighted time in this band. The 26 °C limit was therefore found to be a good compromise. The no peak penalty ($\lambda = 0$) had a more pronounced impact of the total savings (29.9%), with peak demand only dropping by 10.0% as there was little disincentive to the cooling, ventilation and lighting loads occurring simultaneously, and comfort compliance was reduced to 93.9%. A higher value of λ resulted in a greater reduction in peak demand, but with a slightly smaller savings percentage, and $\lambda = 10$ had a peak reduction of 40.3% with an almost negligible increase in energy cost. Results indicate that energy saving and peak reduction are partially conflicting goals and the weight can be chosen based on tariff and utility goals.

Table 7. Sensitivity of the integrated strategy to the comfort limit and peak-demand weight

Upper comfort limit (°C)	Peak weight λ (kWh/kW)	Total electricity (kWh)	Total savings (%)	Peak demand (kW)	Peak reduction (%)	Occupants in 22–26 °C band (%)	Degree-hours above 26 °C (K·h/day)
25	3	11,696	24.6	36.7	36.5	97.2	0.00
26 (base)	3	11,416	26.4	36.8	36.4	98.5	0.05
27	3	11,137	28.2	36.3	37.3	58.7	4.58
26	0	10,873	29.9	52.0	10.0	93.9	0.13
26	10	11,451	26.2	34.5	40.3	98.2	0.07

DISCUSSION

Results indicate that an IoT-enabled optimization strategy makes significant reductions in the electricity consumed by buildings and peak demand, while maintaining the building's occupants' conditions, and that the level of benefit depends on how the sensor is applied. There are two findings that stand out. The baseline consumption has been found to depend mainly on its use time, as its load profile was very well explained by the hour of the week and only weakly by occupancy and weather during working hours. This is typical of buildings with systems being scheduled instead of demand driven systems and is indicative of a high potential for control based on what is actually happening in the building as is suggested by the reviews of metering and sensing in buildings (Ahmad et al., 2016; Pérez-Lombard et al., 2008).

Secondly, there were varying strengths of simple rules and optimization. Occupancy rules (S1) performed well in terms of energy saving (as per operating-building energy evidence (Agarwal et al., 2010; Nguyen & Aiello, 2013)), but did nothing for peak demand and there was a noticeable discomfort because the setpoint was increased without considering thermal loads. Optimization-based control, on the other hand, took advantage of the building's thermal mass: it pre-cooled when loads were low, and relaxed cooling within the comfort zone at peak hours, and programmed lighting, ventilation and cooling. This is the behavior that predictive control is expected to provide (Afram & Janabi-Sharifi,

2014; Oldewurtel et al., 2012), and the outcome agrees with the reviews that suggest integrated optimization as a promising direction to pursue energy and comfort management (Dounis & Caraiscos, 2009; Kathirgamanathan et al., 2021; Mariano-Hernández et al., 2021; Shaikh et al., 2014).

This scenario comparison also helps bring into focus where savings come from. The greatest single opportunity was lighting, which was always on 100 percent, on a prescribed schedule, and in an area that was often either empty or well daylit, and at the same time each kilowatt of lighting saved also resulted in a kilowatt of cooling load saved. Cooling and fan savings were dependent on the relaxation of the over-cooled baseline setpoint, and also on demand-controlled ventilation. The sensitivity analysis indicates that reducing peak demand is a different objective than reducing energy and that the most effective peak reduction was obtained for the smallest of the energy reductions, while in turn, the lowest peak weight at a small cost of energy obtained most of the possible peak reduction. It also applies to demand-side management, where load reduction and shifting lead to system reliability and tariff savings (Palensky & Dietrich, 2011), and roadmaps, focused on intelligent control of buildings to move them towards net zero (Kolokotsa et al., 2011).

These comfort results demonstrate that beyond energy evaluation, there is a need to assess comfort. The baseline was well performing with regard to comfort, but it was overcooled resulting in an occupant comfort of approximately 22.9 °C, which is higher than the ASHRAE comfort range of up to 26 °C (ASHRAE, 2020); the baseline was not performing as well as the optimized scenarios with regard to illuminance, since fixed schedules did not match actual occupancy (CEN, 2021). In the meantime, the rule-based strategy demonstrates how aggressive saving can lead to the loss of comfort. The integrated strategy maintained comfort and illuminance compliance close to 98–99% and achieved a more significant energy savings, as comfort is explicitly considered and given a penalty if it is not met.

The Sunday results serve as a helpful warning. If the occupancy of the building can be foreseen, a deep setback is an energy-saving alternative, but if the occupancy is not foreseen, the building must be recovered from a warm state quickly, and this may be an energy expense greater than the baseline's behavior of allowing a few occupants to leave while the temperature drifts within an acceptable range. Practical implementations should be considering thus the cases of days or zones where the occupancy is not certain, limit the temperature ceiling when the space is not occupied or add a recovery cost in the optimization.

Last but not least, the data quality results remind us that optimization relies on reliable sensing. The cleaning pipeline restored a complete data set for these streams with approximately 3% problematic readings, however, detection of injected spikes was not perfect and a conservative filter necessarily labeled some real transitions (Pearson, 2005). In practice, these errors have the potential of leading a controller astray, hence the optimized scenarios have local safeguards, based on direct measurements. The accuracy, calibration and fault detection of the sensors should thus be considered part of the control system (Dong et al., 2019).

CONCLUSION

This study proposed and tested a smart energy management system for buildings based on optimization and using data from various IoT sensors. A joint management of cooling and ventilation loads with lighting load was achieved by the use of a rolling-horizon linear program, which saved 26.4% total electricity use, 35.4% controllable-load electricity use, and 36.4% peak demand over 28 days relative to a schedule-based baseline, and maintained 98.5% of occupant-weighted time in the comfort band and satisfied the illuminance requirement for 98.9% of occupied hours. This decrease in consumption was statistically significant and substantial. Energy saving was achieved in large part by simple occupancy rules, peak saving was increased and comfort was reduced, and lighting and HVAC optimizations added in varying amounts. Sensitivity analysis demonstrated that the upper comfort limit and the peak demand weight drive a compromise between energy saving and peak reduction and comfort which operators can adjust.

The applications are simple. Operators of a building should start by sub-metering significant loads and looking at occupancy and illuminance sensors, as the baseline analysis reveals how much use is based on schedules, and not need. Lighting control with daylight harvesting and occupancy sensing represents a low complexity first step with a high return and predictive control of HVAC provides additional savings and peak reduction when thermal inertia can be exploited. Time-varying tariffs and demand-charge structures that incentivize the greatest reductions at peak demand times can help encourage adoption, as can requirements for sensor accuracy and good data from the sensors.

There are certain understandings that limit the study. Simulations of the sensors and the building and not measured savings were simulated, thus, the results presented are indicative of the approach's potential rather than actual results from a real building. The savings are a maximum, since the same thermal model was used to simulate the building's behavior, model mismatch, unmodeled equipment dynamics, and sensor failures would lead to lower savings. The test period consisted of just 28 days of cooling dominated weather in one climate and the building was not optimized for heating/humidity control, there was only one building model with three zones and plug loads were not controllable. Energy tariffs and economic analysis were not modeled, the setback strategy did not work well on Sundays when the occupancy was not forecasted, and occupant behavior, such as the manual override, was not modeled.

Future research is thus required to validate the approach in a physical pilot installation using real IoT sensors, to model the thermal one using measurements, and to test the approach for robustness to model error or sensor failures, such as by using adaptive or learning-based models. The extensions feature year-round operation (including heating), humidity control, indoor air quality limitations, on-site generation, storage and time-of-use tariffs, forecasting of occupancy and weather through machine learning and taking into account occupant feedback and personalised comfort. It would also help to identify the situations in which either of the other optimizers or the data-driven predictive control is more desirable.

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