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Blockchain + IoT sensor network to measure, evaluate and incentivize personal environmental accounting and efficient energy use in indoor spaces

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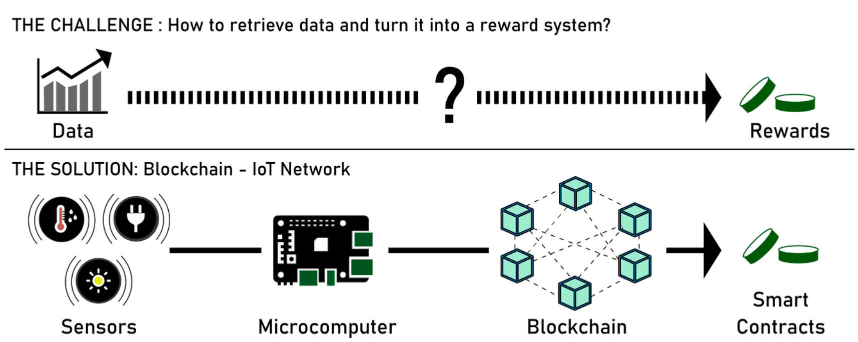
HIGHLIGHTS

- Blockchain + IoT network is developed to connect energy data to a reward system.
- This can incentivize demand response by building users.
- Metrics related to energy, health, and carbon emissions are proposed.

GRAPHICAL ABSTRACT



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ABSTRACT

Electric demand flexibility in buildings is highly dependent on occupant behavior. Evaluating and incentivizing these behaviors can provide grid-responsive support and encourage demand response (DR) participation. To achieve these goals, we developed an infrastructure for connecting Internet of Things (IoT) sensors to a distributed ledger (blockchain network) for long-term monitoring of energy and environmental performance. This study presents a novel Blockchain + IoT paradigm for the building science research community, applied in a real-world application. This Blockchain + IoT Network (BIN) uses Raspberry Pi minicomputers as platforms for connecting sensors to a blockchain network, to provide and analyze real-time indoor environmental quality (IEQ), energy, and carbon intensity data. As part of the study, we propose various metrics to evaluate the environmental footprints of building users. Novel algorithms for normalizing energy usage and carbon intensity, with consideration of a variety of related environmental factors, are executed as smart contracts on the blockchain network. All measurements and the smart contract transactions are reported and visualized on live dashboards. The use of smart contract allocates tokens based on the reward algorithms to incentivize individuals' energy conservation, and similarly to DR pricing, can help influence occupant consumption patterns towards carbon reduction goals. We further test the smart contract's algorithm in relation to real sensor data we have collected in two case studies: single-unit households and carbon intensity in the energy market. The combination

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of proposed metrics translates measured sensor data into token awards, demonstrates upper and lower limits dictated by the grid generation mix profile, and indicates that there is the potential for load shifting to minimize carbon emissions without considering the scale of consumption.

1. Introduction

The building sector represents almost 40 % of global energy consumption and related greenhouse gas (GHG) emissions [1], and the current energy demand is projected to have a 50 % increase by 2050, owing to climate change, urbanization, and pollution [2,3]. This future energy consumption growth will further impact the power grid operation and power system management in urban infrastructure [4]. Buildings are dynamic systems and building users contribute to a large variance in electrical energy consumption due to their highly-varied usage behaviors [5]. As we move towards a net-zero emissions economy and distributed-decentralized energy management, it is critical to balance the supply and demand by reducing or shifting building users' electricity usage during peak periods [6,7]. To facilitate energy flexibility on the power grid level, demand response (DR) has been deemed to be a cost-effective technique for demand reduction and ancillary services [8–10]. Recent research has demonstrated a broad range of DR potential by promoting the interaction with and responsiveness of the customers. For example, Mohsenian-Rad et al. proposed an automatic coordination between users by deploying two-way digital communication to determine the optimal energy consumption schedule for each user and therefore, to facilitate an autonomous demand-side energy management system. Chen et al. [11] developed a residential load scheduling program for DR management and reported that over half of the load demand could be realized as flexible loads by optimizing and rescheduling working time. Their results also showed that approximately 10 % of daily electricity cost can be conserved by employing the load flexibility of air conditioning without sacrificing the occupant's thermal comfort. Yu et al. [12] introduced a smart home integrated management (SIM) model suggesting that peak loads can be reduced by 29.3 % – 49.3 % through shifting the timing of building residents' electricity consumption and consequently, to flatten the load curve and realize "peak shaving and valley filling".

In buildings, efficiency is typically evaluated with the energy consumption per unit floor area. Energy use is not hard to monitor, but its magnitude involves multiple economic and environmental factors, so when normalized to floor area it allows for the direct comparison of two spaces regardless of scale or magnitude of operations. It is worth noting that the relationship between the use of energy and the production of emissions is not always linear [13] and a linear relationship does not typically apply to grid-based electricity, which is produced by a constantly changing mix of generators utilizing different fuels, different technologies, and operating at different efficiencies based on their age and upkeep [14,15]. Given the fact that it is dependent upon a number of factors including outdoor/indoor environmental conditions, appliance usage, and occupancy duration in the buildings [16], it remains worth investigating how to engage/incentivize individuals in DR efforts and change their energy behavior accordingly to provide the grid-responsive support, peak demand shaving, and reduce carbon emission.

A number of studies have been conducted in real buildings to examine the impact of human behavior on building energy loads [17–20]. However, limited studies have focused on how individuals contribute to the building energy usage level and large carbon intensity [21,22]. Gilani et al. [23] concluded that the effects of averaging building energy patterns downplay individual impacts at different spatial scales within a building. Kyrö et al. [24] reported that individual resident's activities are the most significant contributor making up to one-third of the overall housing carbon footprint. The individual-based approach models each individual's presence, actions, and activities. Here the "individual" is defined as a specific person or persons sharing energy costs in a unit and/or room. The outcomes of identifying individual energy consumption profiles include inferring the presence of a specific person in a certain space, the appliances used by a specific person or a unit, or the control action of a specific person or persons in a unit.

In this study, we aim to reflect real-time patterns of energy demand and carbon intensity in buildings together with human wellbeing and thermal comfort requirements in buildings. We developed a sensor network connected to a blockchain infrastructure for long-term monitoring in buildings and for the creation of experimental incentives for DR engagement. This advanced Internet of Things (IoT) metering infrastructure can be distributed in multiple building rooms and zones to provide high-resolution information on occupant energy behavior and to help alleviate peak loads. Additionally, it allows us to measure individual contribution to energy flexibility, instead of the total consumption of a large population in a thermal zone or a building, and to incentivize individuals' load shifting and flexibility of electricity usage during peak periods on the power grid level.

1.1. Blockchain and Internet of Things (IoT) background

The continuous expansion and development of low-cost IoT sensors enable affordable and scalable research in the built environment. IoT generally refers to network-addressable devices allowing the measurement of invisible interactions, events, and processes in the interplay between buildings and their occupants [25,26]. The associated development of open wireless technology such as Bluetooth and Wi-Fi presents opportunities to distribute pervasive wireless sensing devices for energy use and occupant health and wellbeing monitoring.

In traditional IoT systems, the party collecting the information is also in control of the end devices. This allows that party full access to the information collected by the sensors. However, this centralized method of data collection limits the ability to share information between different parties (e.g., the electricity company has access to the information collected from the smart meter it deploys, and the individual tenant cannot choose to share that information with any other party). By connecting the sensors to a blockchain network, the end-unit device can maintain control over who has access to the information they collect. As data is collected locally, the blockchain only has access to the data through a smart contract. The smart contract can only query data made available by the code on the end unit (in our system, the Raspberry Pi (RPi), and cannot retrieve any other type of data collected by the end unit. In order to receive tokens, some data has to be shared, but it is up to the users who participate in this network. Anonymity is maintained as no personal identifiers are shared other than the RPi blockchain address.

As the name suggests, blockchain networks organize information in a chain of blocks, each of which stores a set of transactions at a given time. Blocks are joined together by referring to the previous block to form a chain. Whenever a transaction is performed, where the exchange of data and the agreed conditions are met, the blockchain-defined application logic can be automatically executed. This protocol is known as a Smart Contract [27]. Smart contracts are applications running on the blockchain, which execute this "agreement." Blockchain technology has been classified into three types: public blockchain, private blockchain, and consortium blockchain [28]. Our BIN monitoring system employs a proof-of-authority, instead of a proof-of-work consensus mechanism [29] so that it does not require energy-intensive mining practices, and at the same time still allows for the scalability of blockchain networks. Anyone connected to the network can deploy the system, execute the code and send transactions to the network. Through the blockchain, tokens (digital assets) can be assigned to the end units based on a set of rules defined by the smart contract. In this study, we propose energy and environmental performance metrics that are translated into algorithms executed by a smart contract, which assign tokens to the end units based on their performance over time. This is meant to create an incentive for improvement over time. It is also meant to provide awareness and visibility of the performance of individual building users. We also gain the ability to share information with smart contracts. In this use case, the smart contract will automatically allocate reward tokens based on the readings from the sensors of the end units. Therefore, using a blockchain network to connect IoT sensors across different spaces presents a major advantage: devices can be connected to the network while each user/end unit maintains control over its data.

Many researchers have deployed IoT networks in buildings in order to collect data on environmental and energy performance and health-related factors in the indoor environment. Zou et al. [30] designed an IoT platform to detect occupancy and adjust the ventilation rates accordingly based on the number of occupants in each zone for energy saving. Magno et al. [31] combined motion sensors and light sensors to adjust artificial light intensity and therefore minimize energy waste. Tagliabue et al. [32] collected indoor air quality (IAQ) related measurements and reflected the information to the ventilation system automation through the IoT network. In terms of the IoT application for DR, Conejo et al. [33] metered the consumption of individual devices using IoT techniques to manage individual user DR participation at the hourly load level. Caron and Kesidis [34] shared IoT enabled DR engagement with the smart grids to offer consumers a dynamic pricing scheme. Shreenidhi et al. [35] developed a smart grid based IoT paradigm that supports DR energy management by controlling the appliances according to the consumption of power during high peak hours.

However, research work on IoT and blockchain is limited. It is acknowledged that a wide range of IoT applications has been used for a variety of purposes [26] and blockchain technology has been applied to both financial and non-financial systems [36]. Previous studies in this field focused on theoretically examining the potential benefit of integrating IoT and blockchain [37–41], without deployment in real buildings. This is the first attempt, to our knowledge, to develop and experiment with a Blockchain-IoT paradigm for the building science research community, though some startups and trials have already been deployed. A Finnish energy company called Fortum offers a blockchain-based solution that enables consumers to control appliances over the Internet in connected homes, and therefore optimize their energy demand and reduce energy bills [42]. A non-profit organization called ElectriCChain also uses blockchain solutions to collect live solar data from monitoring devices (solar inverters, data loggers, RPis) and reward the generation with SolarCoins [43,44]. In the United States, ClearTrace [45]uses blockchain for certifying and rewarding sustainability efforts with Swytch tokens. Tokens are produced based on smart meter data, IoT devices, and other smart devices that can be used to reduce CO_2 emissions. A recent review study [46] concluded that the blockchain-enabled IoT technology could be greatly helpful for identifying occupant energy usage/waste patterns, securing indoor environment monitoring data, and improving building performance auditing.

1.2. Scope of paper

The objective of this work is to propose and test this blockchain + IoT (BIN) monitoring system. This paper is organized as follows:

- Section 2 introduces our state-of-the-art BIN monitoring system for continuous, real-time, low-cost measurements of IEQ parameters and energy usage
- Section 3 presents energy and carbon metrics for the evaluation of the energy performance of individuals based on sensor readings for normalizing and benchmarking energy usage and carbon intensity considering a variety of related environmental factors, which can be executed as a smart contract on the blockchain network to incentivize DR participation.
- In Section 4 and 5, we further apply these algorithms to two case studies that we collected over a period of several months and present the case study results to demonstrate how these incentives could improve DR by building users.
- Section 6 and 7 highlights the key features of the developed BIN system and discusses how the BIN system can help evaluate and incentivize the spatial and temporal variations of personal environmental performance.

2. Methodological proposal: The Blockchain + IoT network (BIN)

2.1. BIN monitoring infrastructure

To clarify each component of our BIN monitoring system, Fig. 1 illustrates an IoT sensing system, a local blockchain network and the data visualization dashboard. More detailed explanations of each part of the system are presented in the following sections.

2.2. Blockchain infrastructure

A blockchain network operates between a cloud-based stack (on AWS) and RPi end units. We use a private instance of the Ethereum blockchain [47] for the blockchain network, with the Geth Ethereum Client [48], which is a popular open-source software. When a new end unit (RPi) is added to the network, the application on the Full Node will add it to the dashboard and find it with ether. A dashboard running on the Full Node allows for the monitoring of the system and displays information such as the list of RPis connected to the network, the application version they are running, and the list of sensors connected to each RPi. In addition, each RPi generates a blockchain address as part of the setup process. This address represents the RPi on the blockchain. For example, when tokens are sent by the smart contract, they are sent to the RPi blockchain address.

2.2.1. System components

Fig. 2 is a schematic diagram of the system. There are 2 types of endpoint stacks in the network.

1) Full Node: This stack is deployed on AWS (as a Kubernetes cluster) and contains a blockchain node and a Golang application as well as Influx database (InfluxDB), and blockchain explorer applications. It is used to monitor and control the network and to deploy the smart contracts. The Full Node also contains a dashboard.
2) End units: This stack is deployed on RPis. The RPis contain the applications running within a docker container. The docker image includes an InfluxDB instance used to store the data locally. It also contains connectivity to the sensors, from which it reads data into the InfluxDB. The collected data is available for the smart contracts to query via the application running on the RPi. The BIN application that runs on the RPi is constantly listening to the blockchain. When the application on the RPi identifies a request for data coming from a smart contract, it will pull that information from the InfluxDB and send it to the smart contract. Each RPi is associated with a blockchain address, that allows it to identify transactions targeted at it. Each RPi also has a dedicated graphic user interface which is accessible locally and tracks its token balance and a list of the sensors connected to that on the current RPi.

Note that the term *network* refers to the entire system; i.e., all the deployed full nodes and RPi nodes. The network has one Full Node, and multiple RPi nodes.

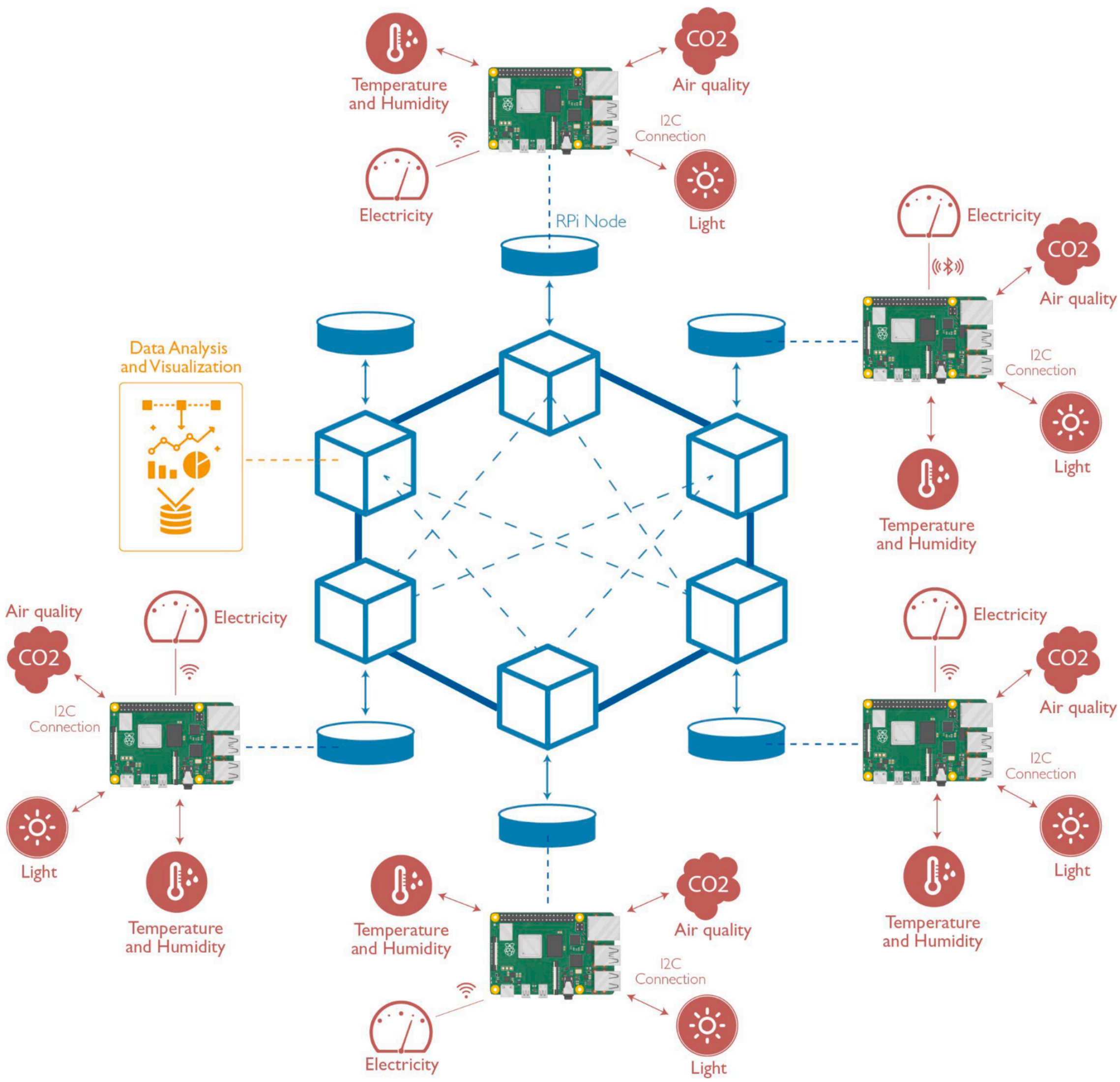

Fig. 1. Schematic overview of the IEQ and energy monitoring system.

2.2.2. Data storage

An Influx database (InfluxDB) is deployed locally on each end unit. InfluxDB is a time series database which we use to store the readings from the sensors. The RPi collects the readings from the sensors and records it in the InfluxDB using Python scripts. In addition to storing the raw data, processed data can also be stored: for example, the Python code can be used to calculate the hourly mean value of the readings from a sensor. The information on the local InfluxDB is available for consumption by the smart contract. This allows implementing sophisticated token allocation algorithms as described in this paper. For efficiency, we do not use the blockchain network for data storage, only for the smart contract operation. The data is stored on the influx database installed on each RPi locally and queried by the blockchain to execute the smart contracts. The influx database allows for real-time monitoring in high resolution. It is optional to collect the data on the cloud as well, which we currently have as a backup for the system but is not mandatory for the system to work.

A common challenge in working with IoT sensors that are within access of the end-users, especially when the data is stored locally as is performed in this application, is increased system vulnerability to malicious users. The advantage of using blockchain is that the data origin is identified using the blockchain address, so unreliable sources can be flagged. For the experiment we conducted as described in the following sections, the users opted in to participate because they were interested in data acquisition through our system. For other use cases, where potentially malicious users may participate, another layer of security, built specifically for IoT systems may need to be applied such as suggested in recent research [83].

2.2.3. Smart contracts

Smart contracts are applications that are deployed on the blockchain and execute an “agreement” according to a blockchain-defined set of conditions. In the BIN system, the smart contract periodically checks the sensor value and allocates tokens to the end units (RPis) based on the algorithms detailed in Section 3 below. The smart contracts are written in solidity.

2.2.4. Deploying the infrastructure

To deploy the Full Node, we use Terraform. After Terraform has created the virtual machines (VMs), we use Kubernetes to deploy the Full Node services (Grafana, InfluxDB, Golang app) on the Full Node virtual machine.

To deploy the RPi nodes, we use a Docker image based on the Alpine operating system, so the installation of the entire system and its many applications on each node is easy and streamlined. As part of the application deployment, the users also deploy the Python code

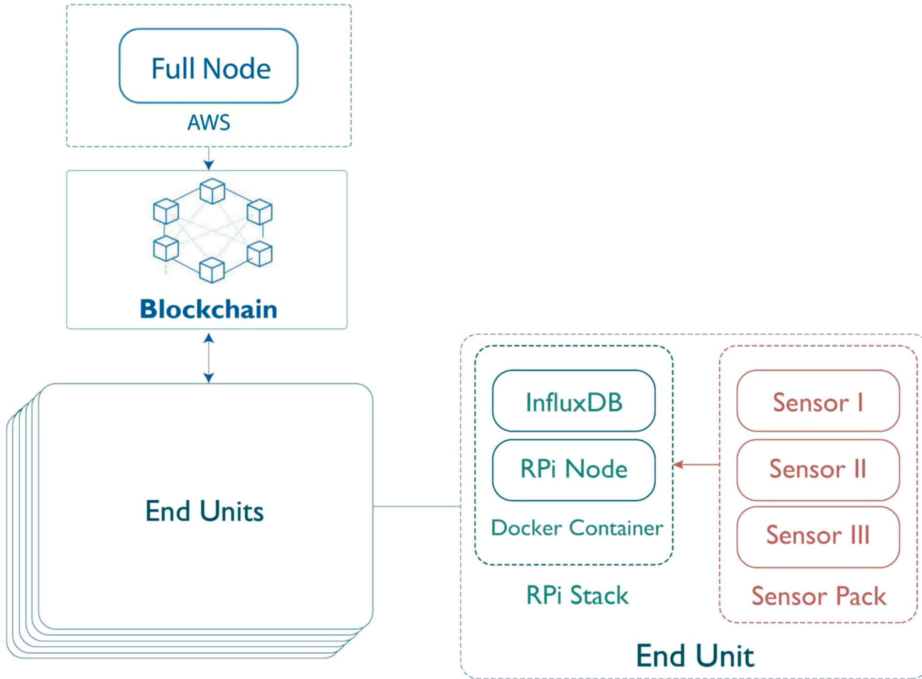

Fig. 2. Schematic overview of the system infrastructure.

repository. Once the end unit has been set up, it will automatically keep running, even if it was rebooted. This is designed to reduce the maintenance required for the system to a minimum.

2.3. Sensor reading acquisition and data visualization

2.3.1. Sensors

As described above, the system was designed to track IEQ and occupant energy use in individual rooms or zones within a building in order to incentivize building occupants' DR participation. We use a network of low-cost sensors distributed throughout several spaces. The sensing system comprises individual sensors connected to the RPis in one of two methods:

1) Through I2C connection: I2C (Inter-Integrated Circuit), a bus interface connection protocol for serial communication. I2C, or 2-wire interface, is a simple and popular protocol that allows one or more master devices, in this case, the RPi, to communicate with multiple IoT devices. The master device(s) has the ability to control the connected sensors or to receive data from them. This is the method we're currently using for our deployments.
2) When additional sensors need to be added to the RPi node, beyond the I2C connections, we can connect them through a Bluetooth connection: when wired connection to the RPi is challenging or not possible because of the number of devices or their location in the room, we use Adafruit ItsyBitsy (Nordic Semiconductor NRF52840) bluetooth microcontrollers. For ItsyBitsy, the Adafruit Bluefruit library was used to facilitate Bluetooth transmissions, and on the RPi, the bluepy Python library (version 1.3.0) [49] was used to receive and manage Bluetooth communications. The RPi then pairs with the available ItsyBitsy microcontrollers and receives data push from each paired ItsyBitsy microcontroller once per minute. It is worth noting that per the Bluetooth LE standard, a maximum of 7 Bluetooth slave devices (in this case ItsyBitsy microcontrollers) can be connected to a single Bluetooth master device (in this case a RPi) [50]. However, this limit could be easily overcome by using a Bluetooth mesh architecture [51]. Thus the BIN system could be scalable to any amount of sensors that a particular study or research mission might require.

The RPi aggregates the data using an Influx Database (version 5.3.1) [52]. In the current iteration, the BIN system monitors the temperature, relative humidity, CO_2 concentration, particulate matter with an aerodynamic diameter less than 2.5 μm (PM2.5), visible light intensity, infrared (IR) light intensity, ultraviolet (UV) index, and gross energy consumption. The sensors were selected based on their popularity in IoT and indoor monitoring applications. Fig. 3 visualizes the pipeline of the sensor data flow.

Temperature and relative humidity have been shown to have a large impact on occupant thermal comfort [53]. In addition, maintaining a certain level of thermal comfort has been proven to be an important factor in hampering DR engagement [54,55]. Temperature and relative humidity measurements were taken with a SHTC3 temperature and relative humidity sensor (Temperature range: -40 °C – 125 °C and accuracy: ± 0.2 °C; Relative humidity range: 0 % – 100 % and accuracy: $\pm 2\%$). Previous studies have demonstrated the reliability of deploying SHTC3 in the field of thermal comfort monitoring [56,57], and its low cost makes it an attractive choice.

Elevated indoor CO_2 concentrations have been linked to decreased focus and other cognitive functions [58], and can indicate increased occupancy in spaces [59]. CO_2 concentration measurements were taken using a self-calibrated infrared absorption CO_2 sensor (T6713, measurement range: 0–5,000 ppm, accuracy: $\pm 3\%$). The T6713 has been widely used to measure local CO_2 clouds for indoor environment settings [60], for an air pollution monitoring protocol [61], and low-cost indoor environmental monitoring [62].

Exposure to PM2.5 has been linked with many health problems including cardiovascular diseases, respiratory diseases, and neurodevelopmental disorders [63]. Because of the risks that it presents, it is important to monitor PM2.5 concentration as an IAQ indicator. PM2.5 concentration measurements were taken with a SPS30 particle concentration sensor (Range: 0–1000 μg/m^3, accuracy: ± 10 %, and resolution: 1 μg/m^3). The SPS30 was shown to be effective in tracking PM2.5 concentration [64], and was reported to be fairly accurate for moderate PM2.5 concentrations (<2,000 μg/m^3) in occupational exposure

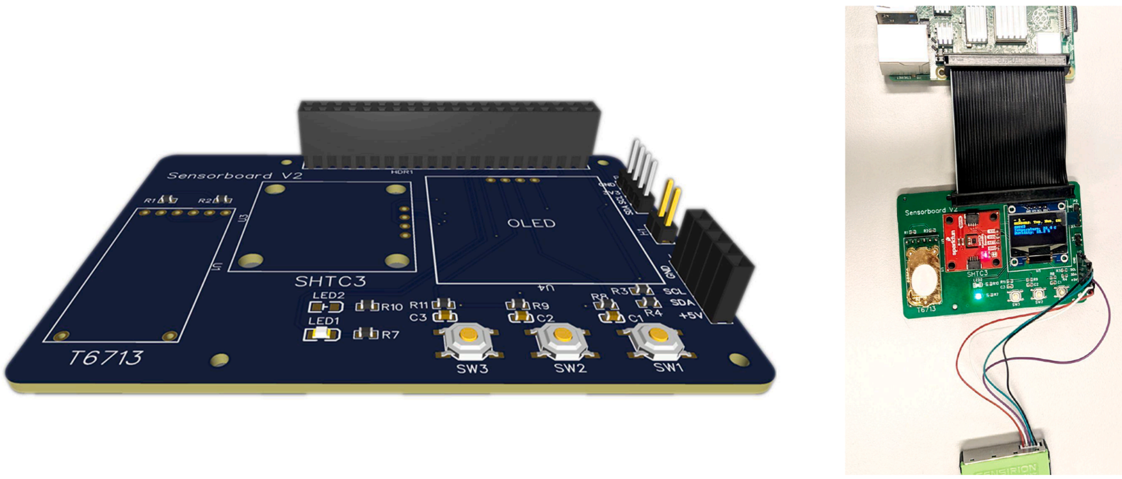

Fig. 3. PCB board and sensor kit connected to RPi.

assessment [66].

Many studies have identified that the effective use of daylighting instead of artificial lighting helps reduce building energy use considerably, though the exact amount will depend on climate, light sources, and building design [66–68]. Furthermore, indoor lighting has been shown to impact occupant health and work performance [69]. As such, the BIN system rethinks and evaluates the indoor built environment design and personal energy usage based on the indoor visible light intensity, IR light intensity, and UV index measurements taken using an SI1145.

Of chief importance is the measurement of energy consumption in order to evaluate occupant energy use. In this study, lighting and plug-load energy use were considered to monitor and determine personal energy usage profiles. We have two alternative methods for measuring the energy load in a room:

1) IoT plug load sensor: we use the Kasa Smart WiFi Plug with energy monitoring in all of the room's outlets. This is a low-cost device that is UL certified and connects directly to the outlet to monitor its energy load, without requiring any wiring or installation. It follows the IEEE 802.11b/g/n protocol. It is a 2.4 GHz wireless device, compatible with iOS 10 + and Android 5.0 + phones. The Smart plug operates at 100-120VAC, 15A (Power range: 0–1.8 KW).
2) Panel-box installed energy meter: the second method relies on monitoring the power draw of those circuits on a circuit breaker using an EG4115 (Voltage range: 0 V – 277 V) with split-core current transformers (Current range: 0 A − 100 A, current accuracy: ±1%). The device computes AC power consumption on board based on these two measurements and the phase angle. In several studies, the EG4115 was used to measure the efficacy of different orientations of solar PV panels [70], was used to measure power consumption in a year-long study of microgrids [71], and to collect data for simulating energy use in a solar microgrid [72]. It is worth noting that the EG4115 is more expensive than the other sensors used for this study, but it comes with CAT III overvoltage protection.

2.3.2. PCB (Printed circuit Board)

A custom PCB board was developed, which connects the sensors to the RPi via a ribbon connector (Fig. 3). To add additional visibility to the system operation, a small OLED display was incorporated into the board. The display presents readings from the sensors, allowing the users to keep an eye on it easily. The PCB board also has buttons, which currently are used to navigate the information presented on the OLED display. In addition, the PCB board has an I2C extension connector, to allow for the addition of more sensors in the future.

As part of the system, the RPis run a Python code that queries the sensors for information and then sends it to the local InfluxDB. The Python code also controls the OLED display on the board. The system was designed to be easily modified - add additional sensors, adjust the functionality of the buttons or the information shared on display.

2.3.3. Data visualization

For the presentation of real-time personal environmental accounting, the data is then displayed on a Grafana dashboard (Fig. 4) which is highly customizable and also allows users to quickly add new variables when the BIN network needs to be scaled. The Grafana Dashboard pulls data from the InfluxDB. In the pilot version of the BIN network, the Grafana is installed on Full Node but this is not an essential aspect of the system, as the data is collected locally on the RPi. In future iterations, it is possible to remove the Grafana from the Full Node and install it locally on each end unit and the system will maintain its core functionality.

3. Benchmarking metrics for smart contracts

The blockchain network allows for the implementation of smart contracts to allocate tokens based on the readings from the sensors connected to each endpoint. In order for the smart contract to incentivize sustainable user behavior, it was necessary to come up with metrics to evaluate the users' performance.

The development of metrics to allow the measurement and comparison of different aspects of sustainability for different spaces was an important element of this study. One of the most widely used metrics in energy benchmarking is energy use intensity (EUI), which represents annual energy consumption normalized by gross floor area (Eq. (1)). However, this metric considers energy usage alone and ignores matters of indoor comfort and health [73]. This yields kBtu/m^2 and allows different sized spaces to be compared against one another directly to determine which space uses the least energy. While this is an important metric, it fails to capture many important aspects of how a space may be used sustainably and provides little feedback on whether or not that energy was used efficiently given the purpose and utilization of this space. As a result, an extensive body of work emerged in recent years with concerns about this normalization factor [74,75].

$$EUI = \frac{\sum_{i=1}^{n} elec_i \times \frac{365}{7} \times 0.003412}{area} \quad (1)$$

where:

n = the number of electric readings.

$elec_i$ = the electric consumption metered by the i^{th} reading in Wh.

365/7 = a value that converts a week of electricity into its annual equivalent.

0.003412 = a value that converts Wh to kBtu.

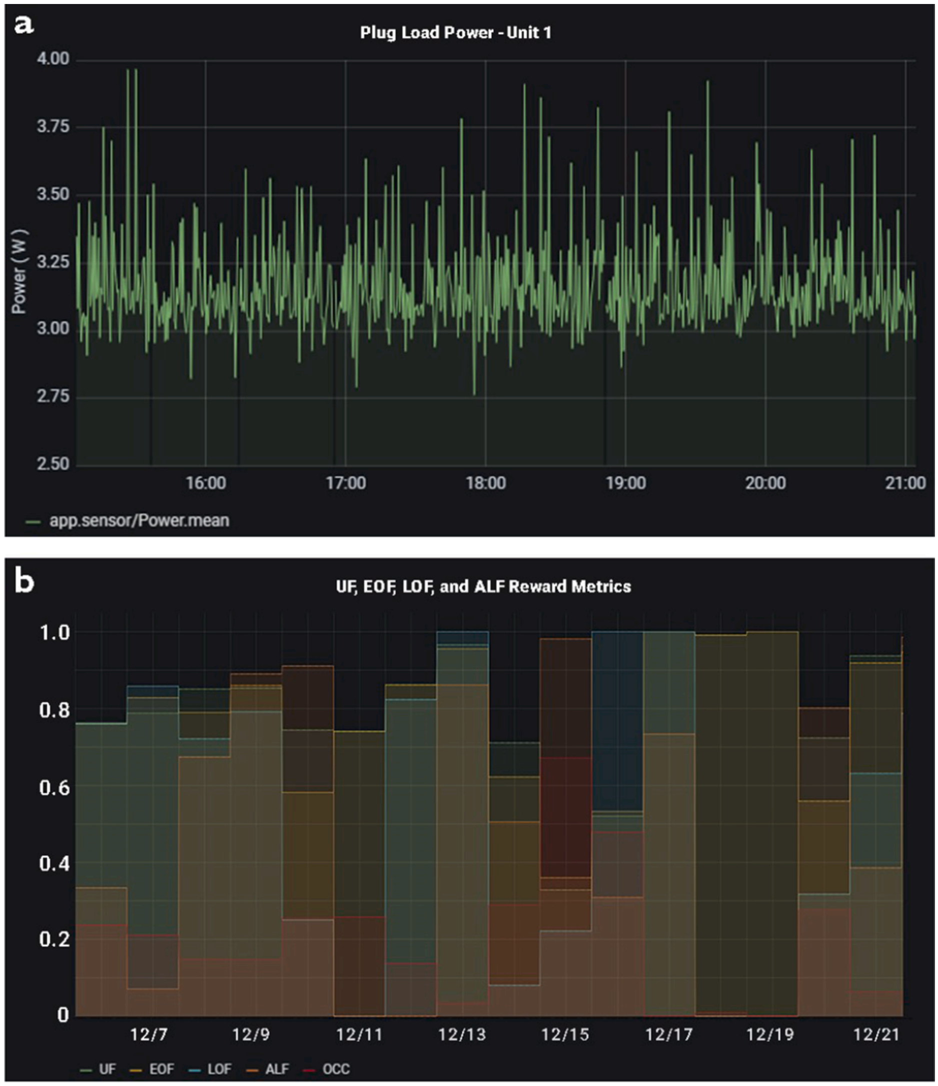

Fig. 4. A snapshot of a) raw data dashboard of plug load and b) reward metrics dashboard.

area = the area of the space being measured in gross square meter (m^2).

In this case, additional and/or different normalizations can help determine the more efficient space. Ultimately, it is important to consider other factors than just the total amount of energy a space consumes to determine if the space is using its resources efficiently. To this end, several additional metrics were developed to be reported in parallel with EUI that aim to capture other aspects of efficient and sustainable use of spaces. Since occupancy was not measured in this dataset, the environmental parameter of CO_2 was used as a proxy instead: the threshold value used to determine occupancy was 600 parts per million (ppm), which was chosen as the level that an unoccupied household would never reach but which was low enough that an occupied household would be unlikely to reach due to infiltration [76]. The full set of metrics proposed and used in this study are:

1. Energy Use Intensity (EUI)
2. Utilization Factor (UF)
3. Energy Occupancy Factor (EOF)
4. Lighting Occupancy Factor (LOF)
5. Artificial Lighting Factor (ALF)
6. Air Quality Index (AQI)
7. Carbon Intensity (CI)
8. Overall Carbon Optimization (OCO)
9. Marginal Carbon Optimization (MCO)

3.1. Metrics related to the energy consumption

3.1.1. Utilization factor (UF)

The utilization factor (UF) is a metric that simply reports the proportion of time that a space is occupied and ranges between 0 and 1 (Eq. (2)). This metric is completely independent of the reporting of energy consumed and serves as a catch-all for the efficiency of use of the various resources required to construct, maintain, and condition a space. Essentially it seeks to measure the extent to which a space is being utilized given the expenses and inputs required to create and operate that space. This captures the embedded energy of a space and the material resources required to construct it and can be especially useful when monitoring different spaces that share conditioning costs or which are not separately metered for their conditioning costs. As a result, the only means of differentiating the efficiency of the use of these resources is to determine what proportion of time each space (and the associated material and conditioning costs) are actually being utilized.

$$UF = 1 - \frac{CO_{2occ}}{CO_{2tot}} \tag{2}$$

where:

CO_{2occ} = the count of CO_2 sensor readings that were above 600 ppm.
CO_{2tot} = the total count of all CO_2 sensor readings.

3.1.2. Energy occupancy factor (EOF)

Energy occupancy factor (EOF) is a metric that takes another look at the energy usage of space as computed with Eq. (3). Rather than considering the scale of the energy consumption of space given its area, it instead considers whether or not the energy was used when the space was occupied or when it was empty. This metric considers the proportion of energy consumed in a space while the space was occupied versus the total energy consumption of the space. It is a unitless ratio that reports as a value from 0 to 1. Consider an empty unit with a single light on versus a similarly sized unit with three lights on but which is being utilized by several workers. The first unit would have a lower EUI, but arguably is wasting more energy than the second.

$$EOF = 1 - \frac{\sum_{i=1}^{n} occ\_elec_n}{\sum_{i=1}^{n} elec_n} \tag{3}$$

where:
n = the number of electric readings.
$elec_n$ = the electric consumption metered by the n^{th} reading in Wh.
$occ\_elec_n = elec_n$ if CO_{2n} greater than 600 ppm, else 0.

3.1.3. Lighting occupancy factor (LOF)

The lighting occupancy factor (LOF) is very similar to EOF in that it seeks to measure the amount of energy that is wasted through artificial lighting when the space is unoccupied (Eq. (4)). This effect is captured within the EOF but has been pulled out as a separate metric for two reasons. Firstly, lighting represents one of the factors that individuals in a unit are most likely to be able to exert direct control over. Unlike conditioning or embedded material costs, users of a space almost always have some control over lighting in the non-common areas of buildings and images of buildings all lit up and empty at night have become emblematic of this particular type of energy waste. Secondly, in addition to the element of control a user has over lighting, there is an aspect of utility to energy consumption for lighting versus many other energy uses that is directly tied to occupancy. Many uses of a unit may require energy use when the unit is not occupied such as a refrigerator, but there are far fewer reasons that space might need to use energy for lighting if there is no one present. Thus lighting expenditures in unoccupied spaces can be labeled as wasted energy behavior with much greater confidence than overall energy expenditures in unoccupied spaces. Likewise, the LOF is reported as a value between 0 and 1.

$$LOF = 1 - \frac{Lights_{occ}}{Lights_{tot}} \tag{4}$$

where:
$Lights_{occ}$ = the number of readings when lights are on and CO_2 sensor above 600 ppm.
$Lights_{tot}$ = the total number of readings when the lights are on.

3.1.4. Artificial lighting factor (ALF)

The artificial lighting factor (ALF) of a space considers another aspect of whether or not energy expended on lighting is wasteful (Eq. (5)). Unlike LOF, which considers whether or not the space is occupied while the lights are on, ALF considers whether or not there was sufficient natural light such that artificial lights were not necessary, yielding the proportion of the time that artificial lighting was used but was not needed, again as a value between 0 and 1. This works in parallel with LOF as it does not consider whether or not a space was occupied or not and may be more appropriate for spaces that require continuous light of a certain intensity such as common spaces or certain labs.

$$ALF = \frac{Lights_{suff}}{Lights_{tot}} \tag{5}$$

where:
$Lights_{suff}$ = the number of readings when lights are on and natural light is detected.
$Lights_{tot}$ = the total number of readings when the lights are on.

3.2. Metrics related to human wellbeing

The first five metrics are all directly related to the energy expenditure of the space and how the space is being utilized. However, there are other important environmental factors that can be monitored and reported on that provide feedback on how well a space is being managed. One such metric which was considered is the Air Quality Index (AQI) which is evaluated for each measured pollutant and the highest result used (Eq. (6)). The AQI monitors a variety of pollutants and acceptable levels for each and returns a value from 0 to over 300, based on the one which exceeds the recommended levels by the greatest proportion. Each pollutant has a separate AQI table linking concentrations to AQI.

$$AQI = \frac{I_{high} - I_{low}}{C_{high} - C_{low}} \times (C - C_{low}) + I_{low} \tag{6}$$

where:
C = the measured concentration of the pollutant.
C_{low} = the concentration breakpoint on the AQI table that is the first below C.
C_{high} = the concentration breakpoint on the AQI table that is the first above C.
I_{low} = the AQI corresponding to C_{low} on the AQI table.
I_{high} = the AQI corresponding to C_{high} on the AQI table.

3.3. Metrics related to carbon emissions

The final three metrics that were developed also pivot from a strict consideration of energy consumption as a gauge of sustainability by converting the energy used by a space into the magnitude of GHG emissions that were produced as a result. As demand for grid-based electricity is met using a shifting mixture of generation types, the amount of GHG produced per unit of electricity is constantly changing and two users may have different emissions factors at the same time based on their location on the grid. Thus, the relationship between energy consumption and carbon production is not strictly linear. While energy use serves as a metric for many different environmental and economic impacts, carbon production specifically identifies sustainability in regard to climate change.

3.3.1. Carbon intensity (CI)

Carbon Intensity (CI) is a direct extension of the EUI in that it is the magnitude of carbon dioxide (equivalent) produced in kilograms (kg) normalized by the area of the space in which the energy was consumed (m^2). The carbon produced is calculated by multiplying the electricity consumed by the grid's overall emission factor for that time period and dividing by the area. The resulting metric will have a lower bound of 0 kg/m^2 if either no energy is used or if all energy used had an emission factor of 0 MTCDE/MWh. The upper bound is only limited by the energy consumption of the space. While this metric is closely related to EUI, by decoupling energy and carbon opportunities are created to recognize sites that utilize more sustainable power sources and to recognize sites that are able to employ DR techniques to shift their energy consumption to less carbon intensive time periods.

$$CI = \frac{\sum_{i=1}^{n} elec_i \times \frac{365}{7} \times 0.003412 \times OEF_i}{area} \tag{7}$$

where:
n = the number of electric readings.
$elec_i$ = the electric consumption metered by the i^{th} reading in Wh.
365/7 = a value that converts a week of electricity into its annual

equivalent.

0.003412 = a value that converts Wh to kBtu.

OEF_i = the overall emission factor for the grid electricity at the time of the i^{th} reading.

area = the area of the space being measured in gross square meter (m^2).

3.3.2. Overall carbon Optimization (OCO) and marginal carbon Optimization (MCO)

While carbon intensity is a gauge of the magnitude of emissions produced, it does not provide a good measure on how efficiently the electricity was utilized in terms of minimizing the associated emissions because there is no point of comparison to indicate what was achievable as an optimal outcome. Just as EOF and LOF shift the emphasis from the magnitude of electrical consumption to the efficiency of its use, the Overall Carbon Optimization (OCO) and Marginal Carbon Optimization (MCO) metrics do not consider the magnitude of the carbon produced by the space. Instead, these metrics consider the timing of electric use compared to the variations seen in the grid emission factors during that time.

To gauge how effective a space was at minimizing carbon produced per unit of electricity consumed, the carbon produced by the actual power consumption profile and emissions factors must be compared against a meaningful baseline, which is determined by calculating the emissions if total power consumption had been equal but it had been used at a constant rate. Spaces that use a larger portion of their electricity during those times with low emission factors will achieve better scores than those that use more of their electricity during those times with higher emissions factors. The final metrics, OCO and MCO, are calculated by determining the percentage deviation of the actual carbon produced compared to the average baseline. The result can be positive or negative and has upper and lower limits dictated by the grid generation mix profile for that timeframe. OCO is calculated using the overall emission factor for the grid, which considers all of the generation powering the grid at a given time, while MCO is calculated using the marginal emission factor, which only considers the generation units that are being deployed to manage changes in demand on the grid. The relative merits of each are discussed further in Section 5.

$$OCO = \frac{\sum_{i=1}^{n} elec_i \times OEF_i}{\sum_{i=1}^{n} elec_{ave} \times OEF_i} - 1 \tag{8}$$

$$MCO = \frac{\sum_{i=1}^{n} elec_i \times MEF_i}{\sum_{i=1}^{n} elec_{ave} \times MEF_i} - 1 \tag{9}$$

where:

n = the number of electric readings.

$elec_i$ = the electric consumption metered by the i^{th} reading in Wh.

$elec_{ave}$ = the average electric consumption metered in the period.

OEF_i = the overall emission factor for the grid electricity at the time of the i^{th} reading.

MEF_i = the marginal emission factor for the grid electricity at the time of the i^{th} reading.

In summary, each of these metrics is designed to gauge an aspect of sustainability on a weekly basis (or another time unit that would be applicable to a specific case study) for an individual space, providing a comparable result that can be used to evaluate the performance of that space in that area. Each metric serves a dual purpose in this regard by providing a metric for comparison against other similar spaces as well as a means of measuring how the use of a space changes over time. This provides two opportunities to reward desirable DR engagement, first by considering a space's present behavior against that of other spaces in the same timeframe, but also by rewarding improvement in a space if the metric improves compared to the levels seen in recent history. Note that for all nine metrics, lower values indicate better scores.

These scores translate into smart contracts which assign tokens based on the rankings to individual nodes/users/spaces. By delineating a clear path to achieve better performance metrics, these smart contracts are meant to both raise awareness of energy waste and incentivize improved individual DR participation.

4. Energy metrics case study

4.1. Evaluating the performance of the Blockchain + IoT network in single-unit households

The five developed metrics focusing on energy use and occupancy (UF, EUI, EOF, LOF, and ALF) represent a combination of established sustainability metrics and ones that were newly developed for this project as a result of the literature review. In order to test the energy utilization metrics discussed in Section 3, we used, as a case study, sensor data that we collected from 6 small single-unit households. This included the monitoring of electric consumption, carbon dioxide levels, and a variety of air contaminants. The sensor data collected was representative of all of the sensors to be used in this project except for those used to monitor lighting conditions. These sensors were deployed across three winter seasons with several months of data being collected in each season and monitoring a different set of households each year. Specifically, data collected during the 2019–2020 winter season was used to test the developed individualized sustainability metrics as this season contained the largest number of units that were occupied and were also monitored for both electric consumption and carbon dioxide levels, which would allow us to test the UF, EUI, and EOF metrics. As emission factor data was only available for this region at annual average increments, the three emissions focused metrics (CI, OCO, and MCO) are explored in Section 5 in a separate case study.

The test set that was used included 5 units, all of which were monitored for a total of 26 weeks during a cold winter. Four of the units were occupied structures being utilized as single-family homes and the fifth unit was an unoccupied structure, located at a different geographical location. The metrics being tested were highly reliant on occupancy and the metrics from this unoccupied household were skewing the average values that the other households were being compared against. The weekly metrics calculated for this structure were not included when calculating the average value of the metric against which the individual units would be evaluated.

The test data of small single-unit households were used to evaluate the effectiveness of the developed metrics for the evaluation of sustainability in spaces. All of the metrics developed in this study were computed in Python (version 3.9.0) to take in the raw data from the sensors and to incentivize tokens to households based on an award algorithm. The algorithm compares the UF, EUI, and EOF metrics for a household against the metrics of the other households that week. Additionally, each single-unit household's metrics for that week were compared to its average score in the prior 4 weeks. Households that received a score that was 20 % lower than the average score for the household that week or the average score for that household in the previous 4 weeks were awarded a coin. As each metric was evaluated separately and as a coin could be awarded in each metric for performance against peers, performance against self, or both there was the potential for each household to receive as many as 6 reward tokens in each week.

4.2. Energy metrics case study results and discussion

As the raw data was provided in the form of well-formatted CSV files, this stage mostly consisted of dropping unused sensor data and retaining only the households of interest. The figures below show two examples of the data that was collected. Only the electric consumption and the carbon dioxide sensor readings were retained to calculate UF, EUI, and EOF. Fig. 4(a) illustrates the CO_2 concentration and power consumption of a typical occupied household. Power consumption has a floor of 0 W as there are times when all appliances and other uses are turned off, however carbon dioxide has a floor of about 450 ppm as this represents the average atmospheric concentration. Fig. 4(b) shows the unoccupied unit with the primary difference being that the carbon dioxide remains mostly level at the atmospheric concentration.

Once the relevant data had been handled by dataframes, it was evaluated week by week to determine the UF, EUI, and EOF metrics for each household. The first step in this process was to consider the carbon dioxide level and to compare this against a threshold level to assign a boolean value of occupied or not for that hour. The occupied boolean value was used to calculate the utilization factor as well as to determine which electric readings to include in the occupied use of electricity for EOF. The lighting sensor data had been included in the household data. A similar method would have been used to determine whether or not the lights were on or off and whether or not sufficient natural light was present to remove the necessity of using artificial lighting. Both of those boolean values would have been used in the calculation of the lighting occupancy factor as well as the artificial lighting factor.

Fig. 6 shows the results of the metric calculations for all five households that were monitored across the 26-week time span. In addition to the weekly metrics from the five households, also presented is the average weekly value of the metrics for the four households which were occupied. This average was used as the point of comparison for awarding tokens based on performance versus peers. As can be seen from Fig. 5, the unoccupied household is an outlier for all three metrics, particularly for the metrics which included occupancy as a part of the calculation, which is why it was excluded. These plots explain how the values being tracked in the UF and EUI metrics are both reflected in the EOF. While UF tracks the level of occupancy and EUI tracks the intensity of electrical usage, EOF considers when energy is being used while space is being occupied. Thus, EOF is only high when there is energy being consumed and the space is unoccupied and is only low when the space is highly occupied. As Fig. 5 demonstrates, this interplay occurred in Unit 4 especially well as there are numerous weeks in which a high UF correlates to a high EOF, but in week 2 the spike in UF is not mirrored in the EOF because energy usage dropped when the space was unoccupied. Overall, these results indicated that the metrics reflected the qualities they were intended to represent and showed sufficient differences and

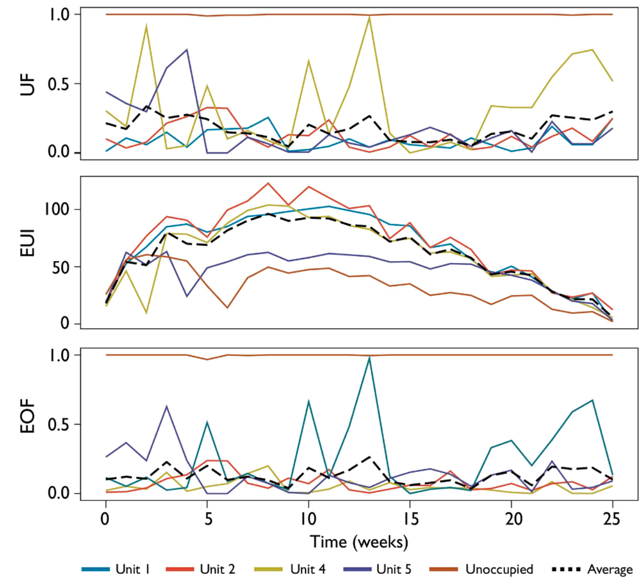

Fig. 6. The results of the metric calculations for five households.

variability between the spaces such that the threshold of 20 % less than the average calculated value was sufficient to award tokens based on performance versus peers as well as compared against past behaviors.

Once the metrics had been calculated for each week for all 5 households, it was possible to send those results through the algorithm to determine when the reward token should be awarded to each household. Figs. 7 and 8 show an example of the evaluation of each of the three metrics for a single household. The first two charts in Fig. 7 and Fig. 8 are the raw data values from the carbon dioxide sensor and the electric meter. The third chart is a replicated version of the charts above showing how that metric was calculated across all monitoring weeks for each household, with the results for the household being considered highlighted in red and the dashed line showing the average value against which it would be compared. The bottom chart included in Figs. 6 and 7

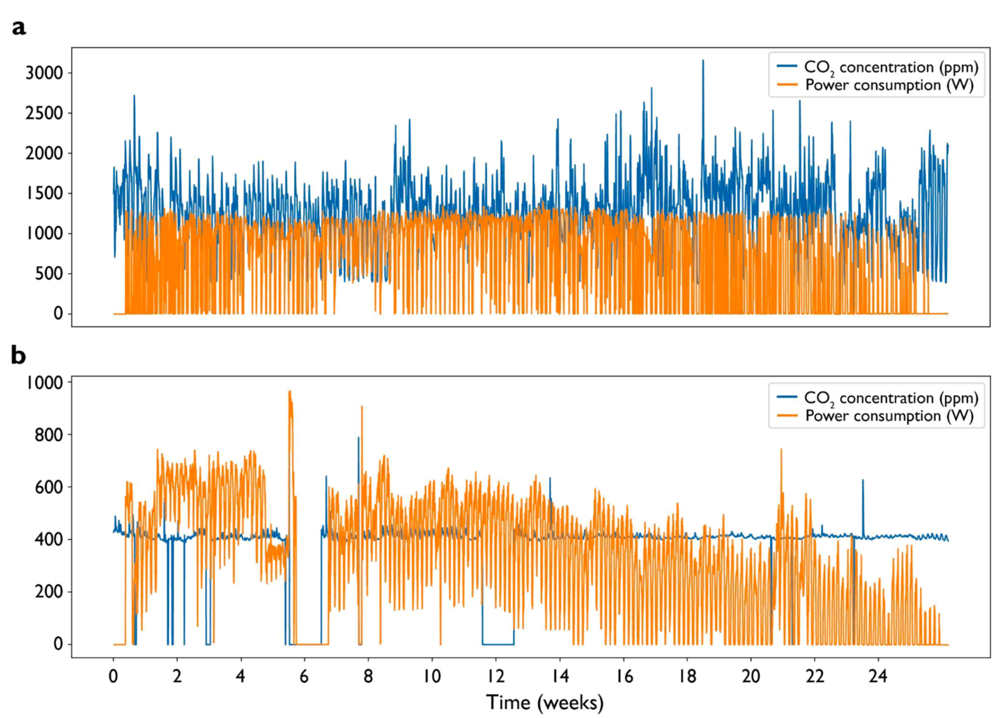

Fig. 5. (a) CO_2 concentration and power consumption of Unit 1; (b) CO_2 concentration and power consumption of the unoccupied household.

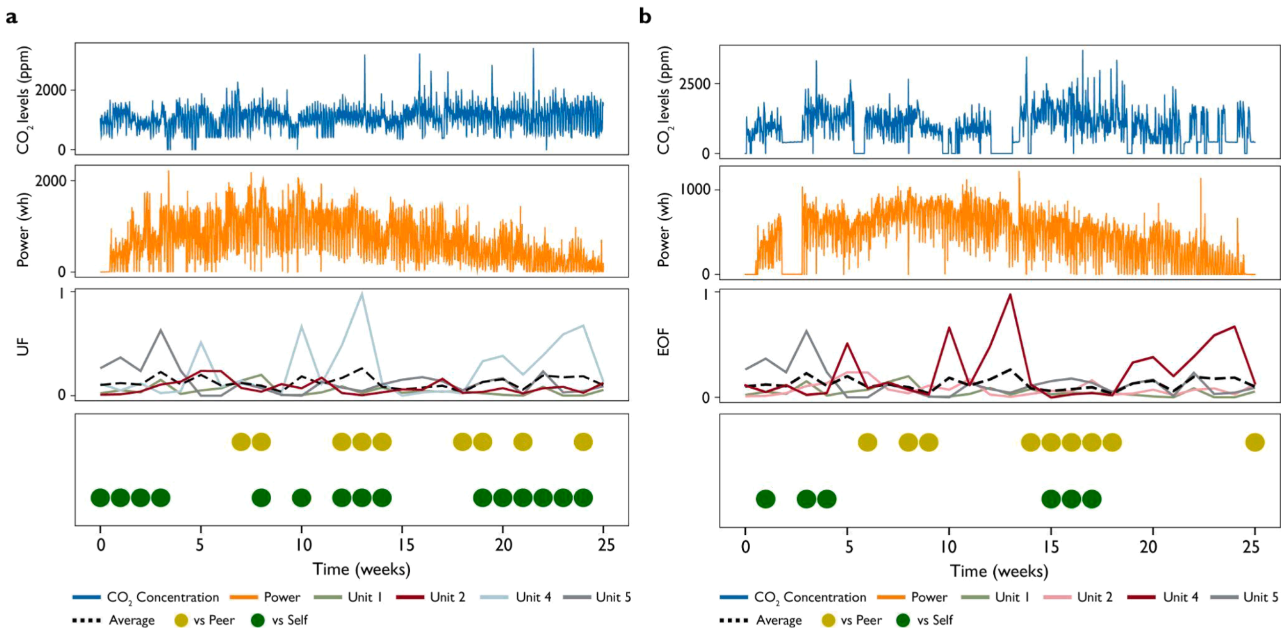

Fig. 7. Computed (a) UF metric for Unit 2 and(b) EOF metric for Unit 4.

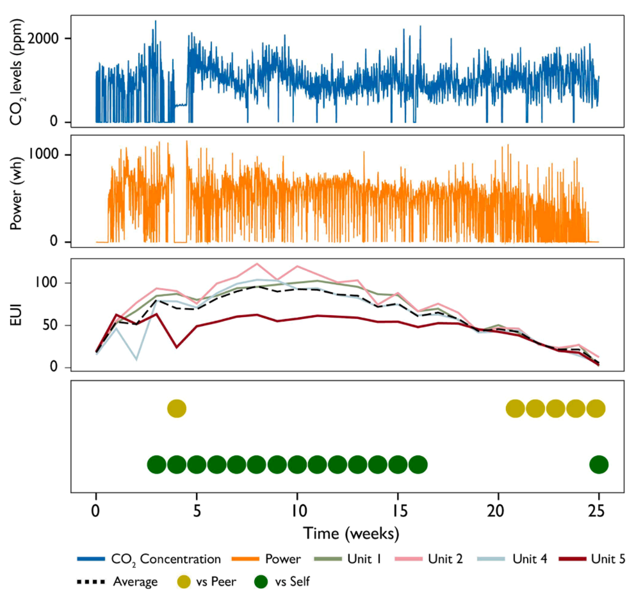

Fig. 8. CO_2 levels, power consumption, and calculated EUI for Unit 5.

shows how the household being considered was actually awarded based on the calculated metric. The combination of these four charts shows how the measured sensor data translates into token awards and confirms the anticipated results. Specifically, it illustrates that households were awarded tokens only in those weeks where the sensors actually reflected the sustainable behaviors that were desired.

While we demonstrate these 5 units because of an available dataset we used for this case study, the system can be easily scaled up. Scaling up is only limited by the capacity of the blockchain network. Currently our network allows for hundreds of transactions per minute. If this capacity is reached, there are solutions to extend the system capacity. The public Ethereum network has proven to work with an enormous number of users.

5. Carbon metrics case study

5.1. *Evaluating the performance of the BIN network in near real-time carbon accounting*

As discussed previously, carbon emissions and energy consumption are not linearly linked. This introduces the possibility that the timing of energy use could have a significant impact on greenhouse gas emissions. The questions then become 1) what is the scale of impact that such timing might provide and 2) can timely feedback on the real-time or future emission factor be provided to consumers so that it might be acted upon? This information could be particularly useful to users whose consumption of energy is immutable but where the timing of that consumption is adjustable.

In order to gauge the utility of Carbon Intensity (CI), Overall Carbon Optimization (OCO), and Marginal Carbon Optimization (MCO) a case study was carried out using the initial set of sensors deployed in an office space in Philadelphia, PA. The sensor set utilized for this study has been collecting the full set of sensor data in the occupied office space for more than half a year, however the data set is limited in that only a single space was monitored. As a result, these metrics could not be generated for multiple spaces and compared. Instead, the purpose was to gauge the potential technical barriers in collecting the emission factor data in real time as well as the magnitude of potential impact that access to such information might provide.

The organization managing the monitored space is a load-serving entity that procures energy on the spot market. As such, the emissions associated with the electricity used by that organization are highly reflective of the generation mix within the PJM sub-region in which they operate. The emission factor changes over the course of the day as demand shifts and the availability of renewables waxes and wanes. Standard carbon accounting practices do not account for these variations, instead using an average annual emission factor, but they can be significant. The generation mix for the PJM RFCE subregion was observed in real-time over 90 days between November 2021 and February 2022 and sustained periods were recorded when the emission factor was as low as 0.26 MTCDE/MWh and as high as 0.46 MTCDE/MWh, deviations of roughly 30 % from the average values that would be used in carbon accounting.

A further refinement of real-time emission factors is to consider the impact of the actual generation capacity that will be used to meet changing demand. The PJM grid operator calls on generating units around the region to come online or to change the amount of energy they are feeding into the grid to maintain the balance of supply vs demand. The emission factors of those specific generation units can translate into an assessment of the immediate impact of your actions should you increase or decrease your own energy consumption. The potential range in the marginal emission factor is greater than that of the overall emission factor as it could be as low as 0 MTCDE/MWh or greater than 1 MTCDE/MWh if renewable or coal is on the margin.

Regardless of the mechanism used to measure the carbon impact of electrical use, there is a significant difference in the emissions created in supplying electricity at different points in time. Further, it is evident that a consideration of the marginal emission factor can illuminate the outsized impact that the timing of electric consumption may play in minimizing emissions. This leaves the question: can information regarding these real-time emissions rates be meaningfully transmitted to consumers in such a way that they are able to take timely action? As a part of their activities, PJM provides large amounts of data regarding the generation capacity that supplies energy to the grid, including an API which provides near real-time information on both the current generation mix and the marginal emission factor. The emission factor data was collected through the PJM API over a span of 90 days from November 2021 to January 2022.

The overall emission factor was calculated as the average of the emissions factors of the different generation units feeding into the grid in any given hour, weighted by the amount of electricity fed into the grid by each unit. Thus, it represents an average MTCDE/MWh for the PJM grid. The PJM API reported the capacity deployed across the grid by energy sources (coal, gas, hydro, wind, etc.) in megawatts of capacity. A sample of this data can be seen in Fig. 9, which shows how natural gas and hydro are largely used to handle short term demand fluctuations. This information is updated hourly but there is typically a lag of 1–2 h between the publish time and the time frame represented by the data. Further, while the overall emission factor does change significantly over the course of days, the hour-to-hour variations observed tend to be incremental due to the nature of how they are calculated. This makes the overall emission factor less useful for snap, in-the-moment decisions, but potentially impactful for near to mid-term planning and scheduling of operations. Methodologically it is an attractive metric to utilize as its calculation mirrors the method by which the annual emission factors are calculated, simply aggregating energy produced and emissions released over a smaller time frame.

While the overall emission factor is calculated using the generation mix, the marginal emission factor is reported directly by the PJM API, eliminating the need for any calculation. The marginal emission factor is an average of the emission factors for the generating unit(s) that were most recently used to meet the most recent change in demand, weighted by the capacity of those units. Because the marginal emission factor is calculated as the average of many fewer generating units than are considered in the overall emission factor and the turnover of the units is high the marginal emission factors have a larger range and are more volatile than the overall emission factors, as can be viewed in comparison to the overall emission factors in Fig. 10. As such, it is reported by the PJM API at 5-minute intervals with a typical lag between the measured time and publish time of 10–15 min.

The space that was monitored is an office suite that was regularly occupied during the time frame. Temperature, humidity, lighting, and air quality readings were taken by sensors in the space. These sensor readings were collected at regular interval using a Python script running on a local RPi and pushed to an Influx database hosted remotely on AWS. Electrical consumption data for the space was monitored directly at the circuit breaker box using Onset power sensors, including the monitoring of electrical consumption across three circuits serving the space, data from which can be accessed using a web API.

A separate RPi executed a script made calls to both PJM API as well as the Onset API to retrieve and merge the two sets of data using the timestamps, correlating the most recent overall and marginal emission factors with each set of energy readings. Once the electrical data was merged with the overall and marginal emission factors, near-real time carbon emissions were calculated by multiplying the electricity consumed each minute by the overall emissions factor for that period and displayed using a Grafana dashboard along with the emission factors and power consumption. Additionally, for each daily period in the 90-day data set, the collected data was used to generate CI, OCO, and MCO metrics. A final set of Python scripts was used to make calls to a third API to retrieve current and forecast weather conditions which will be used in future research on this data set.

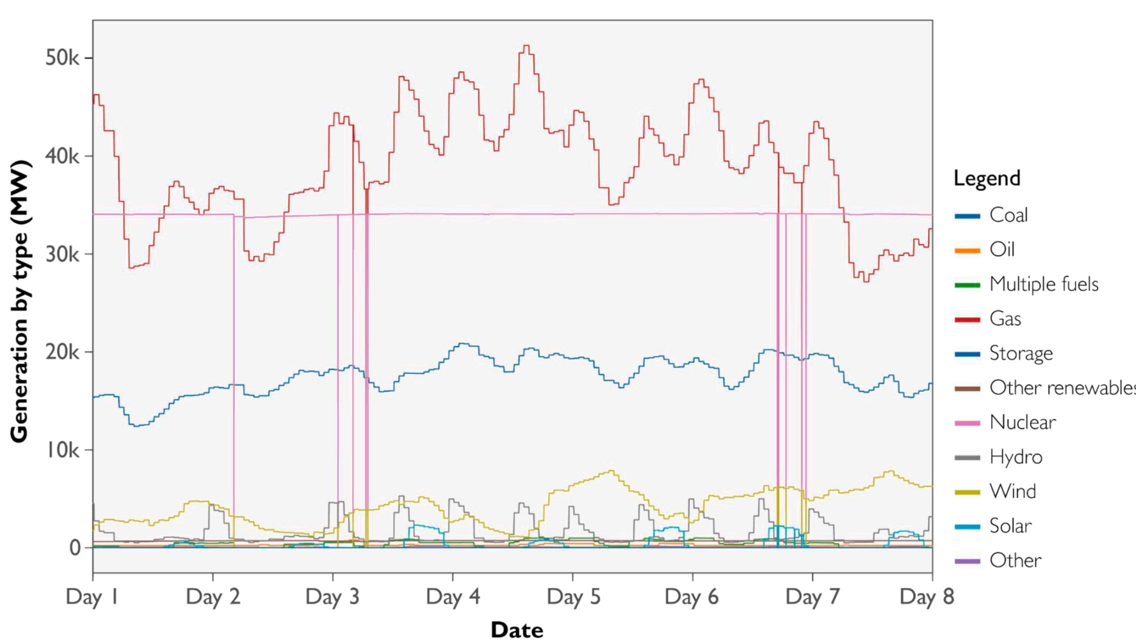

Fig. 9. A sample of the generation mix data from the PJM API.

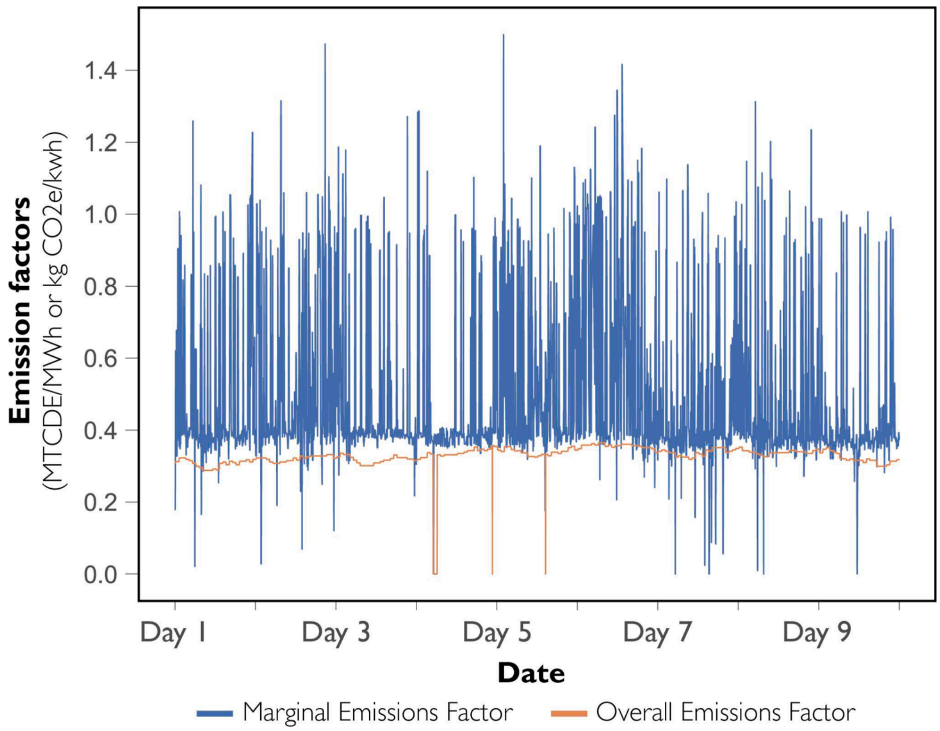

Fig. 10. The overall EF calculated from the generation mix vs the marginal EF.

5.2. Carbon metrics case study results and discussion

The results of the study were promising. Firstly, no substantial technological barriers prevented the collection and management of the data from the different sources, particularly obtaining the near real-time emission factors from PJM and merging this data with the local sensor data being collected. Once the final set of Python scripts was developed, the data collection was able to proceed smoothly and without interruption for months. A sample of the results of this data collection can be seen in Fig. 11. In order, these show the electric consumption monitored across the three circuits, the resulting carbon using the overall emission factors, and the resulting carbon using the marginal emission factors. This demonstrates how the significant volatility seen in the marginal emission factors demonstrated in Fig. 11 impact the resulting carbon calculations.

Secondly, significant shifts in both the overall and marginal emissions factors were observed in this period, indicating that there is the potential for load shifting to minimize carbon emissions without considering the scale of consumption. Thirdly, marked differences between the overall and marginal emission factors exist such that changing power consumption at a given point in time may have an outsized impact depending on the generation that is currently being deployed to deal with changing demand. Both of these points may be seen in the sample data in Fig. 11. Finally, as high emission factor periods correlate to periods of high demand on the grid, actions taken using this information should lead to overall decreased peak demand.

Significant limits still exist regarding the potential for near real-time carbon metrics in terms of their applicability to demand-response as the technique was employed in this study. While the metrics calculated are an excellent indicator of the sustainability of past energy behaviors, the lag in reporting of emissions data through PJM and the volatility of the marginal emissions factors makes it difficult to act on the information collected in a timely fashion. Even without the lag, there are limits to the changes in energy consumption that could be enacted in real-time in response to carbon information. While there are some concerns over applicability, overall trends show it may be a useful predictor over hours-long time scales. Of much greater utility would be the ability to plan for times that were forecast to have a higher emission factor so that schedules of personnel and equipment could be adjusted accordingly. Accurate prediction at the 5-minute time scale may prove to be impossible, but the development of probability models may be useful when considering the average marginal emissions factor in one hour compared to another.

There are several aspects of this study that deserve future research. Firstly, while this pilot proved the technical viability of retrieving the necessary information and calculating the novel metrics in near real-time, the limited sensor deployment meant that they could only be calculated for a single space. As a result, there are no points of comparison representing other spaces that might show the type of spread that might be encountered in the scores of ‘sustainable’ spaces vs ‘unsustainable’ spaces. As more spaces are monitored, their CI, OCO, and MCO metrics should be compared.

A sample of the calculated carbon metrics for the space can be found in Figs. 12 and 13. In Fig. 12, the non-linear relationship between carbon and energy can be seen, particularly in the transition between day 1 and day 2, where the EUI decreases while CI decreases. Fig. 13 shows the calculated OCO and MCO metrics for that space, however as feedback on the real time emission factors was not being provided to the users of the space, it is unclear the level of influence occupiers of the space may have on these metrics. The random variations observed, however, show that just by chance it is possible to influence carbon produced by at least a few percent by considering the timing of its use.

A second aspect to study would be to examine how actionable this information is. If a user is provided near real-time feedback, are they able to make meaningful changes to their energy consumption that will then be reflected in improved metric scores? Different users will obviously have different capacities to change the time profile of their power consumption so their ability to control these metrics may be limited. One significant drawback to this technique is the delay between data reporting and the time periods being monitored. This impact is less in the overall emissions factor due to its low volatility, despite the longer time between readings, but the rapid changes in the marginal emission factor mean that the ‘current’ value may differ substantially from the value reported, which represents the conditions 10–15 min earlier. One

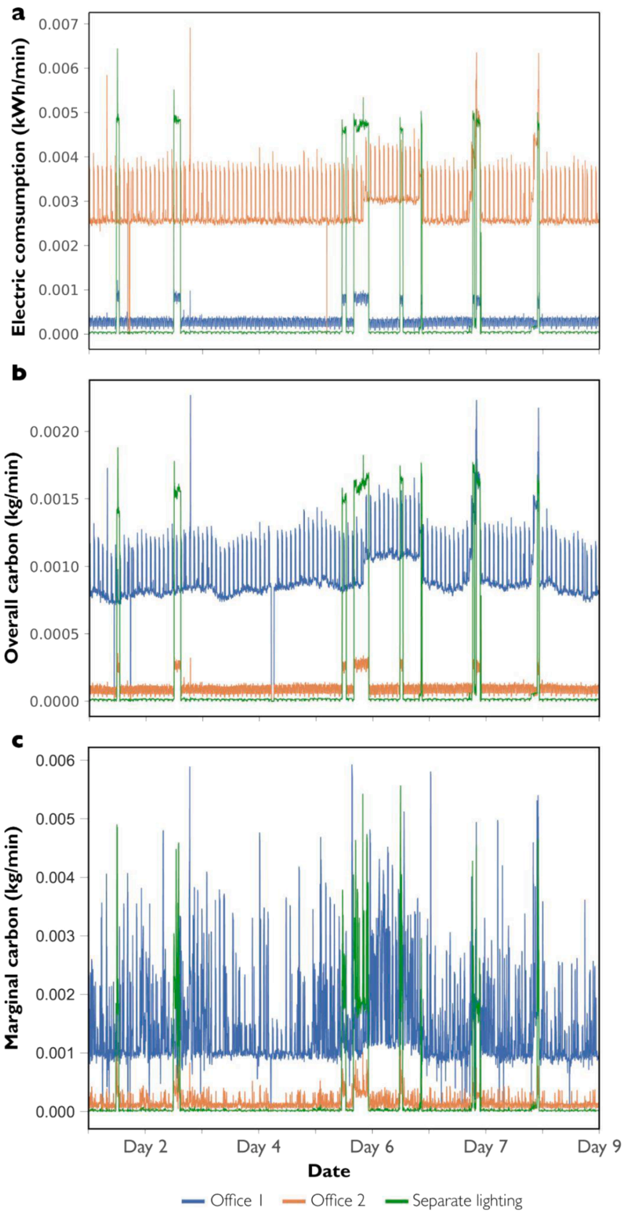

Fig. 11. A) a sample of the data from the three monitored electric circuits in the space; b) the overall emissions factor applied to electric use; c) the marginal emissions factor applied to electric use.

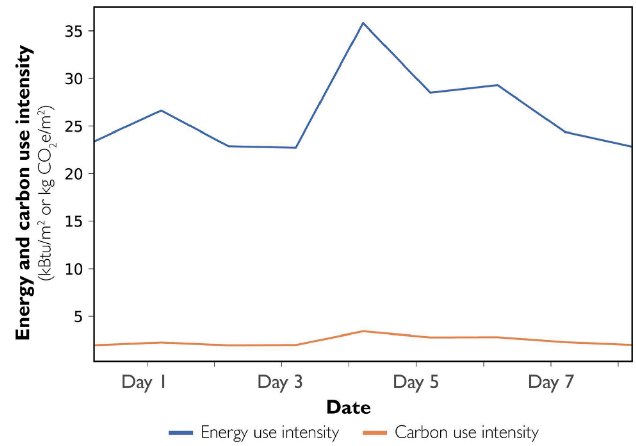

Fig. 12. The Energy Use Intensity (EUI) vs the Carbon Intensity (CI).

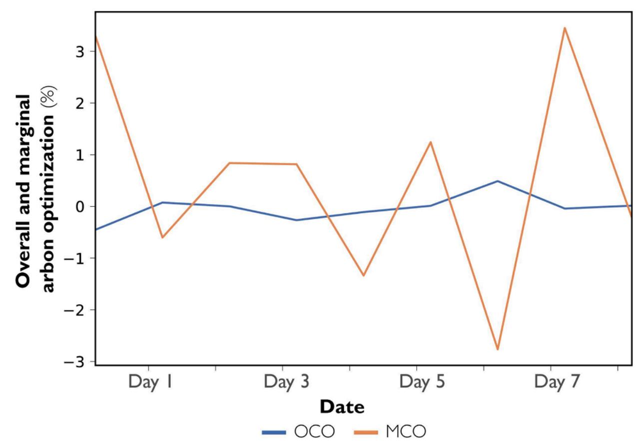

Fig. 13. The Overall Carbon Optimization (OCO) and the Marginal Carbon Optimization (MCO).

possibility of dealing with this volatility would be to do some smoothing of the marginal emissions factors through the use of a rolling average over a span of 30 to 60 min. This would change the meaning of the metric from a precise representation of the emissions impact of changing demand on the grid to a probabilistic representation indicating a likely impact.

One final aspect which should be considered is the potential for machine learning to be utilized for short term prediction of emissions factors using models trained on a combination of grid, weather, and calendar data. Trained models could then be utilized to make predictions of overall and average marginal emissions factors using near term weather forecasts. Fig. 14 shows a sample of this type of data which was collected using the same software framework as the PJM emission factors data. It shows the actual weather conditions displayed against their forecast values at different time-scales out, demonstrating that near term forecasting of many of the most relevant weather variables is highly accurate and could be used to aid the prediction of emission factors. This would allow for the scheduling of power consumption to maximize the utilization of low carbon periods of time, rather than adopting a more reactive stance. To this end, initial weather and weather forecast data sets have been collected and will be applied to the same set of sensor and emissions factor data utilized in this pilot. These same techniques can be applied directly to a prediction of peak grid demand as well, which can aid in traditional peak-shaving and DR efforts.

6. General discussion and future work

Individual energy usage traceability has traditionally faced the problem of achieving effective long-term monitoring with wireless, scalable, and resilient sensors as well as the problem of reliable data acquisition and storage. Existing environmental and energy monitoring platforms such as Ali et al.'s OSBSS prototype acknowledged the importance of having wireless transmission capacity which could help improve the accuracy of generating correct timestamps and enable remote accessibility [77]. Our proposed infrastructure uses I2C connection as well as Bluetooth and Wi-Fi communication to stream data into AWS which handles the concerns of distance of transmission and remote access to data. Data collected by sensors and smart terminals is real-time and reliable. In addition, the greatest advantage of this infrastructure over other existing IoT prototypes lies in the combination of blockchain technology and IoT. As noted by Alkhammash et al. [40] and Jeoung et al. [78] integrating blockchain technique with IoT sensors facilitates scalable and transparent access management. This represents a new approach which removes the restrictions of collecting IEQ and

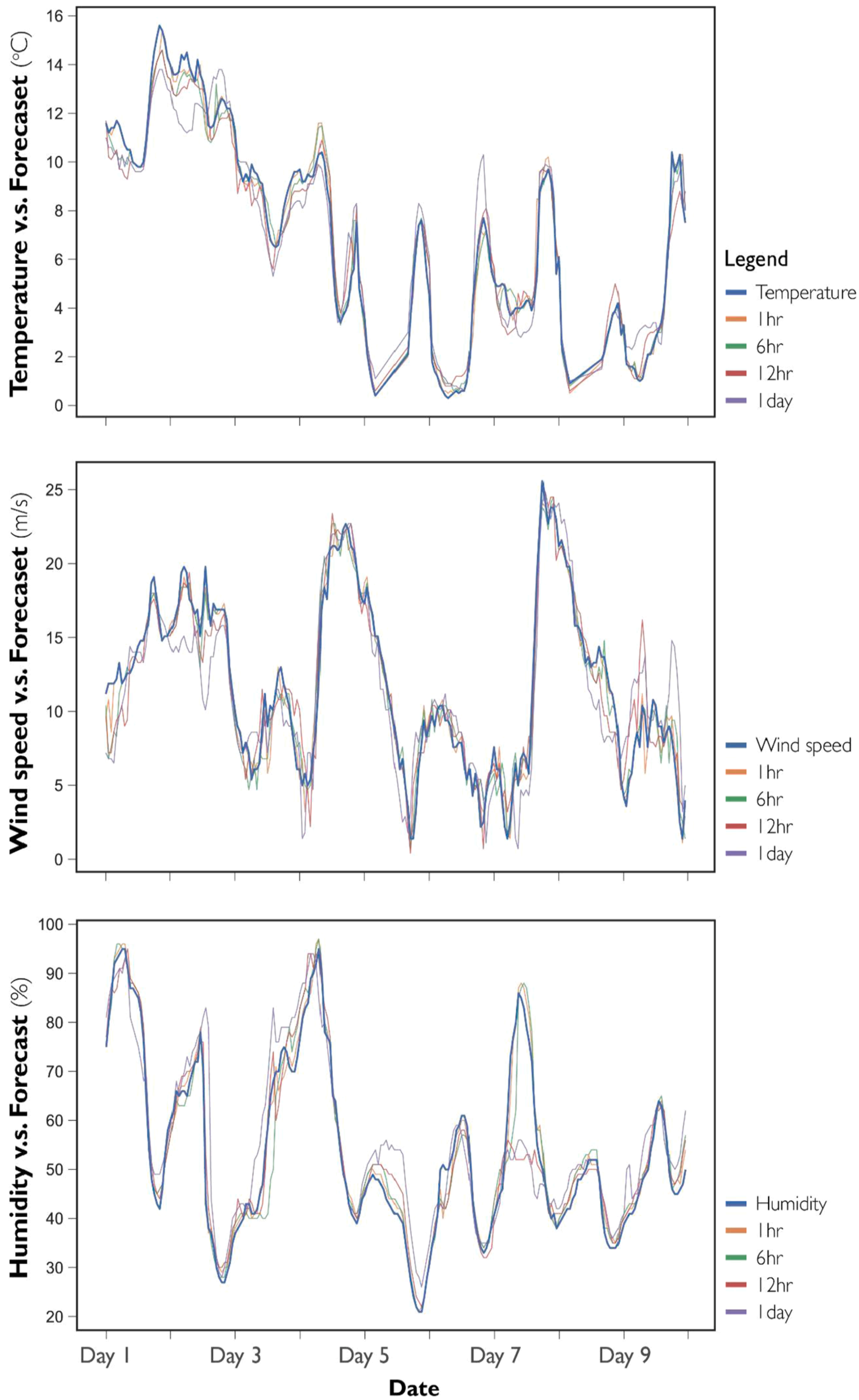

Fig. 14. Real-time weather data vs Forecast weather data at different times.

energy consumption profiles across multiple rooms and buildings while maintaining reasonable costs.

Previous studies are in good agreement with emphasizing the need for a paradigm shift in energy benchmarking to assess relative performance among peer buildings and users [79–81]. The results of the energy metrics case study showed that the metrics accurately measured desirable behaviors as reported by the sensors and that tokens were only awarded at those times when the space performed well against its peers or its own past behavior. Most importantly, incentivizing individual energy use behavior beyond the standard EUI captures the wide scope that cannot be reflected by energy consumption in kilowatt-hour per square meter. Additionally, the prior literature summarizes the importance of shifting from the magnitude of electrical consumption to the efficiency of its use [81,82]. Therefore, we proposed the OCO and MCO metrics to consider the timing of electric use compared to the variations seen in the grid emission factors during that time. The carbon metric case study results showed that near real-time carbon accounting is technologically feasible and can be applied to grid generation mix profiles with the expected outcomes. However, it is worth mentioning a few limitations of our proposed carbon intensity-based metrics. Due to the lack of emissions data for the region where multiple electrical consumers were monitored, this study was only able to apply the carbon-based metrics to a single space. As a result, the calculated metrics were not able to be compared against those of other spaces to evaluate their effectiveness in differentiating their behaviors. In addition, this study demonstrates that it is possible to create a reward system that can identify and incentivize those desired behaviors, but it has not yet been validated whether or not this reward system is sufficient to greatly encourage occupants to change their behaviors in real-world settings. Further refinement of the carbon-based metrics is to incorporate predictive machine learning models and expand their utility to assist in DR and emissions mitigation.

Another limitation of the study is the lack of data on the impact of the smart contract and tokens assigned to each unit on occupant behavior over time. The dataset used for the case study helped evaluate the validity of the metrics for the smart contracts but the tokens were not applied in real time, and users could not observe their performance while the data was collected. Future work will address this as we are currently launching another application of this method to office units where building occupants will receive live data and token counts. We will further monitor changes to their behavior and how the load-shifting and load reduction potential of DR would work accordingly.

In general, of the 9 metrics (each of which can be evaluated for a token reward) developed in this study, only two metrics (i.e., UF and CI) rely on the magnitude of the consumption, energy use intensity, and carbon intensity, though they are normalized by the area of the space being monitored which will have a modest correlation to the number of individuals using the space, on average. Energy and carbon could be similarly normalized by units produced, work hours, customers served, dollars earned, and other environmental factors. Each would have their benefits in specific applications, however, normalization by area has been the industry norm for evaluating the energy use of a space. The development of the additional metrics in this study was in direct response to the limitations of evaluating a space using only normalization by area. The other seven metrics consider the timing of the consumption in regard to whether or not the space was occupied, or the grid emissions factor, which changed based on generation mix. These were designed specifically to deal with the limitations of metrics that rely on the level of consumption with minimal consideration of the level of service provided by that consumption. As they focus on the timing aspects of use rather than the magnitude of consumption, the overall occupancy of the space is of less importance. For example, a household that used 90 % of its electricity while the space was occupied would achieve a better EOF or LOF metric score than a household that only used 50 % of its electricity when the space was occupied, regardless of how much was used in total.

It is worth noting that we opted for a reward-based incentive rather than the penalty-based one due to the following reasons: 1) the focus of this research was on the construction of the blockchain infrastructure and metrics that could be used in the implementation of demand response and to provide feedback to the users of a space. The exact nature of the rewards/penalties of a demand response system would be highly dependent on the contractual arrangement between the provider and the consumer. For example, individuals in office spaces being monitored do not directly pay for utilities, consequently, their energy use behavior cannot be incentivized/penalized through a billing process. 2) since joining this BIN network is completely voluntary, adding penalties may dissuade building occupants from participating at all, as opposed to the opportunity for rewards. 3) higher billing is usually given when a utility company applies a penalty mechanism. However, if no billing can be involved, the smart contract has to execute some type of penalty. Retrieving tokens from a user through a smart contract may not be a viable option for technical reasons such as the users do not have any tokens to lose.

The potential applicability of the proposed BIN monitoring infrastructure will be further explored in future studies. For example, it is worthwhile investigating its applicability of this network for appliance and/or building automation, reacting quickly in response to real-time energy prices and grid emission rates. Also, it is worth exploring the feasibility of an additional "Alerts" component to the infrastructure to provide real-time feedback to users of a space for a variety of notifications, some of which are directly related to the metrics/rewards ("You left the lights on", "Energy use unusually high this hour", "Emission rates high, consider deferring electrical use", etc.) and others which would contain useful information that derived from the sensor data being gathered but which did not directly feed into any of the metrics ("Room temperature is overheated", "Excessive CO_2 levels, consider ventilating the space", etc.). Incorporating automation would be a natural extension of that from a technology perspective as the event signal mechanism would already be in place. A simple option would be for the monitoring system to be paired with a traditional occupancy sensor with some control algorithm for lights or other electric uses, which would assist in the performance of several metrics. In addition, the applicability for more complex building automation across large scale building systems is also worth exploring. This would be substantially enhanced by an improved predictive component incorporating future grid conditions and anticipated local demand, which would allow for optimized scheduling of loads to meet demand while minimizing waste and the use of energy in peak times. If employed broadly across the grid, a means of coordinating these automated responses across many users would need to be developed that would work with the decentralized nature of the blockchain system to avoid rebound effects.

Finally, the BIN system was designed to provide a flexible and expandable, environment that will allow a community of researchers, students and building users to explore various Blockchain - IoT use cases. In the future we see the initial setup expanding to include additional sensors, end units, smart contracts, and use cases.

7. Conclusion

A Blockchain + IoT Network (BIN) infrastructure proposed in this study provides a strategy to acquire real-time IEQ, energy usage, and near real-time carbon accounting. To our knowledge, this is the first study to synthesize blockchain techniques and low-cost IoT sensors for incentivizing the building users' DR participation. Monitoring and visualization of occupant energy behavior have the potential to shed light on the spatial and temporal variations of personal environmental performance. The real-time IEQ and energy dashboard supplies individual energy information and feedback that can motivate building users to take energy-efficient behaviors and therefore can lead to electric demand flexibility. In addition, the metrics that we proposed in this study help normalize benchmark energy use and carbon intensity by taking various measures into account. The resultant EUI, UF, EOF, LOF, ALF, CI, OCO, and MCO values are directly related to an individual's energy expenditure and carbon emissions and our developed smart contract on the blockchain network takes the computed results to incentivize energy-efficient and environmentally sustainable behaviors.

The results of this study are promising given the unified collection and management of data that are merged from different sources. The BIN system has been running and testing for months which demonstrates excellent performance over time. Significant shifts in both the overall and marginal emissions factors were observed in this period. Future applications of behavior change campaigns may be less effective for DR engagement in the short term, but we believe the attitudes and behavior of building users will be affected over a longer periods of time by this information. We designed this BIN infrastructure to be scalable, expandable, and applicable to the wide network of commercial, academic, and residential buildings which attempt to address electric flexibility issues and mitigate climate change.

CRediT authorship contribution statement

Nan Ma: Project administration, Visualization, Writing - original draft, Writing - review & editing. **Alex Waegel:** Data curation, Formal analysis, Investigation, Methodology, Writing - original draft. **Max Hakkarainen:** Data curation, Investigation, Software, Writing - original draft. **William W. Braham:** Conceptualization, Funding acquisition, Resources, Supervision, Writing - review & editing. **Lior Glass:** Conceptualization, Investigation, Methodology, Software, Supervision, Writing - original draft, Writing - review & editing. **Dorit Aviv:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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