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Blockchain-based solution for energy demand-side management of residential buildings

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ABSTRACT

Smart homes, connected through a network, can optimize the energy consumption and general load shape of their area. In this work, a blockchain-based smart solution is presented for demand-side management of residential buildings in a neighborhood to improve Peaks to Average Ratios (PAR) of power load, reduce energy consumption, and increase the thermal comfort of occupants by modeling heating, illumination, and appliance systems. For real-time power and temperature monitoring of the neighborhood, a transient numerical physical model has been developed. The simulator has been validated with data measured from a building in Northern Italy. Then, a neighborhood with 2,000 households has been modeled for different occupancy patterns, initial values, and boundary conditions. Two different control scenarios, namely basic and smart, have been considered. In the basic scenario, everything is managed by occupants except the boiler, which is controlled by the indoor temperature of the home. Instead, in the smart scenario, a blockchain-based network has been introduced for buildings to exchange a parameter called the Probability of the Next Hour (PNH). Ethereum Solidity has been deployed for smart contract development in the blockchain. The results show that using blockchain-connected smart controllers aimed at demand-side management can improve PAR, comfort level, and energy efficiency of buildings, which can bring about CO_2 reduction on an urban and even global scale.

1. Introduction

The smart city concept means using electronic methods, sensors, and devices to enhance the citizens' quality of life. Achieving the highest efficiency and optimizing energy consumption are the main objectives of smart cities from the energy point of view (Boukhechba et al., 2017; Calvillo et al., 2016). Buildings are one of the primary energy consumers in Europe accounting for 40 percent of total use based on the ODYSEE and MURE databases (Schmidt & Åhlund, 2018). Energy consumption in most of the European countries is higher in winter compared to summer (Fateh, Borelli, Spoladore, & Devia, 2019). Reducing about 20% of energy consumption can eliminate about 50% CO2 emission (Fateh, Borelli, Weinläder, & Devia, 2019). Therefore, finding a smart solution to reduce the energy consumption of existing buildings without intervention on the building envelope can help to reach the target on an urban and even global scale.

A network of connected smart homes can reform the energy load shape and decrease the energy consumption on different scales based on the size of the network. On the other hand, conventional methods of Demand-Side Management (DSM) such as Demand Response (DR), which is a motivational measure to reduce the end-users' energy consumptions, is receiving the same signal to shift the time of their appliance consumption to all consumers, so there is a risk of shifting to the same time and making an even higher peak at another time (Chang et al., 2013; Y Li et al., 2012; Roche et al., 2015; Roozbehani et al., 2012). Overall, by adopting DSM techniques utility companies consider improving energy efficiency, reliability, and power quality of homes (Lokeshgupta & Sivasubramani, 2019). In short, the smart solution can predict behaviors to prevent undesirable conditions. A Neighborhood Area Network (NAN) is a concept that smart homes communicate through a network to coordinate their actions to manage energy in a neighborhood area (Celik et al., 2017). In a recent review study by Groppi et al. (2021), it was found that using sector coupling and DSM solutions in smart energy islands, lead to reduction of surplus electricity consumption and improvement of the grid ability to host variable

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Nomenclatures

Symbols

$\dot{E}$	Energy Rate, W
m	Mass, kg
$\dot{m}$	Mass Flow Rate, kg/s
ρ	Density, kg/m^3
t	Time, s
h	Time, h
C	Specific Heat Capacity, J/kgK
T	Temperature, K
$\overline{T}$	Mean Temperature, K
T^0	The temperature in the Previous Timestep, K
k	Thermal Conductivity, W/mK
U	Thermal Transmittance, W/m^2K
R	Thermal Resistance, m^2K/W
A	Surface, m^2
d	Thickness, m
D	Diameter, m
r	Radius, m
L	Length, m
Nu	Nusselt Number
Re	Reynolds Number
Pr	Prandtl Number
Ra	Rayleigh Number
g	Gravitational Acceleration, m/s^2
β	Coefficient of Volume Expansion, $1/K$
ν	Kinematic Viscosity, m^2/s
μ	Dynamic Viscosity, $kg/(m.s)$
y	Height, m
α	Thermal Diffusivity, m^2/s
n	Number
E_v	Average Luminance Level, lux
K_i	Luminance Efficacy, lux/W
w_r	Geometric Mean Sunrise Hour Angle, $^\circ$
λ	Latitude, rad
δ	Solar Declination, rad
Γ	Day Angle, rad

Subscripts

he	Heating
il	Illumination
b	Boiler
p	Pipe
r	Radiator
f	Fluid
wall	Wall
win	Window
i	Inlet
o	Outlet
in	Inside
out	Outside
indoor	Indoor
outdoor	Outdoor
a	Ambient Air
gap	Window Gap
oc	Occupants
ro	Rooms
dl	Day Length
sr	Sunrise
ss	Sunset
day	Day of Year
nom	Nominal
min	Minimum
max	Maximum

Abbreviations

DSM	Demand-Side Management
DELM	Dynamic Electrical Load Management
DDSM	Dynamic DSM
DR	Demand Response
NAN	Neighborhood Area Network
PAR	Peak to Average Ratio
IoT	Internet of Things
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
PNH	Probability of the Next Hour
NONCE	Number Only Used Once
ID	Identifier

renewable energy sources. There are different approaches for management and coordination of energy resources in smart buildings such as game theory (Khalid & Javaid, 2019), heuristics (Dao et al., 2019), genetic algorithms (Sharifi & Maghouli, 2019), stochastic predictive models (Salehpour et al., 2021; Zhang et al., 2018) and optimization techniques (Hossain et al., 2021; Yahia & Pradhan, 2020). Further details about the development and optimization algorithm of DSM can be found in a recent review by Sharda et al. (2021).

Based on communication and control architectures of the system, there are two different types of networks: centralized and decentralized. In centralized coordination, there is a central operator device that has access to all data and makes decisions for home consumptions. One drawback of centralized coordination is that it is not scalable (Celik et al., 2017; Dao et al., 2019). Moreover, in centralized management systems, owing to the lack of sufficient efficiency in the presence of distributed generation resources, competitive mechanisms in the market, and exposing the information under the centralized operation, many researchers have been fascinated by the development of decentralized systems (Boudoudouh & Maâroufi, 2018; L. Li & Yu, 2020; Nasiri et al., 2020). It seems the most reliable architecture belongs to decentralized management (Harmouch et al., 2018). In decentralized coordination, devices exchange their data without any central operator, which leads to private ownership, and what is more due to their flexibility, plug and play features make them popular in applications (Salehpour et al., 2021). There are three different types of decentralized network: fully independent, partially independent, and fully dependent.

In the fully dependent structure, smart homes communicate with a central entity without sharing any data with other homes. In this architecture, the smart homes decide, while in the centralized model, the decisions are taken by a central entity. Mediwaththe et al. (2016) developed an energy trading system to manage demand-side load in a NAN. The users can trade their surplus energy with the grid and the community energy storage devices. They used a fully dependent decentralized model for exchange between users. Their model can provide peak load leveling for the grid and can benefit users financially.

In that of partially independent, end-users communicate with each other and the central entity. Deng et al. (2014) formulated a partially independent game, which users can interact with, for residential energy consumption scheduling. Their results showed that their proposed approach could shift the peak-hour demand, and it minimizes the peak-to-average ratio (PAR). They also investigated the scalability of their model and the impact of the user number, with a positive assessment. The computation time resulted dependent on the user who converges slowest, instead of the summation of computation time of all users. It was also observed that the scalability grew linearly, not exponentially, with the possibility of accommodating millions of users or even more on high-performance computers.

In that of fully independent, consumers only interact with other homes located in their neighborhood, without the interference of any central entity. Chen et al. (2014) examined a DSM scenario. In their model, users try to minimize their energy costs by shifting their peak-time consumption. They formulated a game for users to compete in, minimizing their cost in a fully independent network. In their model, it is not necessary to exchange users' private information. Harmouch et al. (2018) developed a decentralized system to manage energy for a single microgrid and microgrid cluster. They implemented a decentralized multiagent energy management system to manage a microgrid cluster with a fault tolerance feature. Durillon et al. (2020) proposed a decentralized energy management program in a neighborhood to reduce grid peak, using three different scenarios to compare price, environment, and comfort factors of consumers. Croce et al. (2020) used an Overgrid of new decentralized load control, without any centralized control, which was able to forecast the demand of the aggregated power and make a virtual "community" for smart buildings, and, what is more, ensures minimum inconvenience for the end-users.

Blockchain technology is a protocol used for parties to transfer data without a third party, called a decentralized system (Brilliantova & Thurner, 2018). It can be used to implement energy management (Noor et al., 2018). This technology was used for the first time in developing Bitcoin as a cryptocurrency (Nakamoto, 2008). After a while, by developing this technology, the newer versions, including Blockchain 2.0, which enables smart contracts, and Blockchain 3.0, which brings a higher degree of autonomy, have emerged (Brilliantova & Thurner, 2018). Blockchain is based on a distributed ledger, which is verified by consensus, is not owned by a central authority and all the parties have access to the data (Crosby et al., 2016; Underwood, 2016). In other words, blockchain is a data structure stored and encrypted in blocks located in distributed nodes, using consensus algorithms to define trust (Lu, 2019).

Since blockchain is a distributed ledger of stored data with so many innovative features, it will be widely used to develop the Internet of Things (IoT), especially smart homes (Wang et al., 2019). Blockchain application in smart homes is different from a conventional Bitcoin blockchain (Makhdoom et al., 2019). In other words, Bitcoin blockchain which is the first version of the blockchain, due to lack of smart contracts, cannot be used for smart homes. Dorri et al. (2017; 2016) presented a private and secure blockchain approach in which each smart home is equipped with a miner handling external communication to control, audit and use cloud storage.

Recently there have been studies on using blockchain as distributed energy systems where consumers can exchange their energy directly. Mengelkamp et al., 2018 simulated a local energy market for 100 residential households. They used private blockchain to provide an energy trading platform. Pop et al. (2018) implemented the Ethereum blockchain to collect energy consumption data of IoT smart metering devices. They showed that using blockchain-based distributed DSM at the smart grid level makes the demand response signal being followed highly accurate while reducing the amount of convergence of energy flexibility. Mengelkamp et al. (2018) proposed a peer-to-peer microgrid energy market which consumers and prosumers can trade. They showed that the Brooklyn Microgrid almost satisfies the different market components studied. They also showed that blockchain technology is eligible to operate decentralized microgrid energy markets. Noor et al. (2018) used a game-theoretical approach for a DSM model using blockchain technology. Their proposed model can reduce the electrical grid PAR and smoothen the dips in the load profile, which are caused by supply constraints. They showed that blockchain could facilitate transactions by maintaining trust and transparency. It also improves the implementation of smart decentralized control and payment mechanisms. Li et al. (2019) studied energy DSM, including residential, commercial, and industrial sectors using peer-to-peer real-time energy markets. They implemented smart contracts to make a seamless, secure, and efficient distributed energy system. They showed that using blockchain can result in a significantly flattened schedule of grid electricity procurement. Wen et al. (2021) proposed a blockchain to enhance energy prices for demand-side management using demand response. They suggested a pseud digital identity to enhance users' privacy. In their model, the data is stored in the block of a blockchain, which brings transparency, traceability, and tamper resistance.

As expressed in the literature, using energy DSM methods can reduce the energy consumption of users in a neighborhood. One way is shifting energy consumption, which may lead to creating a peak at another time. Another solution is using a centralized operator for energy management, but this involves a lack of trust, security, and scalability due to the size of data. The alternative method is blockchain, which is a trustable decentralized method for storing and accessing data. Table 1 shows the comparison of previous works for demand-side management. Many centralized and decentralized research projects have been carried out to reduce energy costs of users that lead to decrease the PAR of the load shape. Besides, there are few recent works implementing the blockchain network for energy cost reduction. What is more, there are few papers analyzing the thermal comfort and energy consumption reduction in a neighborhood. There is lack of work on implementing physical modelling of buildings equipped with real-time controllers connected through the blockchain network to directly control the indoor temperatures and appliance time to improve the PAR, energy consumption, and thermal comfort altogether.

The novelty of this work mainly consists of combining physical dynamic modeling of energy demand in residential buildings with blockchain to reduce energy consumption, decreasing the PAR of load shape and improving the thermal comfort altogether without intervention on the building envelope on an urban and even global scale. The heating system of each building is modeled physically to compute the heating energy consumptions and the thermal comforts. The illumination and appliance systems of buildings and occupancy patterns are modeled as well to calculate energy consumption. Then, a neighborhood of buildings is modeled in two scenarios to compare the results of PAR, energy consumption, and thermal comfort. A smart scenario is presented in which buildings are connected by a blockchain network to share the probability of use together.

In summary, the main contributions of the current study compared to the previous literature review are:

- Proposing and implementing a blockchain solution for real-time control of heating and appliance systems of buildings in a neighborhood area
- Presenting a smart scenario that improves the PAR, energy consumption, and thermal comfort of the neighborhood area without considering energy pricing
- Physical modeling of the heating system of buildings to consider the real-time thermal comfort of occupants
- Directly controlling the indoor temperatures and appliance time to improve the energy usage of the neighborhood
- Performing improvement in PAR, energy consumption, and thermal comfort by just controlling the temperature and time of use with the least equipment
- Simulating the illumination system based on sunrise and sunset modeling

This paper is arranged as follows: Section 2 presents the modeling of buildings and the neighborhood by considering heating, illumination, and appliance systems. What is more, the section introduces the blockchain model and control methodology for demand-side management of buildings in a neighborhood area. Section 3 performs and analyzes the results obtained from the current study including validation, load, energy, and comfort comparisons, and scalability. Section 4 states the

Table 1
Comparison of similar work in the scientific literature.

Ref.	Coordination	Contributions	PAR reduction	Energy consumption reduction	Comfort level increase
Mohsenian-Rad et al. (2010)	Partially independent decentralized	• Minimizing energy cost and PAR in total load • Presenting a solution to prevent users from cheating and misleading	14%	-	-
Logenthiran et al. (2012)	Centralized	• Presenting a generalized technique based on load shifting	18.3%	-	-
Li et al. (2012)	Fully dependent decentralized	• Investigating the possibility of rebound peak from the optimal automated DR algorithm • Comparing multiple approaches to reduce the rebound peak	19.4 - 33.9%.	-	-
Niro et al. (2013)	Centralized	• Modeling refrigerators thermodynamically to reduce peak demand, improving losses and voltage profiles	21.4% and 41.5%	-	-
Chen et al. (2014)	Fully independent decentralized	• Implementing an instantaneous load billing scheme • Exchanging estimated information by users in a decentralized network • Developing a novel aggregative game to model users' strategic behaviors	30.31%	-	-
Deng et al. (2014)	Partially independent decentralized	• Considering users' interaction and the temporally coupled constraint • Transforming the coupled-constraint game into a decoupled one by dual decomposition	19%	-	-
Safdarian et al. (2016)	Fully dependent decentralized	• Solving the load reschedule problem non-sequentially by customers • Having separate objectives for different players	16.8%	-	-
Mediwaththe et. al (2016)	Decentralized	• Developing a noncooperative dynamic repeated game • Investigating a day-ahead decentralized energy management framework	13.5%	10.5%	-
Javaid et al. (2017)	Decentralized	• Proposing a Genetic BPSO algorithm to solve load management • Testing with the simulative consideration of an HEM system in Real-Time Pricing	34%	-	-
Mengelkamp et al., 2018	Blockchain	• Evaluating the blockchain network as an information system for microgrid energy markets • Presenting of the Brooklyn Microgrid • Implementing a private blockchain to sustain and operate a microgrid energy market	-	-	-
Lokeshgupta & Sivasubramani (2019)	Centralized	• Implementing multi-objective home energy management with battery energy storage system • Including practical constraints of the controllable appliances and battery storage system • Comparing 6 scenarios with different possible operating conditions	9%	-	-
Li et al. (2019)	Blockchain	• Implementing blockchain on the microgrid energy market considering renewable generation • Implementing proof of stake blockchain algorithm • Proposing a non-cooperative game to interact among various users	-	-	-
Durillon et al. (2020)	Decentralized	• Implementing multi-objective residential energy management • Considering consumer profiles considering 3 different sensitivities • Effect of consumer sensitivities' integration level in grid management	23% and 31%	-	5.4% and 12.7%
Wen et al. (2021)	Blockchain	• Adopting a noncooperative game to model buildings' energy consumptions • Maintaining and managing without the trust of a third-party • Designing a blockchain-based energy optimization schedule law	-	-	-

conclusion.

2. Modeling

In the current study, a neighborhood of buildings is modeled to analyze the energy consumption of heating, illumination, and appliance systems. To model each building, a MATLAB code is developed to model the transient energy consumption of each system by considering thermal comfort measures and occupancy patterns. Each system can be regarded as a distinct one, controlled separately. Then, a blockchain smart contract is developed by Solidity to control the energy consumption of the integrated buildings of a neighborhood.

The heating system is simulated physically and generally, by modeling different components such as boilers, circulating water pipes, and radiators. The heating model is validated by the real data of a building. Next, to model the illumination system, the daylight hours are calculated, by modeling the sunrise and sunset hours of each day, by considering the occupancy patterns and daylight hours the energy consumption versus time. Then, in the appliance system, three shiftable "wet appliances", including a washing machine, a tumble dryer, and a dishwasher are studied by modeling based on probability function and schedules.

Finally, two different scenarios are designed, namely basic and smart, for control methodology to compare the result of energy consumption, load shape, and thermal comfort for the neighborhood. In that of basic, there is no interaction between controllers inside the home, and each controller works in islanded mode. On the other hand, in the smart scenario, each controller integrates with others to predict the probability of energy consumption in the neighborhood through the blockchain network, which is developed using Ethereum smart contracts.

2.1. Heating system

To simulate a heating plant, a transient general physical model containing boilers, circulating water pipes, and radiators, is developed by MATLAB. In the model, the boiler heats circulating water and pumps it to the radiators via pipes schematized in Fig. 1. As the figure shows, the model calculates temperatures and energy consumption during the time and shares the data with the controller for internal controlling and external data sharing. The following outlines the physical modeling of each heating component which can be used for different integration.

By considering the boiler as a control volume with a specific mass and heat capacity containing a furnace for heating up, its energy equation is obtained as (Borelli et al., 2018):

$$(mC)_b\frac{d\overline{T}_b}{dt} = \dot{E}_{he} + \dot{m}_f C_f\left(T_{b,i} - T_{b,o}\right) \tag{1}$$

where m, C, t, and T are mass, specific heat capacity, time, and temperature, respectively. The subscripts b, f, i, and o are boiler, fluid, inlet, and outlet, respectively. It is worth noting that $\overline{T}_b$ indicates the bulk temperature of the boiler. $\dot{E}_{he}$ is the energy consumption rate of the heating system of a household.

The pipe contains the circulating hot water and has thermal loss during transferring to the radiators or returning to the boiler. Therefore, its energy equation is (Borelli et al., 2018; Kolahan et al., 2020; Maadi et al., 2017):

$$(mC)_p\frac{d\overline{T}_p}{dt} = \dot{m}_f C_f\left(T_{p,i} - T_{p,o}\right) + U_p A_p\left(T_a - \overline{T}_p\right) \tag{2}$$

where U and A are the equivalent heat transfer coefficient and contact area, respectively. Subscripts p and a are pipe and the ambient, respectively. It should be mentioned that T_{amb} is the ambient setting which is in contact with the corresponding pipe. Occasionally, it can be considered as the indoor and outdoor temperatures corresponding to the surrounding ambient of the pipe. Also, U_p and A_p, which are in Eq. (2), are pipe equivalent heat transfer coefficient and inside area of the pipe, respectively, derived as (Bergman et al., 2011):

$$U_p = \frac{1}{\frac{1}{h_{p,in}} + \frac{r_{p,in}\ln\left(r_{p,out}/r_{p,in}\right)}{k_p} + \frac{r_{p,in}}{h_{p,out}r_{p,out}}} \tag{3}$$

$$A_p = 2\pi r_{p,in}L_p \tag{4}$$

where r, h, k, and L are the radius, convective heat transfer coefficient, thermal conductivity, and length of the pipe, respectively. Moreover, subscripts *in* and *out* are interior and exterior surfaces of the pipe, respectively.

The interior forced heat transfer coefficient, $h_{p,in}$, of the pipe can be derived from(Maadi, Sabzali, Kolahan, & Wood, 2020):

$$h_{p,in} = \frac{Nu_{p,in}k_f}{D_{p,in}} \tag{5}$$

where $Nu_{p,in}$ is the Nusselt Number, which can be calculated in the circular pipe using (Maadi et al., 2017; Qiu et al., 2015):

$$Nu_{p,in} = 4.36 + \frac{0.086\left(\frac{Re_f Pr_f D_{p,in}}{L_p}\right)^{1.33}}{1 + Pr_f\left(\frac{Re_f D_{p,in}}{L_p}\right)^{0.83}} \tag{6}$$

and Re_f and Pr_f are Reynolds number and Prandtl number of the fluid:

$$Re_f = \frac{4\dot{m}_f}{\pi\mu_f D_{p,in}} \tag{7}$$

$$Pr_f = \frac{\mu_f C_f}{k_f} \tag{8}$$

Also, the exterior free heat transfer coefficient, $h_{p,out}$, of the pipe can be calculated(Maadi et al., 2021):

$$h_{p,out} = \frac{Nu_{p,out}k_a}{D_{p,out}} \tag{9}$$

where k_a is the thermal conductivity of the air and $Nu_{p,out}$ can be found in the circular pipe using (Cengel, 2002):

$$Nu_{p,out} = \left\{0.6 + \frac{0.387Ra_a^{1/6}}{\left[1 + \left(\frac{0.559}{Pr_a}\right)^{9/16}\right]^{8/27}}\right\}^2 \tag{10}$$

and Ra_a and Pr_a are Rayleigh and Prandtl numbers, are given as following (Cengel, 2002):

$$Ra_a = \frac{g\beta\left(T_p - T_{amb}\right)D_{p,out}^3}{\nu_a^2}Pr_a \tag{11}$$

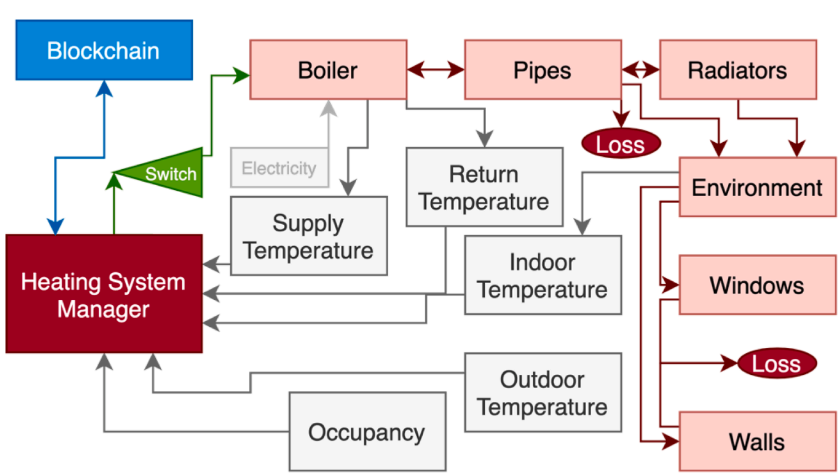


Fig. 1. Heating system flowchart.

$$Pr_a = \frac{\mu_a C_a}{k_a} \tag{12}$$

The energy balance for the radiator is (Borelli et al., 2018):

$$(mC)_r \frac{d\overline{T}_r}{dt} = \dot{m}_f C_f \left(T_{r,i} - T_{r,o}\right) + U_r A_r \left(T_{indoor} - \overline{T}_r\right) \tag{13}$$

where subscripts *r* and *indoor* refer to the radiator and the indoor environment, respectively.

For the natural convection of the radiator, there are two empirical equations based on the Rayleigh number (Churchill & Chu, 1975; Scheibe, 2017):

$$U_r = \frac{Nu_r k_r}{y_r} \tag{14}$$

$$Nu_r = \begin{cases} \left\{ 0.68 + \dfrac{0.67 Ra_r^{0.25}}{\left[1 + \left(\dfrac{0.492}{Pr_r}\right)^{9/16}\right]^{4/9}} \right\}, & Ra_r < 10^9 \\ \left\{ 0.825 + \dfrac{0.387 Ra_r^{1/6}}{\left[1 + \left(\frac{0.492}{Pr_r}\right)^{9/16}\right]^{8/27}} \right\}^{1/2}, & Ra_r > 10^9 \end{cases} \tag{15}$$

where Ra_r and Pr_r can be calculated as follows:

$$Ra_r = \frac{g\beta(T_r - T_a) y_r^3}{\nu_a^2} Pr_a \tag{16}$$

$$Pr_r = \frac{\nu_a}{\alpha_a} \tag{17}$$

In the previous equations, ν_a, α_a, y_r, and k_r are kinematic viscosity, thermal diffusivity, height, and thermal conductivity, respectively, which are given as (McQuillan et al., n.d.):

$$\nu_a = \left(\frac{2.4090 \times 10^8}{T_a^{3/2}} + \frac{2.6737 \times 10^{10}}{T_a^{5/2}}\right)^{-1} \tag{18}$$

$$\alpha_a = \left(-4.3274 + 4.1190 \times 10^{-2} T_a + 1.5556 \times 10^{-4} T_a^2\right) \times 10^{-6} \tag{19}$$

$$k_r = \frac{2.3340 \times 10^{-3} T_a^{3/2}}{164.54 + T_a} \tag{20}$$

The thermal expansion coefficient, β, is given as (Holman, 2010):

$$\beta = \frac{1}{\frac{T_r + T_a}{2}} \tag{21}$$

The indoor environment of the home loses heat to the outdoors through the walls and the windows and is heated up by radiators and pipes, so the energy equation is:

$$(mC)_{indoor} \frac{dT_{indoor}}{dt} = \sum U_r A_r \left(\overline{T}_r - T_{indoor}\right) + \sum U_p A_p \left(\overline{T}_p - T_{indoor}\right) + \left[U_{wall} A_{wall} + U_{win} A_{win}\right]\left(T_{outdoor} - T_{indoor}\right) + \dot{Q}_S \tag{22}$$

where subscripts *wall, win*, and *outdoor* are the wall, window, and outdoors of the home, respectively. U_{wall} and U_{win} are wall and window thermal transmittance, respectively. And $\dot{Q}_S$ is other heat sources including occupants and radiation. It should be mentioned that the thermal capacity of internal and external walls and equipment are considered in the current model.

2.2. Illumination system

The illumination system contains lamps and adjustable switches. Fig. 2 illustrates the flowchart of the illumination system which shows that occupancy and daylight hours affect energy consumption.

The energy consumption of the illumination system per hour can be calculated as (Yao & Steemers, 2005):

$$\dot{E}_{il} = \left(\frac{E_v}{K_i}\right) \times A \times \left(\frac{n_{oc}}{n_{ro}}\right) \tag{23}$$

where $\dot{E}_{il}$ is the energy-consumption rate of illumination in *W*, E_v is the average luminance level for residential buildings which is considered 150 *lux* (Yao & Steemers, 2005), K_i is the luminance efficacy in workplan which is regarded as 92.2 *lum/W* for LED bulbs (Jin et al., 2009), *A* is the floor area of the building in m^2, n_{oc} is the number of occupants at home, and n_{ro} is the number of building rooms.

The day length, which is the time between sunrise and sunset in hours, is given approximately by (Almorox et al., 2005):

$$h_{dl} = w_{sr}/7.5 \tag{24}$$

where w_{sr} is the geometric mean sunrise hour angle on a horizontal surface (degrees) which is given as (Almorox et al., 2005):

$$w_{sr} = \cos^{-1}[(sin5 - \sin\lambda \sin\delta) / (\cos\lambda \cos\delta)] \tag{25}$$

where λ is the latitude of the location, which is considered Genoa-Italy (44.4056°). For evaluation of δ, the solar declination (radians), the Spencer formula is taken into account (Spencer, 1971):

$$\delta = 0.006918 - 0.399912\cos\Gamma + 0.070257 s\sin\Gamma - 0.006758\cos2\Gamma + 0.000907\sin2\Gamma - 0.002697\cos3\Gamma + 0.00148\sin3\Gamma \tag{26}$$

Moreover, Γ is the day angle (radians) which is computed as (Almorox et al., 2005):

$$\Gamma = 2\pi\left(n_{\mathrm{day}} - 1\right)/365 \tag{27}$$

where n_{day} is the day number of the year, starting from the beginning of the year.

The sunrise time (h_{sr}) and sunset time (h_{ss}) for a horizontal surface at sea level are given as (Kambezidis, 1997):

$$h_{sr} = 12 - w_{sr}/15 \tag{28}$$

$$h_{ss} = 12 + w_{sr}/15 \tag{29}$$

2.3. Appliance system

The following outlines the simulation of the appliance system. As Fig. 3 shows, in the current work, three shiftable "wet appliances", including a washing machine, a tumble dryer, and a dishwasher are studied. Schedules for using appliances are defined based on a literature review (Mansouri et al., 1996). Based on the cycles of each appliance,

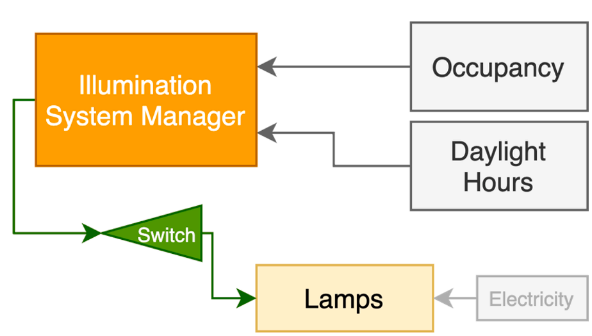


Fig. 2. Illumination system flowchart.

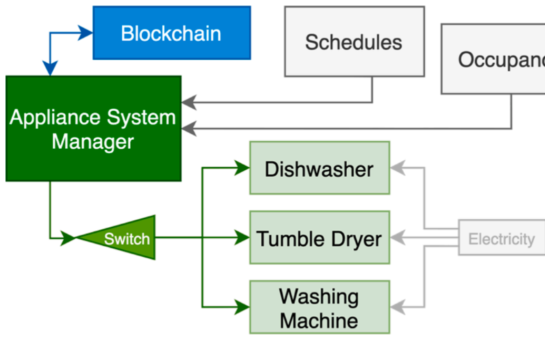


Fig. 3. Appliance system flowchart.

occupancy, awakening time, and scenario, a probability function can be generated to model the appliance system.

As Table 2 shows, according to a survey, the highest average number of washing machine and tumble dryer cycles per week were 8 and 3.4 cycles per household, respectively (Mansouri et al., 1996). However, the tumble dryer is mostly used in autumn and winter. In this survey, the highest average use of a dishwasher was 0.95 cycles per day (Mansouri et al., 1996). The powers of appliances are also shown in this table (Noor et al., 2018).

It should be mentioned that there are high-consumption appliances that are excluded from this study such as a refrigerator, a stove, a kettle, and a microwave oven due to the uncontrollability.

2.4. Occupancy patterns

The occupancy scenarios impact highly the energy consumption of homes, especially in the time of using the heating system. Two parameters should be considered to predict occupancy profile, including the occupant number and occupants' lifestyle (Ren et al., 2013). In other words, the number of occupants and the period of the house is unoccupied during the day are factors influencing the occupancy pattern (Yao & Steemers, 2005).

According to the background history, occupancy patterns are categorized by the occupants' job type. Based on different surveys in Australia (Jazaeri et al., 2019; Ren et al., 2013), there are six different occupancy scenarios of residential buildings, including occupants having a full-time job, being retired, spending the afternoon outside, having a part-time morning job, a part-time afternoon job, and being schoolchildren. Similarly, different scenarios were considered in the UK by job types, including part-time working mornings 1/2, full-time working, part-time working 2/3, not working, and part-time working afternoons 1/2 (Yao & Steemers, 2005). In parallel, three occupancy classes are characterized, namely high occupancy, medium occupancy, and low occupancy based on a percentage of daily hours of one person, and then the percentage of people at home in a family is calculated (Carpino et al., 2018).

In this research, similar to Ref (Yao & Steemers, 2005), five different scenarios based on types of occupants' jobs are considered, which are shown in Table 3. Occupied time affects the operating time of the heating, illumination, and appliance systems, directly.

Table 2
Daily household appliances - level data (Mansouri et al., 1996; Noor et al., 2018).

Appliance	$\dot{E}_{min}$ (W)	$\dot{E}_{nom}$ (W)	$\dot{E}_{max}$ (W)	Cycles
Washing Machine	600	2,500	3,900	8/week
Tumbler Dryer	200	2,200	3,000	3.4/week
Dishwasher	100	1,500	3,100	0.95/day

Table 3
Occupancy pattern for a three-person household (Yao & Steemers, 2005).

Scenarios	Type	Unoccupied period
1	Part-time working morning session 1/2	9:00–13:00
2	Full-time working	9:00–18:00
3	Part-time working 2/3	9:00–16:00
4	Not working	N/A
5	Part-time working afternoon session 1/2	13:00–18:00

2.5. Thermal comfort

Thermal comfort is one of the main indicators for comparing different scenarios in a building. In this work, two classical indicators, namely the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD), are considered as comfort indexes. The PMV index, which was suggested by Fanger (Djongyang et al., 2010; Iso, 2005), is used for the prediction of the mean response of a large group of people based on the ASHRAE thermal sensation scale, which is between -3 and $+3$, namely cold, cool, slightly cool, neutral, slightly warm, warm, and hot. The PPD is the prediction of the percentage of people feeling more than slightly warm or slightly cold, who are dissatisfied thermally (Djongyang et al., 2010).

Based on ASHRAE Standard 55 (Djongyang et al., 2010), for a climate condition with a relative humidity of 50%, a mean relative wind velocity lower than 0.15 *m/s*, a mean radiant temperature equal to air temperature, a metabolic rate of 1.2 *met*, and clothing insulation of 0.9 *clo* in winter, the acceptable indoor temperature range is considered between 23 °C and 26 °C.

2.6. Control methodologies and system integration

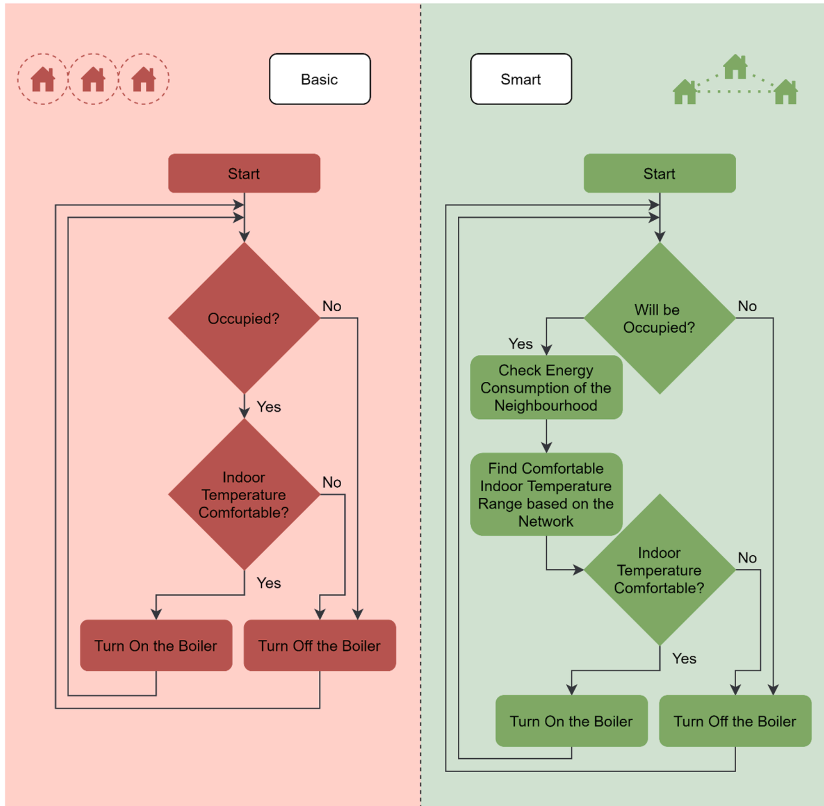
The following outlines the simulation of the neighborhood and control methodology of the buildings by presenting basic and smart scenarios, and how blockchain works in the current study. The basic scenario is an islanded scenario in which each home operates separately, but the smart scenario is a neighborhood that is connected through a blockchain network to manage its consumptions.

2.6.1. Basic scenario

In that of basic, there is no interaction between controllers inside the home, and each controller works in islanded mode. As Fig. 4 shows, in the heating system, the boiler is switched on by the indoor temperature of the home to keep the temperature at the comfort level. In addition, the occupancy pattern is considered in the boiler timing. In the basic scenario, the occupancy pattern is not predictable; this means that the heating system works when occupants return home. This may cause some discomfort problems when they arrive home. For the appliance system, a probability distribution function is considered for operating during the day. Awakening time and occupancy pattern effect the distribution function in the basic scenario. The operating hours of the illumination system are a function of awakening time and daylight hours, which are simulated in this model. In this scenario, the following assumptions are considered:

- The model is transient.
- For modeling each element, a control volume system is considered (Bergman et al., 2011).
- In a heating system, the system of equations is solved implicitly.
- In a heating system, thermal comfort is considered based on the indoor temperatures of the home using the occupancy pattern (Djongyang et al., 2010).
- The initial value of indoor temperature is a random number between 296 and 299 K.
- The boiler power is different for each household.

a) heating system



b) appliance system

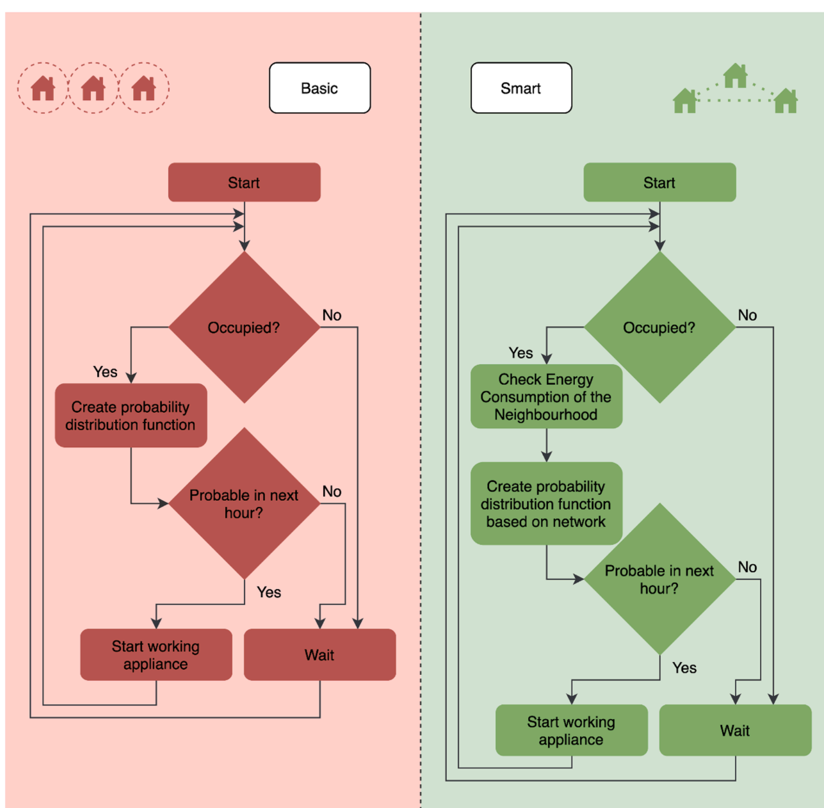


Fig. 4. Control methodologies.

- The surface, volume, and thickness of the walls are considered randomly.
- The illumination system is working based on sleep time and occupancy.
- A probability-based use schedule is considered for appliances.
- The results are during weekdays.
- The controller cannot predict the occupancy pattern.
- Each controller works separately without any access to the other households' data.
- Different occupant scenarios are considered randomly based on Ref (Yao & Steemers, 2005).

In a basic scenario, the power of each appliance ($P_{a,t}$) can be calculated with the following equation:

$$P_{a,t} = P \times OA_t \times WR_t(EOH, OH) \tag{30}$$

where P is the mean power of each appliance, OA_t is a Boolean value for each occupancy pattern that shows the home is occupied and the occupants are awake, and WR_t is weighted random, a number between 0 and 1, which is a function of daily expected operating hours (*EOH*) and daily occupied hours (*OH*).

2.6.2. Smart scenario

In the smart scenario, a smart controller is considered in this paper. Each household integrates with others to predict the probability of energy consumption in the neighborhood. Unlike the basic controller, the smart type can predict occupancy patterns. It can access data that show the Probability of the Next Hour (PNH). The PNH is a float number between zero and one which is used separately for each system of a home such as heating, appliances, and illumination. It shows the probability of energy use in the next hour, which is predicted by each controller. For the heating system, the PNH is a function of current indoor temperature, occupancy, comfort temperature limits, and the average PNH from the neighborhood. For appliances, PNH is a function of occupancy, the average PNH, and usage cycle. For illumination, it is a function of occupancy and the average PNH. Each controller calculates PNH for each hour and sends it to the network to share with other controllers in the same neighborhood. The goals of the smart scenario are to decrease energy consumption and to improve load shape and thermal comfort in the neighborhood. In the heating system, in addition to that of basic, the PNH can affect the boiler switch. In this model, a probability function can help the system to store heat inside the home by increasing the temperature of the home to reach the highest comfort-level temperature when PNH is low and vice versa. In addition, since the smart controller can predict the occupancy pattern, the heating system can preheat the indoor environment before the occupants arrive. In the appliance system, the PNH parameter is hence helpful to decrease or increase the probability of appliance used to shift time of use to off-peak times. In both scenarios, the probability of using an appliance is a function of occupancy and awakening of occupants, but in the smart scenario, with the help of PNH, the distribution of probability function changes to inform users which time is the best choice to use an appliance. The illumination system works like the basic scenario.

It should be mentioned that, because all the controllers in the smart scenario are connected and affect each other by exchanging data, it should be considered a probability for energy demand to manage the time of energy consumption. A certain model for any alteration in the consumption time pattern may reason for another peak in load shape, which may be worse than the predicted peak in the load. In other words, in this situation, all the controllers take the same decision in the system, which multiplies the load peaks. Therefore, a probability function is considered for controllers' decisions to avoid new peaks.

In the proposed model, all the smart controllers in all the homes have access to all the data in their neighborhoods. This data availability helps smart controllers to find the best solution to decrease the PAR of load shape. The assumptions, which are considered in this section, are similar to that of basic; nevertheless, there are some differences between these two scenarios:

- A probability-based use schedule is considered for appliances based on the average hourly PNH.
- The temperature setpoints can vary based on the average hourly PNH.
- The controller can predict the occupancy pattern for preheating, based on the leaving from and returning to home times.
- Each controller has access to the average PNH of other neighborhood homes, hourly.

In the smart scenario, the power of each appliance ($P_{a,t}$) can be calculated with the following equation:

$$P_{a,t} = P \times OA_t \times WR_t(EOH, OH, \ PNH) \tag{31}$$

where P is the mean power of each appliance, OA_t is a Boolean value for each occupancy pattern that shows the home is occupied and the occupants are awake, and WR_t is weighted random, a number between 0 and 1, which is a function of daily expected operating hours (*EOH*), daily occupied hours (*OH*), and probability of next hour of the network (*PNH*).

The weight of random function versus time is given as:

$$W_t = \frac{EOH}{OH} \times \ (1 - PNH) \tag{32}$$

Therefore, the WR_t can be generated based on the weight function (W_t).

For the heating system, the smart controller changes the indoor set-point temperature based on the predicted occupancy and mean PNH of the neighborhood. Thus, the set-point temperature (T_s) is given as:

$$T_s = \begin{cases} T_{min} & \textit{before leaving} \\ T_{min} + (T_{max} - T_{min}) \times (1 - PNH) & \textit{ocuppancy} \\ T_{min} + (T_{max} - T_{min}) \times (1 + C - PNH) & \textit{before boiler switching off} \end{cases} \tag{33}$$

where T_{min} and T_{max} are the minimum and maximum indoor temperatures for switching the boiler on or off to keep thermal comfort. C is the correction number for heat storage inside the building before switching off the boiler at night to increase thermal comfort during night hours.

2.6.3. Blockchain network

The smart scenario in the current study employs blockchain as the network between controllers to manage the energy consumption of the neighborhood. In the current section, first, the blockchain concepts and structures are explained, which is a distributed ledger technology. Then, it is discussed when and what type of blockchain is needed for the current study. Next, the implementation of smart contracts for the current study is described.

Blockchain, known as distributed ledger technology, has the potential to revolutionize industry due to its immutability, transparency, and redefined trust on a global scale (Underwood, 2016). It is based on a distributed ledger, which is verified by consensus, is not owned by a central authority and all the parties have access to the data (Crosby et al., 2016; Underwood, 2016). In other words, blockchain is a data structure stored and encrypted in blocks located in distributed nodes, using consensus algorithms to define trust (Lu, 2019). There are three core parts in blockchain technology, including block, chain, and network (Wang et al., 2019):

- Block: this is the list of transactions that cannot be modified. When someone records something into it, other nodes can enquire.
- Chain: this is a linking function between blocks.

- Network: this is a set of nodes that are individual computers interconnecting with each other.

Fig. 5 illustrates the structure of a blockchain. As the figure shows, each block is divided into two sections: the header and the body. The header contains a hash of a previous block in the chain, a timestamp which is the number of seconds that have passed since a particular date, NONCE which is an abbreviation for "number only used once", where it is a number added to a hashed block, and the Merkle root which is a hash for verifying the block data (Makhdoom et al., 2019; Wang et al., 2019). Moreover, as Fig. 5 shows, the body contains the transaction information details (Wang et al., 2019). By adding a transaction to the network, it is broadcast to all the nodes. They verify it by validating the transaction signature, add it into a block, and broadcast it to the network. Other nodes verify whether a block is valid or not. They discard invalid blocks to have trustable data in the network (Wang et al., 2019).

Before implementing the blockchain for the model, the following question should be answered: "Is it reasonable to use blockchain for the network?" Fig. 6 shows a list of questions to be answered before using blockchain in the system (Pedersen et al., 2019). In this study, it is assumed that there are different smart controllers inside the homes that need to send and receive data from the database. Hence, it is necessary to have a shared database for the network. This means that different parties are involved in the network and that they can have impacts on it with their data. Besides, there are different energy providers in each region, which are the nodes of the blockchain. None of them can be a trusted node to have all the data. There should be a shared database between them to solve the trust problem in the neighborhood network. In the expressed model, the transactions are the energy consumption of the home for each hour. Therefore, it is possible to find a constant transaction type to log data in the blockchain. It should be remembered that each smart controller requires the data logs of other neighborhood homes. Thus, based on the figure, using blockchain can be useful to solve this problem.

The next question is: "What type of blockchain is needed?" To answer this question, it needs to be mentioned that the data should be stored publicly to be accessible to other devices in the neighborhood. However, only the parties who have permission can write data. In other words, reading the data is public, but writing data to the blockchain is permitted only to valid homes. This means that a permissioned public blockchain may be the best solution for this case.

In this study, to model the blockchain system and develop smart contracts on the blockchain network, Ethereum Solidity is used (Dannen, 2017; *The Solidity Contract-Oriented Programming Language*, n.d.; Wood, 2014), which is a commercial framework for developing blockchain-based smart contract codes.

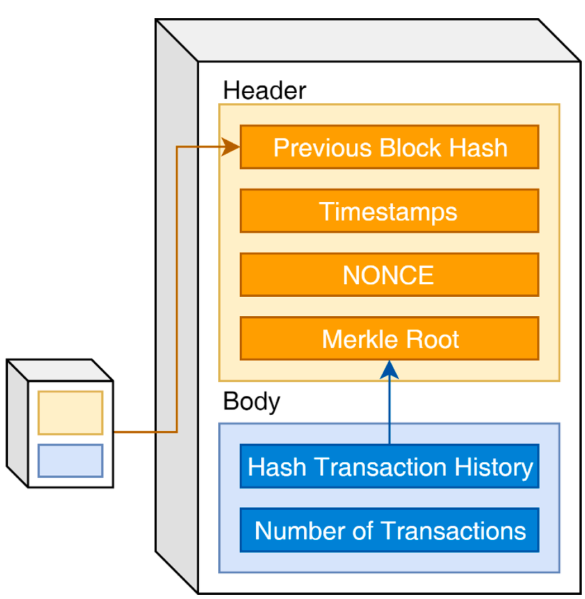


Fig. 5. Structure of a blockchain (Wang et al., 2019).

In this model, each home is connected to the blockchain network. As Fig. 7 shows, they send one transaction per hour to the network, containing information including the Identifier (ID) of the home, the PNH, and the timestamp. The smart contract checks the validity of the ID and the timestamp of each transaction. After verification, the PNH of the connected home will change the mean PNH which is stored in the smart contract.

The smart controllers receive the mean PNH of their neighborhood from the network. They can manage their consumption based on it. When the PNH has a high value, it means that in the next hour, the consumption will be high, so the controller should decrease consumption in that hour.

The system can categorize the times into three groups of low, mid, and high consumption compared to historical usage of the region. Thus, they can manage energy use to improve load shape by changing the probability weighting function of the appliance system and by changing the operating temperature of the heating system.

In particular, the smart contract rules of the model are as follows:

- Each home that is included in the neighborhood has permission to send data.
- Each home can send data only once per hour.
- The timestamp shows the hours that have passed since January 1st, 1970 (UTC).
- The timestamp of each transaction should be the same as the current timestamp.
- The ID of each home will not be stored in the smart contract for security reasons; its hash will be stored to check the validity of the transactions.
- There is no need to store all the PNHs to reduce the size of data stored in the blockchain. In other words, the average value of PNH will be stored instead of all the data.
- Each home that is included in the neighborhood has access to the mean PNH.

The main advantage of blockchain technology is that all the users have access to the data of their neighborhood with no third-party intervening. Therefore, due to the availability of information over time, it can be used by smart controllers inside homes to manage the energy consumption of those homes.

In the proposed model, the only data that are public in the blockchain are the average PNH of the neighborhood and the number of homes that logged the data for the current hour. In each log, users send the PNH of their next hour, and the smart contract merely updates the average based on the number of homes that logged their PNH. In addition, the hash IDs of homes that logged in the last hour and the hash IDs of homes that have permission to log are stored privately in the smart contract and that is not accessible in public.

3. Results and discussion

In the current study, a model is presented and implemented to simulate the energy consumption of a neighborhood. The heating system of each building is modeled physically to compute the heating energy consumptions and the thermal comforts. The heating system is validated with the real data of a building in northern Italy. The illumination and appliance systems of buildings and occupancy patterns are also modeled to calculate energy consumption. Then, a neighborhood of buildings is modeled in two scenarios to compare the results. In the basic scenario, the buildings controlled are islanded. In the smart scenario, buildings are connected by a blockchain network to share the probability of use altogether. Next, the results of both scenarios are compared and

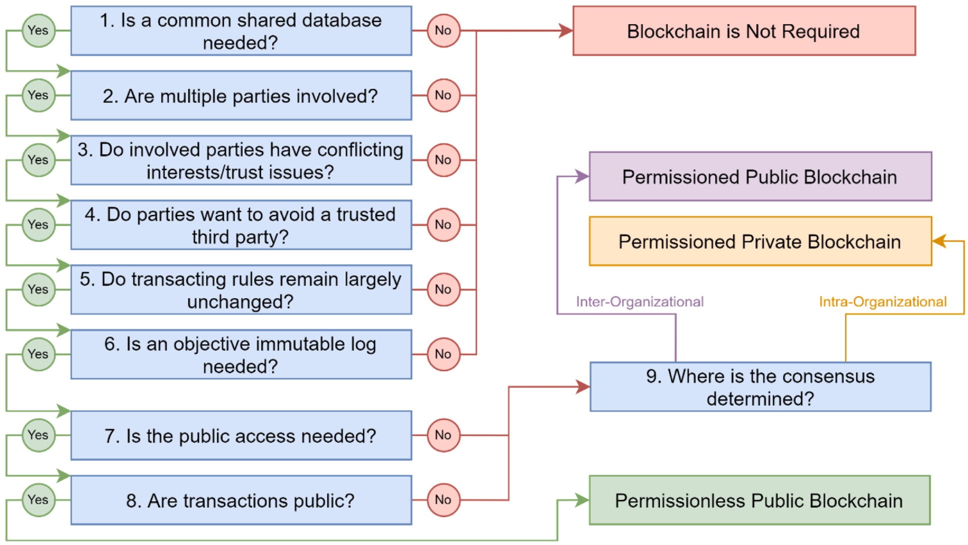


Fig. 6. When to use blockchains and which type of blockchain is needed (Pedersen et al., 2019).

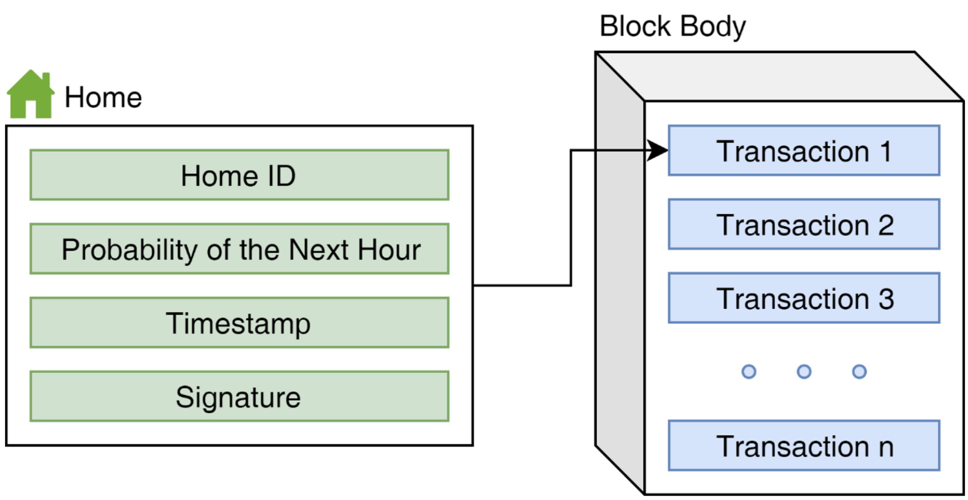


Fig. 7. The scheme of the blockchain network.

discussed based on the load shape, energy consumption, and thermal comfort.

3.1. Validation

In this section, the simulated heating system is implemented for a specific case study building to compare the results of the numerical model with the real data of the building. The case study is a 5-story building with 20 apartments, located in northern Italy (Fig. 8). The building has two sides, identical in structure, each with its stairwell. Radiators are made of aluminum and equipped with a thermostatic valve to regulate the flow of boiler circulating water.

The indoor and outdoor temperatures and fluid supply and return temperatures were logged on two days, April 1st and 2nd. The circulating water temperatures were measured by K-type and RTD sensors. The indoor and outdoor temperatures were measured by digital thermometers with a 0.5-degree range of error. The boiler was controlled by supply temperature, which was turned off when the supply temperature reached 55 °C, turned on when it reached 30 °C. Also, the boiler turned off during the night from 22:30 to 5:30. The required input values of the model are shown in Table 4.

Fig. 9 illustrates the model of a heating plant of the whole building

Fig. 8. The simulated building in Northern Italy (Borelli et al., 2018).

Table 4
The case study building properties (Borelli et al., 2018, 2014).

Building	
Mass flow rate	$1.3\ \frac{kg}{s}$
Surface	$2217.6\ m^2$
Net Volume	$6725.3\ m^3$
Emissivity	0.3
Thermal Inertia	$2.5\ \times 10^8 \frac{J}{K}$
Liminal external resistance	$0.04 \frac{m^2K}{W}$
Free gain	$9000W$
Fluid	
Mass flow rate	$1.3\ \frac{kg}{s}$
Density of fluid	$980\ \frac{kg}{m^3}$
Specific heat capacity of fluid	$4186\ \frac{J}{kgK}$
Pipes	
Pipe length	$125\ m$
Pipe wall conductivity	$390\ \frac{W}{m.K}$
The density of pipe wall	$8920\ \frac{kg}{m^3}$
Specific heat capacity of the pipe wall	$385\ \frac{J}{kgK}$
Inner pipe diameter	$0.025\ m$
Outer pipe diameter	$0.03\ m$
External convective heat transfer	$10\ \frac{W}{m^2K}$
Radiators	
Specific heat capacity of radiator wall	$880\ \frac{J}{kgK}$
Radiator mass	$35\ kg$
Number of radiators (per apartment)	6

and the circulating loop inside the modeled apartment, schematically. In this model, there is a boiler inside the building plant, and there is a water loop pumped to all 20 apartments. Each apartment has circulating water pipes, and six radiators, which heat the indoor environment. It is assumed that 1/20 of the total mass flow rate, circulates to each apartment (Borelli et al., 2014). It is also considered that all apartments have the same structural characteristics and physical properties (Borelli et al., 2014).

The heating system is validated by comparing the supply and return temperature of an existing building (Borelli et al., 2018, 2014). Fig. 10 shows the supply and return temperatures numerically and experimentally. When the boiler is operating, from 5:30 to 22:30, there are small discrepancies in the supply and return temperatures of the numerical model with real data obtained by the sensors. In other words, during the operating time, the obtained error of the numerical model is less than 1%. However, there is an unexpected increment of the temperature at the 24th hour of experimental logged data; it causes a considerable error at the 29th hour of the model. Based on the results, good agreement is observed between the current numerical simulation, shown in Fig. 10, and experimental logged data of the building.

3.2. Neighborhood size

In this section, different neighborhood sizes are modeled and examined based on the assumptions of Section 2.6.1 for the basic scenario to find the best size that gives reasonable results with the lowest computational effort. Neighborhoods with 10, 20, 50, 100, 200, 500, 1,000, 2,000, 5,000, and 10,000 households are compared in Fig. 11. As the figure shows, the results are compared based on the PAR of the power load shape, the execution time of the code, and the mean power of each household. In this work, the neighborhood with a size of 2,000 households, which has a 1.3% PAR difference compared to that of 10,000 and 5.3 times faster than it, is considered.

3.3. Load shape

In this section, the load shapes of the neighborhood in basic and smart scenarios are compared. The neighborhood is simulated based on the assumptions in Section 2.6 for a neighborhood with a size of 2,000

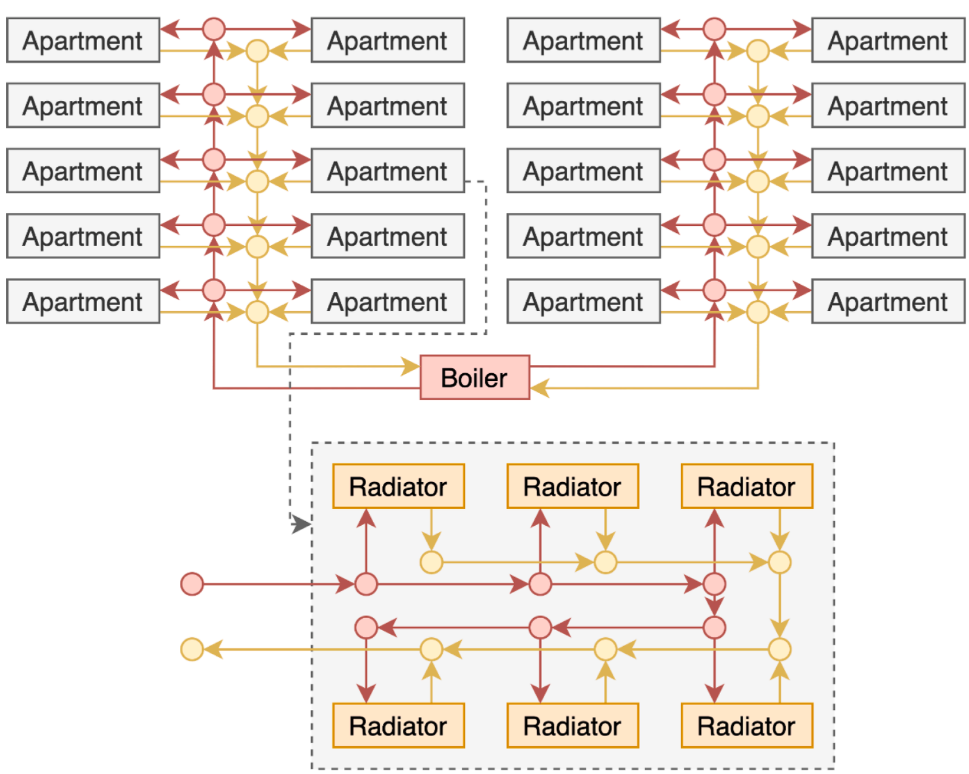


Fig. 9. Scheme of the heating system of the apartment.

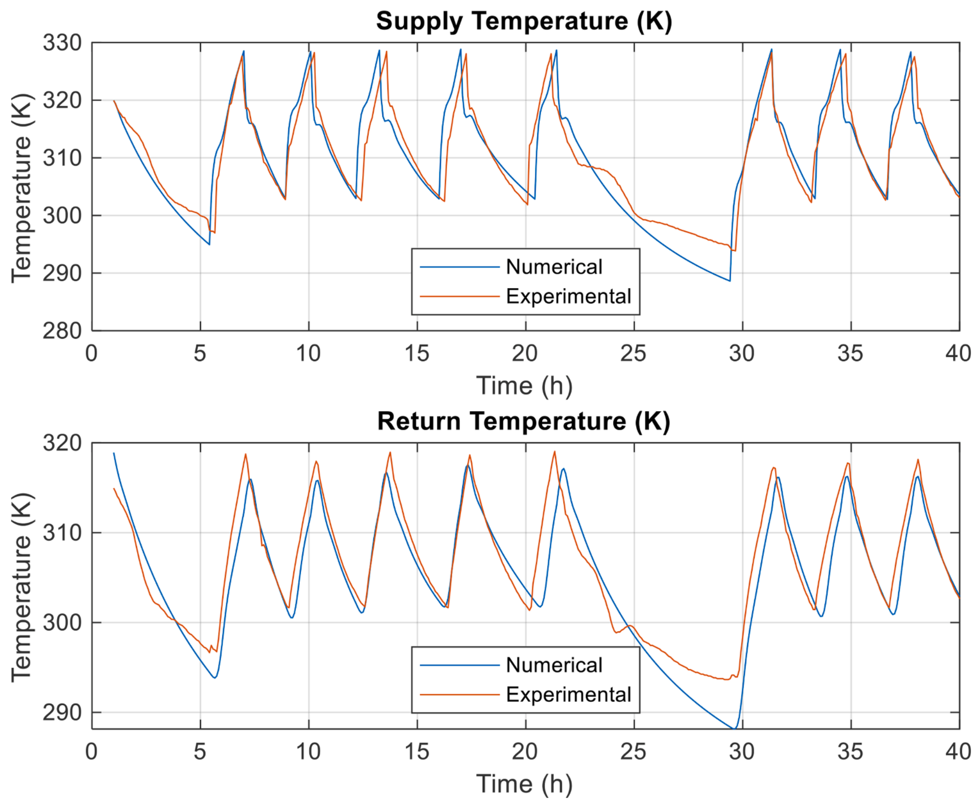


Fig. 10. Experimental (Borelli et al., 2014) and the current numerical supply and return temperatures.

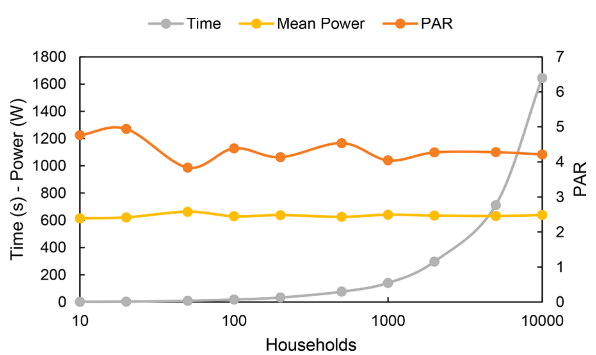


Fig. 11. Neighborhood size study.

homes. The same initial conditions and boundary layers are considered to compare the basic and smart scenarios. However, each building has different conditions and occupancy patterns. In the current simulation of the neighborhood, the climatic data were acquired on 10 days between November 1st and March 1st in Genova, Italy, during the cold season, and the results are an average of 10 days. Fig. 12, illustrates the average power load shape of the neighborhood for the basic scenario of 2,000 homes. As the figure shows, there are three main peaks, at 13:00, 16:00, and 18:00, which are the time of arriving home for different occupancy scenarios. The worst one is at 18:00, which creates a PAR of 4.3 during the day studied.

In general, it is shown that in the basic scenario, there is a peak of energy consumption in the evening, which leads to making high PAR.

As discussed in this paper, in the smart scenario, all the homes studied contain a smart controller that has access to PNH data of neighbors' homes. Besides, each home sends PNHs for heating and appliance systems to the blockchain network hourly to update the mean PNH of the neighborhood.

In the heating system, PNH is calculated based on the indoor

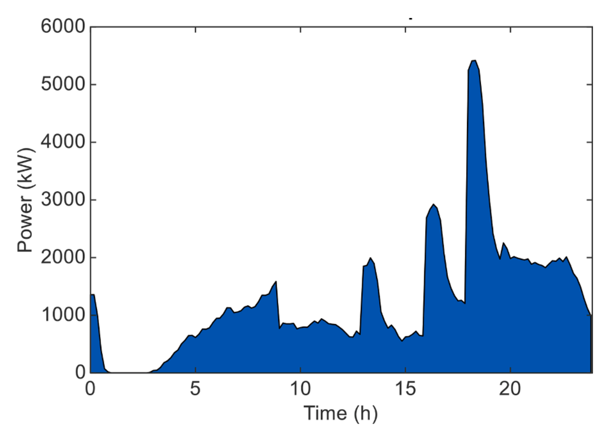


Fig. 12. Power load shape of the integrated two thousand households (Basic Scenario).

temperature. In other words, there is an indirect correlation between PNH and indoor temperature. The PNH of the appliance system is calculated based on occupancy patterns and daily and weekly probabilities of use. In simple words, based on the daily and weekly history of use, a PNH can be generated, which shows the probability of next hour use.

On the other hand, the mean value of PNH can be accessed by controllers inside the homes through the blockchain network. The PNH can change the assigned indoor temperatures to switch the boiler on and off. This means that when PNH is adequately high, the switching temperatures decrease, due to switching on and off at lower temperatures in the comfort region. In addition, the probability of an appliance can change by multiplying the PNH to it. Therefore, it can reduce the power load peaks, and it shifts the loads to off-peak times.

For modeling, it should be mentioned that all the homes' initial and boundary conditions are the same as those of basic.

Fig. 13 shows the power load shape of the smart scenario for the same neighborhood as the basic scenario. As the numbers show, the locations of peaks and valleys are almost the same as those of basic in Fig. 12. However, the peaks of load shape in the smart scenario are milder.

By comparing power load shapes of basic and smart scenarios, the highest peak in both is at 18:00. As Fig. 13 shows, the highest peak of the basic scenario is around 5,000 kW, while that of smart is around 3,500 kW. The second highest peaks in both cases are at 16:00, around 3,000 and 2,500 kW for those of basic and smart, respectively. The third large peak that is about 2,000 kW is around 13:00, which is almost the same as the basic scenario. Also, in the morning the slope of power in the smart scenario is lower than the basic scenario.

The main systems that affect the load shape are heating and appliance systems. The illumination system operates the same in both scenarios, so it does not change the load shape or PAR. The reason for the decreased load shape of the heating system is the preheating before arriving and keeping the temperature as low as possible to maintain thermal comfort at high demand times. Also, for the appliance system due to a change of probability distribution function the load shifts on the valleys in the smart scenario.

By comparing basic and smart scenarios under the same conditions, using the smart controller could decrease the PAR value from 4.3 to 3.6, which is a 15% improvement. As the figure shows, the main peaks are on arrival times for different occupancy patterns in both basic and smart scenarios, which are at 13:00, 16:00, and 18:00. In general, the power peaks in the smart scenario are milder than in the basic scenario.

3.4. Energy consumption

Decreasing energy consumption is one of the main goals for implementing the smart scenario. As expressed in this paper, there are three systems in each home, including heating, appliances, and illumination. Fig. 14 shows the average energy rate of each home during the simulation grouped by each system. As the results show, the designed smart controllers can affect heating and appliance systems compared to the basic ones, while that of illumination is constant in both scenarios.

In the smart scenario, the energy consumption of the heating system is 15% lower than that of the basic scenario. The reason for energy consumption reduction is that in the smart scenario the controller tries to keep the temperature to the lowest possible not to lose comfortability. What is more, it tries to decrease energy consumption before the time of leaving home.

That of the appliance system also decreases to 3.8%, but that of illumination remains constant. The results show that the change in the energy consumption of the heating system is much larger compared to others.

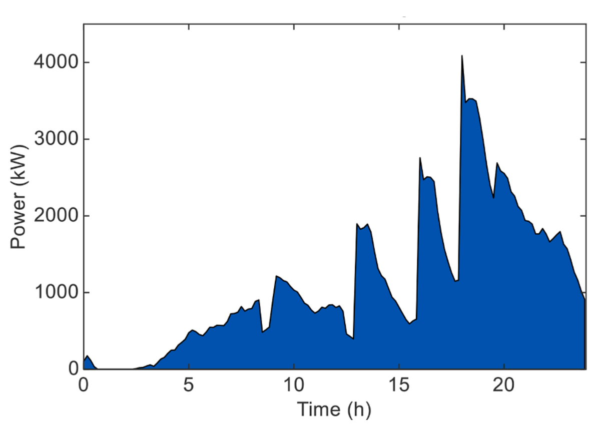


Fig. 13. Power load shape of the integrated two thousand households (Smart Scenario).

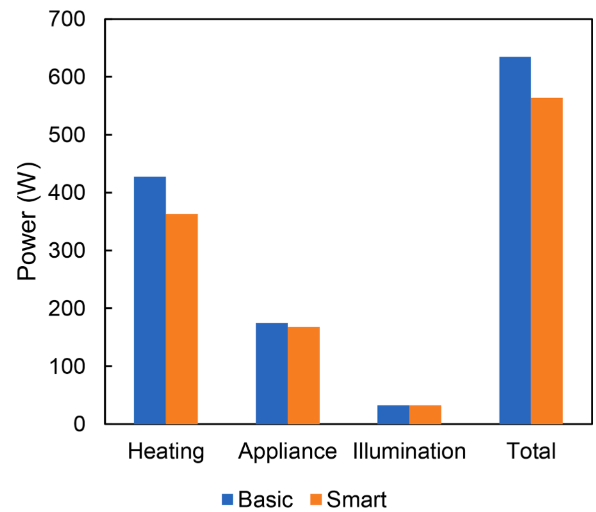


Fig. 14. Mean power per household.

3.5. Thermal comfort

The other parameter which is investigated in this research study is the comfort level of occupants. In this section, the average comfort level of occupants in a neighborhood is compared in basic and smart scenarios.

Fig. 15 shows the average comfort percentage in different occupancy patterns by comparing basic and smart scenarios. In general, the smart scenario improves the thermal comfort in all the occupancies compared to that of basic. As the figure shows, the highest improvement is in the arriving hours and the night hours. In the arriving hours, the cause of the improvement is preheating the environment by predicting the arrival time. Also for the nights, the reason is keeping the temperature as high as possible in the last hours that the boiler is on.

Chart (a) in the figure shows the average comfortability of occupants of homes that have part-time working morning sessions ½. In this occupancy pattern, occupants leave home at 9:00 and arrive home at 13:00. As the figure shows, in the basic scenario, there are low comfort levels during arriving hours at 13:00 and 14:00 which reach 77% and 86%. However, in those of smart, they are 89% and 94%, which are higher. During the evening, the comfort level is almost the same for both basic and smart scenarios. Around 21:00, in the smart scenario, the system tries to store the heat by heating the environment. As a result, the comfort percentage is higher at night in the smart scenario compared to basic. As a matter of fact, the heating system switches off before the occupants leave the home to decrease the energy consumption in the smart scenario, which causes a drop of 3% in the comfort percentage.

The average comfort percentage of people with a full-time job is shown in chart (b) of the figure. As the chart shows, it has the same trend as chart (a) in comfortability during the day. The main difference is in the arriving hours, which have lower percentages compared to chart (a). The main reason for this drop is longer unoccupied hours which cause the loss of more stored heat of the building. Charts (c) and (e), which are for different types of part-time job, have the same trends as well, but the unoccupied hours are different. Chart (d) is for people who do not work, so the heating is on during the day and there is not great discomfort during the daytime hours.

In general, the smart scenario improves the comfortability of occupants. The highest improvement is in the arriving hours and the night hours. In the arriving hours, the cause of the improvement is preheating the environment by predicting the arrival time. Also for the nights, the reason is keeping the temperature as high as possible in the last hours that the boiler is on.

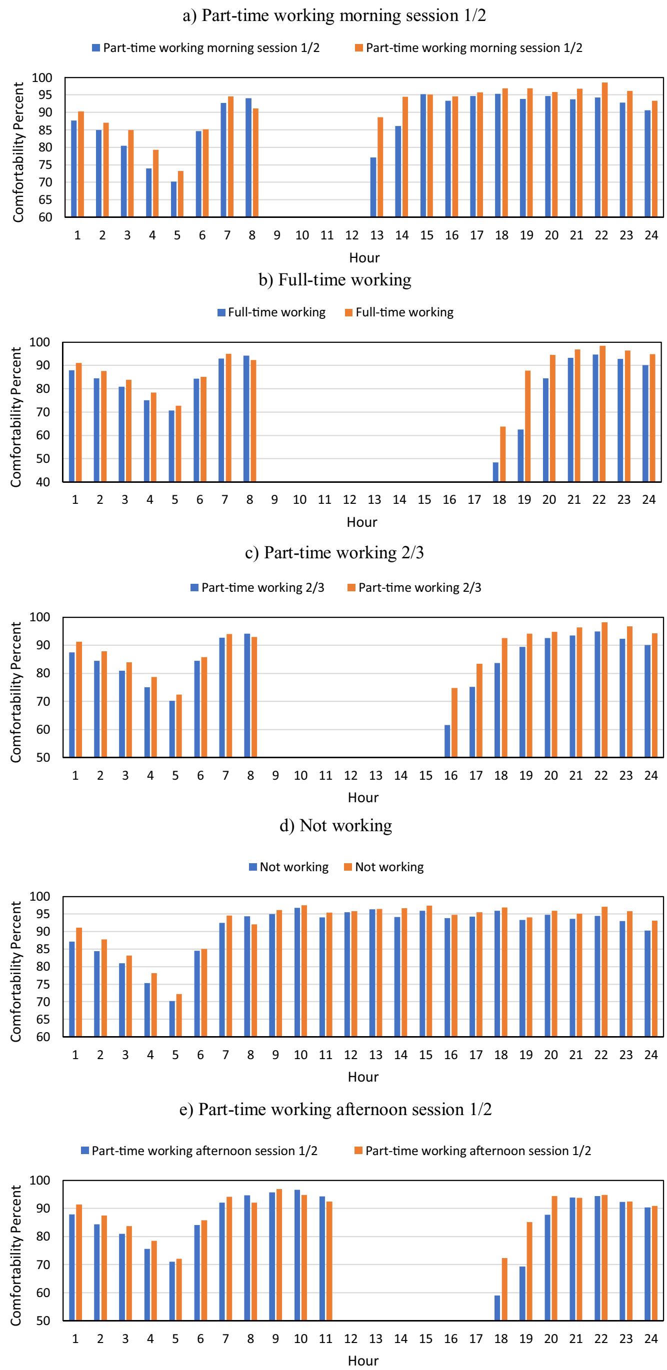


Fig. 15. Average comfort percentage versus time (24 hours).

3.6. Comparision

In the present research, a model is presented and implemented to simulate the energy consumption of a neighborhood. Two scenarios are simulated, namely basic and smart, to show the effect of using smart controllers which are connected through a blockchain network. As the results show, using a smart controller interacting through the blockchain decreases the PAR by 15% compared to that of basic, and it decreases total energy consumption by 11%. The smart scenario also brings 7% more thermal comfort compared to the basic scenario.

The comparison between different types of work due to the difference of baseline cases is not feasible. However, Table 1 compares the improvement of PAR, energy consumption, and comfort level which are achieved in the literature.

As the table shows, the PAR improvements were reported in the range of 9% to 41.5% in previous works. Mediwaththe et al. (2016) proposed day-ahead decentralized energy management and they achieved 13.5% PAR improvement compared to their baseline case while they reduced the energy consumption by 10.5%. Durrilon et al. (2020) implemented multi-objective energy management. They compared the PAR and user satisfaction in three different scenarios. In the first scenario which was a grid-oriented scenario, they achieved a 31% improvement in PAR and a 5.4% increment in global users' satisfaction. In the second and third scenarios, which were mixed approach and customer-centered respectively, they achieved 23% PAR improvement and 12.7% satisfaction increment.

As discussed in this paper, in the smart scenario, we achieved 15% PAR improvement, 11% energy consumption reduction, and a 7% thermal comfort increment.

3.7. Scalability

One of the drawbacks of the blockchain system is scalability, especially in proof-of-work (PoW). When the number of transactions per second increases inside the network, the maintenance costs will increase. Currently, in the Ethereum blockchain, the transaction limit is about 7-15 per second which is higher than the needs in this model. In the proposed model each home sends one transaction per hour, which means that about 54,000 homes can be connected to a PoW blockchain. In the current study, each neighborhood has separated blockchain networks. In other words, in each blockchain network, there are less than 2,000 homes, and the network is local.

However, the computational capability is the requirement of PoW consensus for the security of the network. In other words, any effort at simplifying the PoW consensus means losing the security of the network. In the PoW algorithm, each miner validates the transactions to avoid network threats by competing to solve a mathematical problem to create a new block (Puthal & Mohanty, 2019). In the Ethereum blockchain, the time of generating a new block is between 10 and 20 seconds which is less than bitcoin but is not enough for IoT purposes (Red, 2017; Salimitari & Chatterjee, 2018).

In the current research, the permissioned Ethereum blockchain is considered. This kind of blockchain consumes energy almost the same as centralized networks, which is much less than public permissionless blockchains (Sedlmeir et al., 2021). Because the permissioned blockchain is separated from the public Ethereum mainnet, the consensus algorithm can be customized or changed to improve the performance of the network (*Ethereum Mainnet for Enterprise*, n.d.).

The blockchain implemented in the current study as MVP is a permissioned Ethereum based on PoW consensus which is not suitable for large scales. In other words, a simple PoW blockchain is used to show the results of implementing blockchain in a neighborhood. However, in the scaling up and production the consensus should change to proof-of-authentication to improve the performance (Maitra et al., 2020; Puthal et al., 2019; Puthal & Mohanty, 2019).

In proof-of-authentication, the miners are trusted nodes for authentication blocks to add into the distributed ledger. The miners authenticate each block and its source. Each trusted node that authenticates first each block receives one trust unit. Otherwise, each trusted miner who performs the wrong authentication loses a trust unit and it converts to a normal node after a certain number of false authentications. This solution significantly reduces the computational procedure of validating the transactions (Puthal et al., 2019; Puthal & Mohanty, 2019).

In general, to scale up implementation, proof-of-authentication is suggested due to significant computational improvement.

4. Conclusions

In this paper, a novel approach to building energy management in smart neighborhoods is proposed through the integration of dynamic modeling of energy demand with blockchain technology. For this purpose, the heating, illumination, and appliance systems of a residential building are simulated using a transient model developed by MATLAB. The heating system is validated with reasonable agreement by real building logged data in Northern Italy. Wet appliances including a washing machine, a tumble dryer, and a dishwasher for which their use times are shiftable, were studied as modeling the appliance system. The illumination system is simulated by taking into account sunrise and sunset times by considering the movement of the sun and the earth. Then, different occupancy patterns are studied by comparing energy consumptions and comfort levels. Next, a neighborhood is examined using 2,000 homes with different occupancy patterns, initial values, and boundary conditions. In the basic scenario, everything is controlled by occupants except the boiler, which is controlled by the indoor temperature of the home. In the smart scenario, a blockchain-based network is deployed using a Solidity Ethereum smart contract to reduce the PAR of power load, energy consumption and to improve thermal comfort in the neighborhood, using a parameter called PNH.

As the results show, using a smart controller interacting through the blockchain decreases the PAR by 15% compared to that of basic, and it decreases total energy consumption by 11%. The smart scenario brings 7% more thermal comfort compared to the basic scenario. The power load shapes in both scenarios have almost the same trend, which has peaks at the arrival times of occupants. But the peaks in the smart scenario are milder than those of basic. The highest peak of the basic scenario is around 5,000 kW, while that of smart is around 3,500 kW.

The smart solution decreases the energy consumption of the neighborhood, especially the heating system, due to keeping the temperature to the lowest possible and trying to decrease energy consumption before the time of leaving the home. The highest improvement is in the arriving hours and the night hours. In the arriving hours, the cause of the improvement is preheating the environment by predicting the arrival time. Also for the nights, the reason is keeping the temperature as high as possible in the last hours that the boiler is on.

In the current study, in the aspect of scalability, each home sends one transaction per hour, which means that about 54,000 homes can be connected to one blockchain with a proof-of-work consensus protocol. In general, to scale up the implementation, proof-of-authentication is suggested due to significant computational improvement.

The results achieved can be capitalized to support international policy aimed at GHG emission reduction and climate change mitigation. The strategy of the United Nations and of the many countries that have signed the Paris Agreement require concrete technologies and actions to be applied in order to reach the expected goals. Our work can effectively contribute for instance to the Covenant of Mayors promoted by the EU to foster the European strategy to zero emission communities and to other similar programmes that need operative tools to be translated into reality. The application of blockchain technology to energy management of residential buildings is therefore a real option to pursue the objectives at the heart of these international policies.

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.

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