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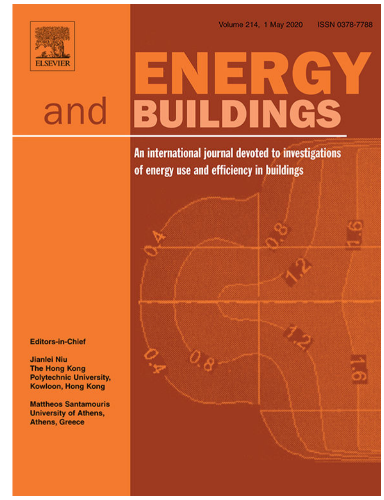

An experimental method for building energy need evaluation at real operative conditions. A case study validation

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An experimental method for building energy need evaluation at real operative conditions. A case study validation.

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Abstract

Building energy consumption reduction is fundamental to achieve sustainable green design and environmental impact lowering. Thermo-physics, different uses over time, heating/cooling plant and controlled mechanical ventilation system operation and users' behaviour in the building affects energy saving conditions, indoor environmental quality and people wellbeing. In our research an experimental method for building energy performance evaluation under transient conditions was proposed. Monitoring experimental data of the external and internal microclimate, and of heat flux through each wall, under real dynamic conditions, were used for a real-time post-processing. The proposed method was based on the "modified" degree days calculated by the measured climatic data, taking into account the thermal phase shift and thermal capacity of the various construction materials. An experimental monitoring campaign was carried out for three years on a social housing development in Florence, as the case study. Results assessment provided a linear correlation function between the above mentioned parameters, with a coefficient of determination higher than 80%. The proposed method can be used for building energy consumption prediction that is fundamental for guaranteeing wellbeing, health and energy sustainability with the "green" transition from energy consuming community and buildings to energy producing community and buildings.

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Keywords: building energy consumption; building energy behaviour; experimental monitoring; transient operation conditions; modified degree days; correlation function

1. Introduction

Our present condition described by the commitment made at COP26 in Glasgow [1], by the slowdown of the entire globalized world economy due to the COVID19 pandemic, which initially caused the closure of commercial activities, borders with major limitations on movement, considerable reduction of energy consumption and the production capacity of raw materials for energy uses, and subsequently, the resumption of activities, movements, consequent recovery of the economy, especially in the USA and China and therefore the recovery of energy consumption. We are also faced with a shift in the demand for resources from coal to methane gas, at the same time as a greater demand for energy with respect to the possibility of resuming production, but also with the commitment of all EU countries to reduce CO2 emissions. Nevertheless, the world energy and environmental situation is dramatic: it is well-known that any system does not progress linearly, but by means of some processes with positive and/or negative feedback that can produce effects capable of triggering other worse ones that contribute to the increase in temperature (global warming). On the other hand, the ecological transition and the development of renewable sources is only possible when the environmental impacts due to climate change have already slowed down by 2030. Therefore, all this requires the use of innovative and integrated technological solutions for a substantial change in the structure of cities and buildings, transport networks, energy networks and development models. It is certainly true that all this involves high investments, but the cost of damage is undoubtedly higher.

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In this context, the European Directives [2] on energy the efficiency push towards energy saving in the building sector, which represents 40% of final energy consumption, finalizing interventions to nZEB buildings with balanced energy balances [3].

So, the well-known Smart Readiness Indicator derived from [2,3] can be used for the following objectives: awareness of the importance of rational use of energy, comfort, health and safety benefits of smart technologies and digital services in buildings; promoting investments in smart advanced technologies and integrated renewable resources application; support IoT and Konnex (KNX based on [4]) adoption in the building/construction sector [5,6]. This is certainly feasible in newly designed buildings. For existing and historic buildings, even protected ones, like very many of those in Italy, the question is very complex. It is not always easy and possible to modify plants, by means of mature technologies application, e.g. using methane in a thermodynamically correct way with cogeneration, which in winter would serve for district heating networks or entire cities, and in summer would provide the necessary air conditioning to buildings, offices and commercial centres. During the transition phase, these same systems, if used to the maximum, would allow the use of waste heat from the production of electricity for cooling / heating together with the direct use of electricity for heating with heat pumps in a widespread way, precisely in the existing buildings would represent a crucial step in the transition phase to predominantly electric systems. Plant system solutions, based on adaptivity, reversibility and sustainability concept can be implemented in existing buildings, only by starting from the crucial knowledge of energy consumption also connected to greenhouse gas emission. Most of the recent literature concerns building energy consumption prediction by means of use of different methods which are not easily applicable, especially at the urban built-up area level. An important review has demonstrated that all the recent studies on this subject can be classified in six basic methodological approaches: physical methods, statistical methods, hybrid methods, artificial intelligence, machine learning and (artificial) neural network [7]. In particular, several authors have proposed robust and effective methods based on machine learning and artificial neural network or deep learning algorithms [8-11]. Some authors have suggested different methodological approaches to evaluate and predict energy consumption of non-residential buildings, taking into account the variability of building-plant system operation [12-16]. Due the fact that non-residential buildings (e.g. healthcare facilities, schools, administrative buildings) have fitful load fluctuations over time so that traditional forecasting methods imply limitations in the application of forecasting models, some authors have implemented the Cox proportional hazard model for their energy consumption prediction and efficient energy management [17-19]; others have used the genetic algorithms to target long and short-term memory adaptive neural networks and vector machine support [20,21]. Most recent research on the prediction and monitoring/control of building energy consumption, based on deep learning models, artificial neural networks, smart retrofit solution approaches using IoT task management implementation have highlighted that building-plant system dynamic simulation, ensemble learning based on energy consumption pattern classification and many specific data taking into account design and thermo-physics parameters are necessary [11,16, 22-25]. However, building and plant system data/information is usually limited or difficult to find and transient simulations with the connected model validation require considerable time and computational costs. Building energy prediction is crucial for energy demand and supply balance and building-plant system control and management, but above all, to identify and evaluate, on the basis of the life cycle assessment and therefore the circular economy, the possibility, efficiency and effectiveness of the integrated use of renewable sources not on a single building scale but on a district and/or urban scale of Net Zero Energy communities [26]. As a matter of fact, some authors have proposed a comprehensive energy and cost-effective method for Net Zero Energy Settlements applying

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advanced environmental energy technologies [27]. Other authors have investigated x user-building interaction by means of intensive surveys and energy simulation for the NZE at settlement and community level [28]. In our research, a simple new effective method, based on the “modified” degree days calculated by the measured climatic data taking into account the thermal phase shift and thermal capacity of the different construction materials, was proposed. This method is a simple and easily applicable tool for building energy consumption prediction that is fundamental for guaranteeing wellbeing, health and energy sustainability with the “green” transition from a "consumption community and consumption buildings" to "an energy community and energy producing buildings". The novel contribution of this method concerns the practical possibility of a real-time control of building energy consumption, plant management and user behaviour interaction.

2. Methods and Materials

2.1 *Experimental monitoring/set-up and the case study*

The proposed method is shown in Fig.1 by a flowchart explaining the experimental and numerical process implemented under real operating conditions. The proposed method was derived from the analysis of a real context in Florence. From 2017 to 2021 thermo-hygrometric parameters of the indoor environment of a building section and the corresponding external one, were monitored continuously. The building complex, under study, is owned by Casa spa a subsidiary company of the Florence municipality for social housing management.

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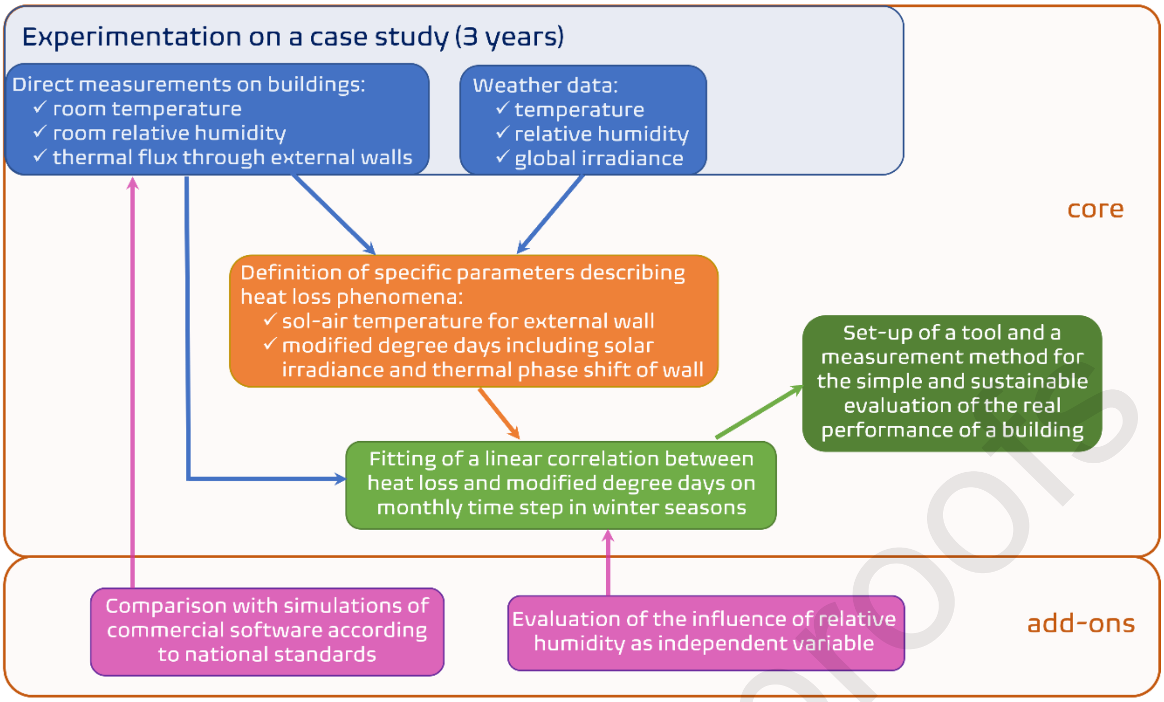

Fig. 1 - Flow-chart showing the proposed method

The building complex meets the nZEB requirements [29]. The building is a typical example of a wooden house: the structural material (wood) is properly insulated by layers of glass/rock wool and the certified/declared total energy consumption is 16 kWh/m^2 per year. Fig. 2 shows some images of the studied building: in particular, the bedrooms of the two flats respectively on the third and fourth floors were investigated by means of an experimental set-up and monitoring system.

Fig. 2 - Some images of the studied building: (left) top view contextualized in the urban area; (centre) front view; (right) three-dimensional scheme used for the experimental set-up development.

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The monitoring system layout was designed to be integrated in the living spaces for a long time (about ten years) ensuring easy removal, management and maintenance and reduced invasiveness in compliance with the use of spaces and environments by the occupants. Some common commercial transducers were installed on the internal walls for air temperature and relative humidity measurement. The basic technical features of these sensors provide an accuracy at ±1° for the air temperature and ±4% for relative humidity. All the outer walls facing South-West, i.e. six for each bedroom, were equipped with 12 flux tiles developed at the University of Florence and amply dealt with in a recent article [30], (Fig.). The flux tiles provided a direct measurement, under transient conditions, of the heat power per unit area, passing through the wall, taking into account the external parameter fluctuations, thermo-physics properties of building materials (e.g. thermal conductivity, specific heat, thermal diffusivity, thermal capacity) and heat loads due to occupants, lighting, equipment, and different uses of the environment, the natural renewal of the air (i.e. manual opening and closing of doors and windows) and heating plant management. The tile sensors were fixed to the wall and detected the thermo-physical and capacitive phenomena of building materials, responding in a short time (minutes) to the impulsive stresses that produce the indoor air temperature variation. The output signal of each tile sensors, directly proportional to the thermal flux passing through it, is connected to the temperature difference between the opposite surfaces of the same tile sensor. The relative measurement error due to this device was 3.5%. The installation was completed collecting all the signals with shielded cables running inside special ducts under the plaster up to the fifth floor, where a commercial analogue data-logger was placed.

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Fig. 3 - Layout of the flux tiles in one bedroom. In the white boxes on the right, cables are collected and sent to Data Acquisition Unit.

Data were registered and collected by a csv file, every 5 minutes by means of the average value of the entire time step. This short time interval was chosen to take into account impulsive and unpredictable user behaviour (e.g. opening windows and doors).

It must be noted that it was not possible to obtain specific information by means of surveys based on questionnaires and / or interviews due to the difficulty of accessing environment and privacy restrictions. The dataset three heating seasons, from November to April during the years 2017-2018, 2019-2020 and 2020-2021 was considered. The corresponding external climatic conditions concerning the hourly values of the air temperature and relative humidity and global solar radiation were provided by the LaMMA CNR-IBIMET Institute for a weather station in Florence. Another system of the Department of Industrial Engineering of Florence, was used for the external climatic data collection. In particular, a pyrheliometer tracking the Sun position, provided the Direct Normal Irradiation values that were post-processed to find out thermal load on the outer surface of monitored wall, due to incident solar radiation.

The different user behaviour of the flats on the third and fourth floor should be noted. They are actually very similar in dimension, functional distribution and thermo-physical properties of building materials and external boundary conditions because they are oriented towards the

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same direction (which means the same incoming solar radiation). However, space use and plant management by the tenants is very different. The indoor measurements demonstrated that temperature levels are markedly different throughout the colder season: e.g., Fig. shows the hourly internal temperature trend from November 1st to April 15th. Clearly these values are almost always below the design limit (20°C) for the third floor (with 17.4°C average value), while they usually exceeded it on the upper floor (with 21.4°C average value).

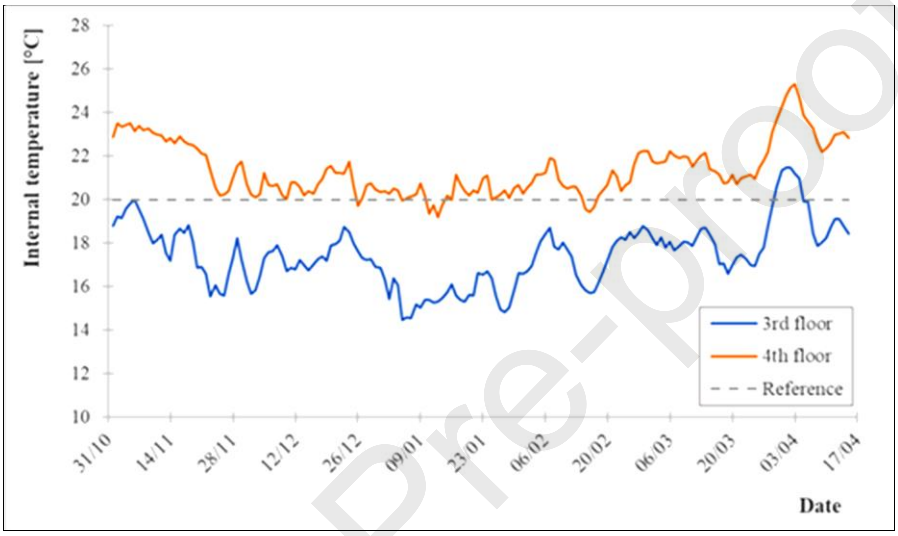

Fig. 4 - Hourly indoor air temperature for the flats on the 3rd and 4th floors during the colder season 2020-2021.

Consequently, total thermal loss is expected with an important variation. In

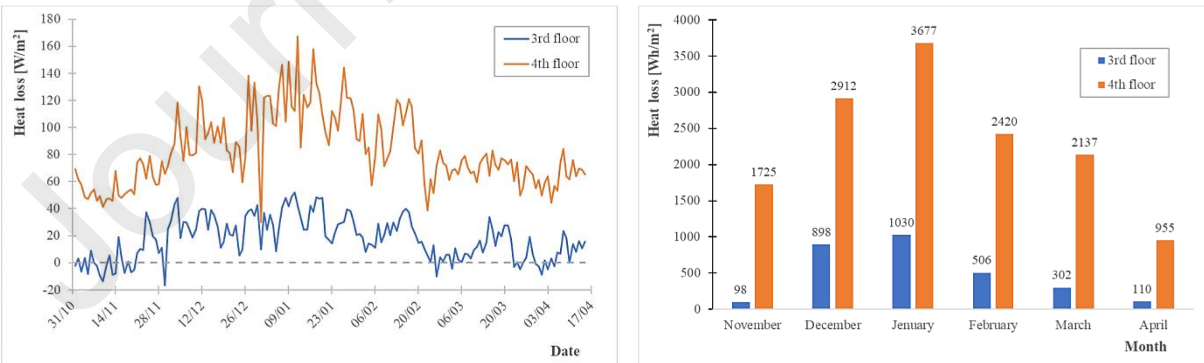

Fig. 5 on the left, the trend of daily heat loss per unit area [Wh/m^2] is provided for the colder period 2020-2021, while the global monthly amount is integrated in the histogram on the right. The comparison between the two flats, highlights that the average difference of 4°C of the average indoor air temperature involves a heat loss that is more than tripled. This means an increase from 2944 Wh/m^2 to 13827 Wh/m^2 for the entire period. It is interesting to

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highlight that the national building energy certification sets a value of 4742 Wh/m^2 of the theoretical design (evaluated by means of a standard climatic database and a constant reference design temperature of 20°C).

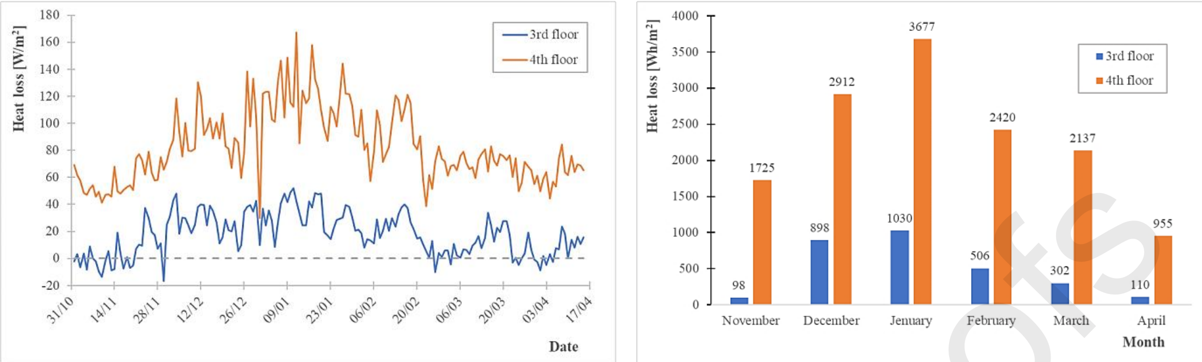

Fig. 5 - Heat loss curves (energy per unit area) for the test walls (left) and monthly energy losses comparison for the two flats (right).

2.2 Experimental data assessment

As explained above, our research was aimed at defining a simple but robust method, easy to use and apply, for the evaluation of the real/transient thermal behaviour of a building. The method is based on the integration in real time and transient conditions, between experimental measurements and a proper transfer function. According to [31], the building thermal energy consumption was connected to the heating degree days *HDD* concept [°C]. Analytically, the heating degree days are provided by the eq. (1):

$$HDD = \sum_{e=1}^{n} (T_o - T_e) \tag{1}$$

where T_e is the external air temperature, T_0 is the reference indoor air temperature suggested for thermal comfort, (known as design air temperature), e is the number of days for the conventional heating season. Italy is divided into six climatic zones (from A to F), from *HDD* under 600 (warmer areas, in the South), up to *HDD* over 3001 (colder areas, in the North). Italian legislation establishes the heating period and the allowed heating daily hours for each climatic zone. Florence stands in the D zone with *HDD* equal to 1821 i.e. the heating plant turned on for 8 hours per day from November 1st to April 15th. The *HDD* is a general parameter that does not consider the real internal and external constrains of buildings on a specific site (i.e. territorial and climatic context). A modified degree days parameter, from here on the *HDD**, was proposed: it took into account the real building-plant system thermo-physical performances at transient operative conditions. The constant indoor reference air temperature T_0 was substituted with the measured values of the T_{mi} that is the real indoor air temperature measured. Consequently, the external air temperature was evaluated considering the effects of incident solar radiation on the building façades. Therefore, the sun-air temperature value T_{ew} was calculated for the external wall with eq. (2):

$$T_{ew} = T_e + \frac{\varphi \cdot \alpha}{h_e} \quad (2)$$

where α is the adsorption coefficient of the wall (e.g. 0.5 for light paintings), h_e is the external heat transfer coefficient (23 W/m^2 °C as usually suggested [32]) and φ is the incoming thermal flux due to solar radiation [W/m^2]. Incident solar radiation was calculated by the measured Normal Direct Irradiance (*DNI*) using the cosine of the incident angle θ on the building façade with hourly values schedule, as eq. (3) shows:

$$\varphi = DNI \cdot cos\theta \quad (3)$$

The hourly values of the angle between the direction of *DNI* and the normal vector to the wall was assessed by means of the on-line SOLPOS-NREL calculator [33]. The global solar radiation used for the T_{ew} calculation (eq.2) was assed adding the contribution of the diffuse and albedo components derived from the weather station. In particular, the external surface of the studied wall was modelled as a vertical plan with its real latitude, longitude and orientation (i.e. the normal vector looks towards south-west, about 238° from nautical azimuth). It is well known that building characteristics have an important impact on the overall energy performance and plant management: periodic thermal transmittance, thermal phase shift and dumping factor play a crucial role affecting the operative regimes of the building-plant system. Current Italian legislation [34] sets specific limits for the thermal transmittance U of newly designed buildings (e.g. from 2019 for the D zone, this limit is U<0.29 W/m^2 °C for external walls), but they do not take into account the thermal phase shift and dumping factor. In particular, only for lightweight walls (surface mass less than 230 kg/m^2), is the periodic thermal transmittance evaluation required, and must be less than 0.10 W/m^2 °C. This last condition is mainly related to summer loads, in the presence of solar radiation values higher than the average value of 290 W/m^2 for the month with the highest solar radiation values. Furthermore, for the same hotter conditions, the standard [35] suggests a thermal phase shift over 8-12 hours in order to have the peak thermal power, due to the incoming heat flux, during the night when cooling is easy accomplished with natural ventilation (i.e. the night purge condition). However, thermal capacity and thermal inertia of any building wall are fundamental parameters affecting the outside and inside temperature gradient both for summer and winter periods. The studied building (popular housing) was designed in compliance with the standards [36,37]. Casa Spa has obtained an energy certification for A4 class building (i.e. 16 kWh/m^2 per year) with a dumping factor and thermal phase shift respectively of 0.084 and 13 hours, obtained by means of dynamic simulations with a standard commercial software validated by European and Italian (i.e. EN-UNI standards) legislation. This last parameter was used to upgrade the *HDD* parameter, coupling every internal measured value (i.e. air temperature, air relative humidity, thermal flux) with the weather data (i.e. air temperature, air relative humidity, solar radiation), but shifted by 13 hours behind. The obtained modified degree days *HDD** are provided in eq. (4):

$$HDD^* = \sum_{e=1}^{n} \left(T_{mi} - T_{ew,s}\right) \tag{4}$$

where $T_{ew,s}$ is the outside wall surface temperature as previously defined, but shifted back in time. In particular, T_{mi} corresponds to the real indoor air temperature measured, that includes the effects due to the energy transfer through glazed surfaces and leakage and/or ventilation. These two phenomena have impulsive effects on the internal air temperature variations. For this reason, the actual measured data of the above measured effective regime indoor air temperature, and not the standard reference constant value of 20°C, were used. The experimental data showed appreciable temperature gradients in conjunction with the windows opening. This fact also occurs in relation to the heating plant management due to the occupants' behaviour.

The new parameter was evaluated for all the days during the periods of interest and then integrated on a monthly scale. The average heat flux values [W/m^2], measured through the walls at third and fourth floor by the installed Tile sensors, were also aggregated in the same time step, obtaining the monthly energy losses per unit area D_e [Wh/m^2] (

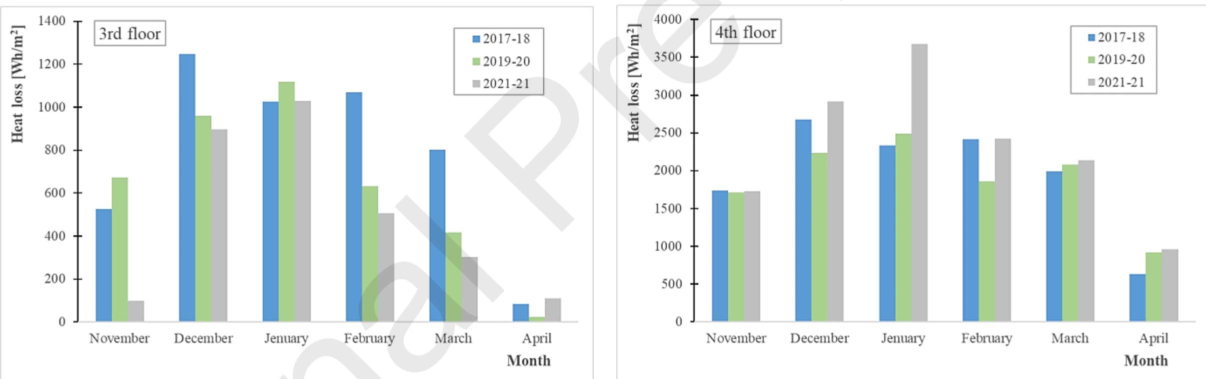

Fig. 6).

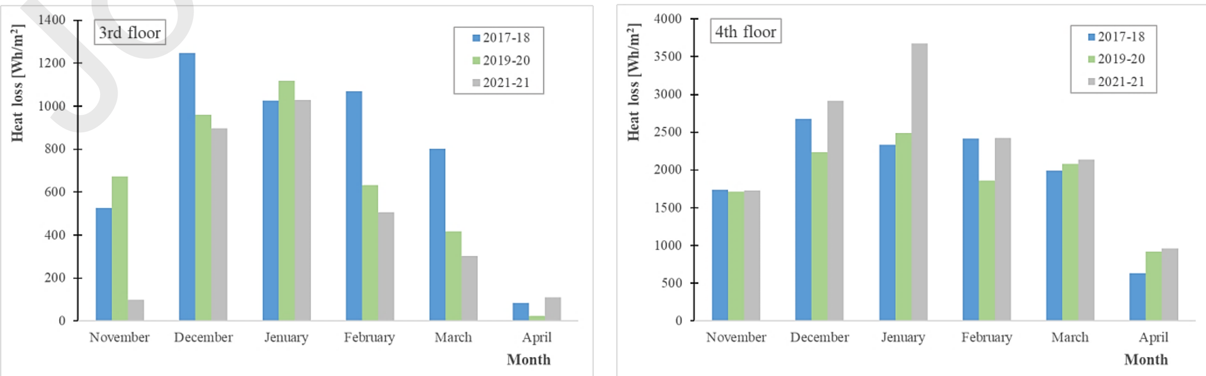

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Fig. 6 - Monthly energy losses for the two flats at 3rd (left) and 4th (right) floor during the three heating seasons under investigation.

Comparison between the total energy losses of the two flats confirm their very different management by the tenants. In the bottom floor the maximum heat loss occurs in December 2017 (1247 Wh/m^2) while 3677 Wh/m^2 are reached in January 2021 in the upper one. It can be deduced that the different plant set-up and internal thermostat temperature cause an important difference between thermal losses with a factor higher than 3 from 3rd to 4th floor. Data collected are provided in Table 1, organized by the reference period and flat.

The reported values represent the thermal operative conditions of the monitored room with the *HDD** matching the corresponding measured heat loss: the overall scatter plot is shown in Fig. . In particular, with reference to 1821 degrees day (due to climate zone D of Florence), the obtained value of *HDD** for the years 2017-2018, 2019-2020, 2020-21, for the 4th floor was respectively 1809, 1627, 1896 and for the 3rd floor was respectively 1416, 1131, 1242.

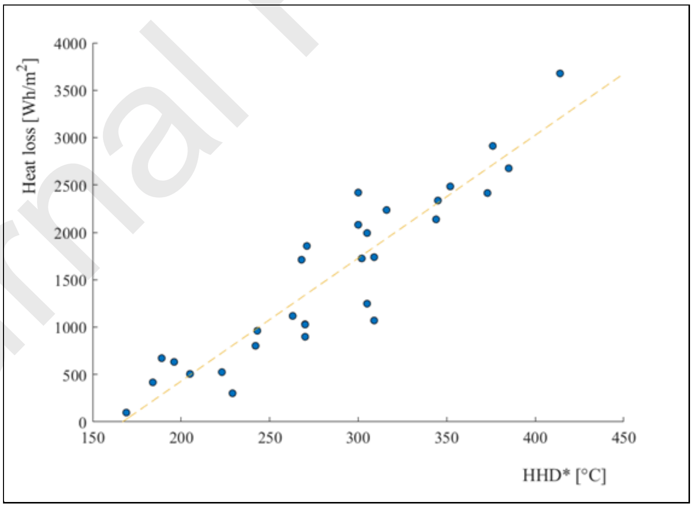

Fig. 7 - Energy loss as a function of modified degree days *HDD**, for the monitored flats and periods.

Tab. 1 - Aggregated data of *HDD** and measured heat loss through the walls for the periods investigated.

Period	Month	3rd Floor *HDD** [°C]	3rd Floor D_e [Wh/m^2]	4th Floor *HDD** [°C]	4th Floor D_e [Wh/m^2]

2017-18	November	223	525	309	1738
	December	305	1247	385	2676
	January	270	1027	345	2336
	February	309	1070	373	2415
	March	242	803	305	1993
	April	68	84	92	633
2019-20	November	189	672	268	1711
	December	243	961	316	2236
	January	263	1118	352	2485
	February	196	632	271	1856
	March	184	417	300	2080
	April	56	23	119	917
2020-21	November	169	98	302	1725
	December	270	898	376	2912
	January	270	1030	415	3677
	February	205	506	300	2420
	March	229	302	344	2137
	April	100	110	160	955

3. Results and Discussion

3.1 *Extrapolation of the linear correlation function*

The displayed data set was used to find out a correlation function between *HDD** and thermal loss through external walls and verify its linearity in the range of interest. All the measurements taken in April were disregarded: this period is usually not fully considered for the heating season as reported in [36] and the parameters integration is partial (limited to 15 days). In particular, the experimental data of April were not considered, because they involved a very low value of the air temperature difference between indoor and outdoor, and a connected degrees day low value, compared to the other months. This fact was due to the working condition of the tile sensors in the presence of both the thermal flux value around zero, and some conditions with reversal of thermal flux. This effects provided an inaccurate result on the heat exchange through the wall studied, very noticeable during the post-processing phase for monthly aggregation.

The matrix with the data from November to March was implemented in the curve fitting tool provided by Matlab® software, obtaining the interpolation with least square method (eq. (5)):

$$D_e = 12.98 \cdot HDD^* - 2166 \tag{5}$$

The linear trend is really significant thanks to a coefficient of determination equal to 0.85 and a normalised Root Mean Square Error of 23%. This means that the modified local degree days are representative of the building thermal behaviour and can be used as a suitable indirect measure of the building energy performance.

*HDD** take into account the wall thermal capacity and thermal phase shift. The same data set was elaborated without shifting the reference time between internal and external conditions (13 hours) and the correlation function decrease in significance, reducing the coefficient of determination to 0.72. Eq. (5) and the statistical parameters related to it, provides a consistent correlation between *HDD** and thermal loss of the monitored façade. The heat loss of the building walls is not easy and directly measurable in situ and the Tile sensors installation needs a proper set-up that is certainly invasive for people/tenants. On the contrary, the internal air temperature detection is a common issue and could be easily managed and stored with standard building/house automation systems. At the same time, the specific external constrains (i.e. air temperature and incident solar radiation) can be derived from local weather stations and building location by simple calculation. In addition, the sun-air temperature value T_{ew} could also be derived by means of experimental data processing by using commercial sensors placed on the outside walls. The proposed *HDD** are of simple application and allow a direct and immediate calculation of the energy needs of different buildings in different real contexts. They can also describe the energy behaviour of different zones of the same building.

4. Conclusions

In this research a simple method, based on "modified" degree days was proposed. *HDD** were evaluated using measured climatic data, thermal phase shift and thermal capacity of the different building materials. The obtained linear correlation function can be used as a basic tool for building energy consumption knowledge and dynamic energy-environmental control, real-time management and regulation of any HVAC plant. The main finding concerns the practical, simple and effective application to any building-plant system, especially if integrated advanced technologies and renewable energies use are the objective of sustainable energy environmental design at urban built-up areas level (i.e. the smart city). The method can be effectively used for building energy consumption prediction that is fundamental for guaranteeing wellbeing, health and energy sustainability with the "green" transition from a "community and buildings of consumption" to "energy community and energy producing buildings". It is important to highlight the interesting aspects of the proposed tool:

- it can be a useful and easy to implement tool for building energy consumption knowledge and dynamic energy-environmental control, real-time management and regulation of any heating ventilation and air conditioning system (HVAC), especially at urban built-up areas level, for the integrated advanced technologies and renewable energies use;
- it is simple and easily replicable without the necessity of invasive experimental set-ups (a wireless internal temperature sensor and site weather data are the only necessary instruments) and without the definition and implementation of a complex method (e.g. physical methods, statistical methods, hybrid methods, artificial intelligence, machine learning and (artificial) neural network etc) that require skills and are not easily usable;
- it provides a simple and practical possibility of a real-time control of building energy consumption, plant management and users' behaviour interaction;
- all the parameters' values used for the correlation include the basic aspect of the users' profile because the two flats, at the same external climatic conditions, have different degree day values and thermal losses, due to the different uses (see the

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indoor air temperature trend, Fig. 5); this confirms the robustness and general validity of the function found;

- the correlation function was implemented and improved taking into account the temperature shift and heat exchange delay which are fundamental parameters for transient analysis and real operation conditions;
- the correlation function can be used for newly designed buildings, but also for existing and historic ones (e.g. cultural heritage), whose thermo-physical and structural characteristics are not usually available, thanks to the strong link between *HDD** and thermal losses (i.e. R^2 equal to 0.72).

Further development of the research foresees that the proposed method is applied and tested on rooms with different orientation and on different floors of the building, but also that it can be extended to the summer condition considering the cooling degree day.

Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could influence their work.

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Highlights

- method for a real-time control of building energy consumption and users' behaviour
- a method easily replicable without invasive experimental set-ups
- the method considers real user behaviour and plant operation conditions
- the method considers temperature shift and heat exchange delay
- the method can be used for newly designed buildings and for existing ones

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