Energy efficiency in the smart home: a model to evaluate the economic and environmental benefits of IoT solutions

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Abstract: In the European Union, residential and commercial buildings together account for slightly less than 40% of primary energy consumption, emitting around 36% of EU greenhouse gas (GHG) emissions. Since the residential sector is one of the main contributors to the country energy balance, countermeasures intended to reduce consumption need to be taken. In this context, new opportunities emerge from the Internet of Things devices for the so-called "smart home". Indeed, energy consumption can be monitored in detail (e.g. lighting, heating, watering), and improved by mean of smart devices. Among all, the present work focuses on heating, which contributes the most to carbon dioxide (CO_2) emissions and leads to high billing costs. Two IoT heating solutions have been considered, i.e. the smart programmable thermostat, which can be remotely controlled, and the smart learning thermostat, which in addition uses artificial intelligence algorithms in order to "learn" from the behaviour of the people at home and regulate the optimal temperature consistently. More specifically, an analytical model has been developed to quantify the potential benefits of smart heating solutions, both in terms of economic and environmental savings. The model takes into consideration both the house features (e.g. thermal transmittance, dispersing surface) and the consumers' profile. It can be applied to every house, as long as this is supplied by a radiator heating system. From the application of the model, it emerges that energy consumption – both in terms of CO_2 emissions and cost – can be reduced from 5% up to about 30%. Anyway, results depend on the user profile and, in particular, on the time spent at home: the more unpredictable the user profile, the higher the savings.

Keywords: energy savings, sustainability, heating, Internet of Things, smart home.

1. Introduction

Current society is highly depending on energy consumption, which entails a significant environmental impact. Fossil fuels (e.g. coal, gas) represent the most consumed resources, bringing to carbon dioxide (CO_2) and other greenhouse gas (GHG) emissions. Many international treaties were introduced in the past years to face this problem (e.g. Kyoto Protocol, United Nations Framework Convention on Climate Change). In particular, the objective of such treaties is to reduce the GHG emissions in the atmosphere and to keep the increase of global temperature under control. In this context, European countries introduced further measures to fight the climate change issue. The so-called Europe2020 is an example: the plan consists in a set of environmental targets focused on emissions cuts, renewables and energy efficiency. In particular, its goals, to be reached by 2020, are: (i) to reduce by 20% the CO_2 emissions compared to 1990 levels, (ii) to increase by 20% the energy efficiency on the basis of EU energy consumption, (iii) to reach 20% of the total energy consumed coming from the renewable resources and (iv) to cover 10% of the total energy consumption of vehicles with biofuels.

In this critical scenario, the residential sector is responsible of a big portion of the total final energy consumption. Residential and commercial buildings together account for around 40% of primary energy consumption, emitting around 36% of EU GHG emissions (European Environmental Agency, 2017). Furthermore, in recent years, energy consumed by buildings even increased. Residential sector is becoming more and more the main contributor to energy balance of countries (Felicetti et al., 2015). Therefore, countermeasures for improving building performance have been taken. Indeed, the new constructed building stocks guarantees consumptions considerably smaller – almost less than the half – than the old ones that were built from the 80s (European Commission, 2015). Nevertheless, further efforts need to be made and different ways need to be explored due to the low demolition and refurbishment rate – i.e. 0.1% and 1.2% respectively (Buildings Performance Institute Europe, 2016). Acting on retrofitting and improvement of existing dwellings could be a sustainable solution to act on the reduction of energy consumption. Energy efficiency, while reducing greenhouse gas emissions and other pollutants, also brings economic savings. Under a citizen's point of view, knowing if a building is enough efficient to save money is an important factor to be taken into consideration: an "inefficient building" not only causes more GHG emissions, but it also brings to higher bills.

In this context, the smart home concept finds its perfect application, thanks to the Internet of Things (IoT). Indeed, the IoT devices can be used for the automatic control of buildings systems (e.g. lighting, heating) for energy savings, comfort, security purposes and so on. IoT energy saving devices could give an important contribution in increasing the efficiency of existing building stocks. Anyway, a person willing to buy a smart home device is not fully aware of advantages and of economic benefits he/she could gain.

Literature also lacks of contributions in this direction. On the one hand, benefits are mostly evaluated for a solution with multiple devices rather than a single smart object. On the other hand, literature is more oriented towards future application (e.g. smart grid/experimental devices). Trying to overcome this situation, the scope of the present study is to develop a model to evaluate the economic and environmental benefits deriving from the implementation of smart devices. The developed model will provide evidence of the reduction in GHG emissions and energy bills by implementing, in particular, heating smart home devices.

The remainder of the paper is organised as follows. The next section summarises the evidences emerged from the literature review, which is focused on the economic and environmental benefits enabled by smart home technologies. The objectives and methodology adopted within the study are described in section 3. Section 4 describes the developed model, and section 5 illustrates the results obtained by applying the model in selected contexts. Results are then discussed and, in the final section, conclusions are drawn and research limitations are identified.

2. Literature review

Literature review aims at investigating the economic and environmental benefits the smart home technologies could bring to final users. Forty-one papers, either contributions from scientific journals or from conference proceedings, were selected for the analysis. The papers were published over 12 years, from 2006 to 2017. Previews reviews were found in the literature, but their studies were focused on the technology itself and on its development rather than on its advantages. The analysed contributions may deal with economic benefits, environmental benefits, or both. Given the interdependency of the two types of benefits, it is very common to find contributions dealing with both economic and environmental benefits. Reducing energy consumption has the double effect of reducing the billing cost and of lowering the environmental impact. Thus, most of the papers consider both the environmental and economic benefits (i.e. 47%), followed by those focusing only on the economic ones (i.e. 41%). Only a few papers introduce only the environmental perspective (i.e. 12%).

Focusing on the economic perspective, the cost of smart devices has always been a concern for customers intended to buy them. Although today it is significantly lower than in the past, it should be considered that it is not always clear the amount of savings the user can get. Many papers deal with this issue and try to quantify the positive impact of the proposed solutions. The benefits depend on the configuration of the smart home scenarios considered by the authors (e.g. level of automation, number of devices installed, number of utilities targeted, number of occupants). For instance, Bozchalui et al. (2012) propose an optimisation model to control the main electrical load with the aim of minimising the total billing cost, and they estimated savings up to 20% on energy cost. Chen et al. (2017) present a human-centric home energy management system, where the smart home understands and then predicts the users' behaviours and preferences in order to efficiently manage the energy devices: electricity consumption can be reduced on average by 14%. Moreover, a new system for intelligent heating floor is proposed by Agesen et al. (2016): by integrating relevant information (e.g. weather forecast, temperature profile) in the system, economical savings up to 12% can be obtained. Morón et al. (2016) study the effect of three different levels of automation for a house, i.e. basic, intermediate or advanced systems. The first one allows an automatic control over the lighting and the air conditioning by means of several types of sensors and actuators. The second allows, in addition, the control over water resources and the electrical power demand of the house. The last one also automatically manages dimmable lights and a multimedia system. The study found that the most beneficial effects are obtained switching from the basic level to the intermediate level (i.e. energy savings have more than doubled). There is instead no much difference between the intermediate and the advanced one. Even if there is a general consensus about the positive effect the technologies have on the consumer bills, there are anyway controversies in the literature. For example, Louis et al. (2015) disagree on the absolute convenience of a full smart home energy management system. Installing too many devices could be counterproductive in term of energy and cost savings, since the electricity consumptions of such devices could offset the benefits achieved by them. The right trade-off between technology deployment and the economic benefits of smart home has to be found.

Focusing on the environmental perspective, the benefits have been generally assessed in terms of CO_2 reduction. The literature seems to agree on the fact that applying smart home technologies in dwellings allow to reduce consumption and therefore to reduce the carbon emissions in the atmosphere. For illustrative purposes, Louis et al. (2014) compare two dwellings, one with 21 home automation devices and one without any, and assess that the potential benefits reachable by the smart house in terms of carbon emissions reduction account for 12.7%. Some authors (e.g. Elkhorchani and Grayaa, 2016) investigate how to reduce carbon emissions through devices using wireless protocols. Ippolito et al. (2013) identify instead the impact that BAC (i.e. Building Automation Control) has on energy performance of a house: the lower the class, the higher the energy consumptions and therefore the higher the benefits from the BAC.

Among the papers dealing with both the economic and the environmental perspectives, a significant theme is represented by the HEMS (i.e. Home Energy Management Systems), which create optimal consumption and production schedules by considering multiple objectives such as energy costs, environmental concerns, load profiles and consumer comfort (Beaudin et al., 2015). Authors exploring this field create algorithms and models to efficiently schedule the households' electric appliances shifting the energy demand either when the electricity price and/or the CO_2 emissions are lower (e.g. Lennvall et al., 2015; Gottwalt et al., 2011; Shirazi and Jadid, 2017; Zhao et al., 2013; Martins and Meneguzzi (2014); Iksana et al. (2013)). Anyway, most of these studies rely on the hypotheses of smart grid deployment, resulting to be still a bit futuristic.

From the analysis of the literature, some gaps emerge. First, papers usually present smart home solutions integrating numerous devices (e.g. for heating, management of appliances, lighting), and the benefits of individual solutions cannot be isolated (e.g. heating only). Second, the type/age/location of the dwellings are usually not considered: this is an important gap, since the features of the building have a huge impact on the total energy consumption, and on the potential reduction enabled by smart devices. Third, the extant literature is more oriented towards future applications (smart grid/experimental devices). There is a scarce focus on solutions that can be already bought in the market, and their possible benefits.

3.Objectives and methodologies

The present study aims to propose a model to evaluate the economic and environmental benefits deriving from the implementation of smart home devices to manage heating systems. The main objective is to assess the potential saving of smart devices by taking into consideration the building characteristics, thus providing a contribution valuable for academics, practitioners and consumers. The following research question was addressed:

RQ – Which are the most convenient IoT heating devices for consumers according to the house technical features and to the occupants' preferences and needs?

In order to answer this RQ, an analytical model was developed. The relevant variables and parameters were identified. Inputs and outputs of the model were defined. Formulas to come up with the desired output (i.e. economic and environmental savings) were then created.

Starting from the characteristics of the house (e.g. size, energy efficiency, number of rooms) and the users' settings (e.g. average time the heating system is on), the model first computes the values related to the starting situation ("initial outputs"), e.g. starting emissions and costs. A smart solution is then introduced, and it will impact on certain parameters (e.g. time the heating system is on, average temperature). The model computes the new outputs, e.g. final emissions and costs, and the savings are calculated. In addition, by considering the investment cost, payback time is evaluated. The model structure is represented in figure 1.

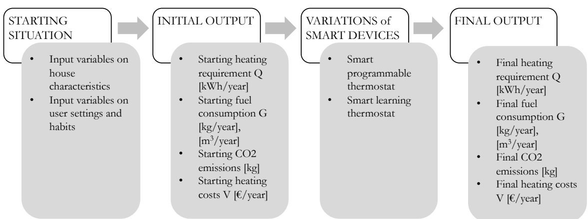

Figure 1: Model structure

In particular, among the possible solutions in the heating field, boundaries were set. Secondary sources, e.g. producers' and retailers' websites, were mainly used to acquire information about the smart solutions. In this regard, two IoT heating solutions – with a different level of users' participation – are considered:

- *Smart programmable thermostat* – users are able to remotely control the thermostat and therefore the heating system running time.
- *Smart thermostat with learning algorithm* – the device has the ability of learning home occupants' preferences and needs, and to program itself consequently (by switching on or off the system). Furthermore, it gives suggestions to the users to save more energy. It can also try to reduce the indoor temperature and maintain it if users do not perceive change in comfort.

The model was applied to selected scenarios – presented in section 5 – which take into account different users' profiles and dwellings.

4. Model development

The model has been developed under two main assumptions.

The first hypothesis regards the baseline scenario (i.e. without smart devices) used to assess the expected benefits: the house is equipped with a programmable thermostat.

The second hypothesis regards the type of heating system: the model has been built up by taking into consideration houses with heating powered by radiators. Under-floor heating cannot be switched on or off intermittently; it requires at least one day to reach the desired temperature and it must be kept in function to warm the environment. Therefore, it would be counterproductive to install a smart thermostat that continuously switches on or off the system.

The model is based on the following variables:

- Heating requirement Q [kWh/year];
- Fuel consumption G_f [kg/year] or [m^3/year]
- Carbon dioxide emissions CO_2 [$kgCO_2$/year];
- Heating costs V (€/year).

The general concept of the model is based on the following reasoning: an initial *heating requirement* [Q_0] and an initial *fuel consumption* [G_0], representing the initial outputs of the model, characterise the house. With these two information, it is possible to know the initial *carbon dioxide emission* [$CO_{2,0}$] due to heating and the initial *heating cost* [V_0].

In order to compute these initial outputs (i.e. Q_0, G_0, $CO_{2,0}$ and V_0), two types of information – describing the starting situation – are needed:

(i) variables related to house characteristics (e.g. opaque surface, internal floor area, fixtures area etc.);

(ii) initial heating system settings defined by the user (e.g. how long the heating system is turned on). These depend on the users' preferences and habits.

In particular, factors affecting the heating requirements (Q) are four, represented by the following formula:

$$Q = t \cdot C_{gg} \cdot \sum_{i=1}^{n} k_i \cdot S_i$$

Where:

- *k* is the thermal transmittance. It is related to material properties and cannot be changed unless structural changes (e.g. exterior insulation finishing system) are introduced;
- S_i is the dispersing surface. It depends on the house footprint configuration and on the heating running time, which depends on users' settings;
- C_{gg} represents the day degrees of the house, i.e. the average temperature, which is set by the municipality;
- *t* is the time the heating system runs every day.

Carbon dioxide emissions depend on the amount of fuel consumed to satisfy a certain amount of heating requirement Q. Different types of fuels can be taken into account (e.g. natural gas, LPG - liquid petroleum gas, diesel fuel). These represent the main energy sources for heating purposes in Italy. Since this work focuses both on the economic and environmental benefits smart solutions can bring, it is important to know which is the starting pollution house contribution. Once the fuel consumption is known, the carbon dioxide emissions caused by the heating system is computed thanks to conversion values (i.e. kg CO_2 per consumed kg fuel). Purchasing choices are based on the monetary value of achievable savings rather than on the environmental ones. Therefore, it is necessary to highlight which is the starting billing cost on which smart devices are going to act on. Purchase cost must indeed be justified by an earning on bills.

Then, through to the introduction of the two IoT solutions, Q and G variate, reducing consequently CO_2 and V. In order to quantify the contribution of each smart solution, users' routine needs to be explored; just after, it is possible to provide reliable and not overestimated figure on savings.

The four variables just exposed (heating requirement Q, fuel consumption G, carbon dioxide emission CO_2 and heating costs V) have an initial value identifying the variables before the introduction of smart devices. These four variables are going to change, differently, according to the type of solution introduced. In particular, the two IoT solutions act on different variables, as reported in the table 1 below.

Table 1: Heating requirement variables impacted by smart solutions

Solution	Day Degrees C_{gg}	Heating time t
Smart programmable thermostat		X
Smart thermostat with learning algorithm	X	X

By introducing a smart programmable thermostat, users are able to remotely control the thermostat and therefore the heating system running time. This device acts on the heating time variable *t*. Introducing instead a smart thermostat with learning algorithm, the device has the ability to learn home occupants' preferences and needs and to program itself consequently (switching on or off the system). Furthermore, it gives suggestions to the users to save more energy. It can also reduce the indoor temperature and maintain it if users do not perceive change in comfort. Variables impacted by such devices are indeed the heating time *t* and the day degrees C_{gg}.

As aforementioned, achievable savings do not just depend on the type of IoT solution considered, but also on users' habits and needs. In particular, the number of hours for which a thermostat is programmed does not often reflect the actual hours in which people are at home. This could happen for two reasons. The first one is that traditional thermostats are not user-friendly and therefore, once set, the user usually does not modify his settings even if his habits change. Second, home occupants may have unexpected events which make them staying out of home for a longer time. As an example, a person may have an unforeseen dinner after work: in this case, the heating system is typically on, even if the person is not at home.

Therefore, in order to assess the benefits it is necessary to deepen the knowledge about users' routine. The average number of hours occupants spend at home between 6.00 am and 10.00 pm during working days and the number of most attended rooms between 6.00 am and 10.00 pm are the key information needed for reducing energy requirements. Indeed, with smart solutions, the heating running time reflects more the user presence at home rather than following a predefined schedule.

Therefore, once the starting values of the four variables Q, G, CO_2, V have been assessed, and all the information on users' habits have been gathered, the last step of the model is the quantification of the benefits enabled by the smart devices. Starting from the calculation of the new heating requirement $Q_{1,i}$ (where i represents the solution i, 1 or 2), then it is possible to calculate the other variables.

The new heating requirement $Q_{1,i}$ is obtained by substituting starting input variables with the information about users' habits. In particular:

- Heating time t_1 is now the average number of hours spent at home for every smart solution considered;
- day degrees C_{gg} decrease in case of a smart learning thermostat.

5.Model application

The model described in the previous section is applied to different scenarios. In particular, different users' profiles are first applied on the same house. Second, supposing a different type of house (mainly in terms of size) for each user profile, the quantification of savings is computed.

Three "personas" have been identified. They represent different lifestyles, habits and needs. In particular, they mainly differ for the number of hours spent at home (only considering the daily timeframe the heating system is on). Besides the time people really spend at home, it is important to consider the time the heating system is on in the starting AS IS situation.

Table 2: Users' profiles

Typology of user	Average time spent at home [hours]	Time the heating system is on in AS IS situation [hours]
"family life" – supposed to be a family with children, housewives or elderly people spending most of the day at home	9	10
"creature of habit" – supposed to be a family of two people, with almost fixed plan along the week	7	9
"unpredictable life" – supposed to be a person living alone, spending most of the day outside	5	7

5.1 Different users' profiles, same house

The reference house is located in the municipality of Reggio nell'Emilia (Italy). Based on its features, the house belongs to class E (relying on the Italian energy certification APE – the energy performance certificate). The main information regarding the reference house are reported in Appendix A (e.g. house dimension, number of rooms, number of radiators, typology of boiler).

Referring to the first hypothesis of the model, the house is equipped with a traditional programmable thermostat, which is assumed to function for a different number of hours depending on the user profile considered (see table 2). Relying on the information available in Appendix A, table 3 reports the initial values of the four variables (i.e. Q, G, CO_2 and V). Starting from these values, savings – which will be different for each user profile – are then calculated.

Table 3: Initial values for input variables

Input variables	family life	creature of habit	unpredictable life
Q_1 [kWh/year]	6,841	6,157	4,789
G_1 [m^3/year]	847	763	593
$CO_{2,1}$ [kgCO_2/year]	1,389	1,250	972
V_1 [€/year]	595	536	417

Moreover, not only savings, but also investments are accounted in the assessment. Table 4 collects economic data of the two devices.

Table 4: Investments for smart heating solutions

Input variables	Purchasing price	Installation cost
Smart programmable thermostat	160 €	40 €
Smart thermostat with learning algorithm	300€	70 €

The two smart solutions are applied – considering the same house characteristics – to the three users' profiles. Relying on the model dynamics explained in Section 4, the outputs for each scenario are elaborated. Tables 5, 6 and 7 show the results respectively for the "family life", "creature of habit" and "unpredictable life" profiles.

Table 5: "Family life" savings

Family life	Smart programmable thermostat		Smart thermostat with learning algorithm	
	Value	**Δ**	**Value**	**Δ**
Q_1 [kWh/year]	6,499	-342	5,724	-1,117
G_1 [m^3/year]	805	-42	709	-138
$CO_{2,1}$ [kgCO_2/year]	1,319	-69	1,162	-227
V_1 [€/year]	565	-30	498	-97

A "family life" profile can save from 5% to 17% on the energy bill – as well as in CO_2 emissions – by respectively implementing a smart programmable thermostat or a thermostat with learning algorithm. Considering instead the cost to buy and install the two smart solutions – as reported in table 4 – the payback time of the investments are almost 7 years for the smart programmable thermostat and about 4 years for the solution with the learning algorithm.

Table 6: "Creature of habit" savings

Creature of habit	Smart programmable thermostat		Smart thermostat with learning algorithm	
	Value	**Δ**	**Value**	**Δ**
Q_1 [kWh/year]	5,473	-684	4,452	-1,705
G_1 [m^3/year]	678	-85	551	-211
$CO_{2,1}$ [kgCO_2/year]	1,111	-139	904	-346
V_1 [€/year]	476	-60	387	-148

In a "creature of habit" profile, energy saving – in terms of both emissions and cost – is instead expected to reach 28% in the smart thermostat with learning algorithm (it is instead 11% in the other solution). Payback times of the investments are almost 3.5 years for the programmable thermostat and 2.5 for the thermostat with learning algorithm.

Table 7: "Unpredictable life" savings

Unpredictable life	Smart programmable thermostat		Smart thermostat with learning algorithm	
	Value	**Δ**	**Value**	**Δ**
Q_1 [kWh/year]	4,105	-684	3,498	-1,291

G_1 [m³/year]	508	-85	433	-160
$CO_{2,1}$ [kgCO_2/year]	833	-139	710	-262
V_1 [€/year]	357	-60	304	-112

Also in the “unpredictable life” profile savings can be high. In particular, this profile can save from 14% up to about 27% on energy emissions and cost by respectively implementing a smart programmable thermostat or a thermostat with learning algorithm. Payback times of the two investments are in this case similar (i.e. 3.4 and 3.3 years respectively).

5.2 Different users’ profiles, different houses

The previous section (§5.1) compares three types of users’ profiles considering the same reference house (e.g. characteristics, dimension, energy efficiency). In this section a more realistic assumption is considered, i.e. the size of the houses depends on the users’ profiles. In particular, taking as reference the energy parameters of the house in §5.1 (see Appendix A), its dimensions are varied:

- “Family life” – 150 m² are kept as in §5.1 (results do not vary for this profile);
- “Creature of habit” – 100 m² are assumed;
- “Unpredictable life” – 70 m² are assumed.

Table 8: “Creature of habit” savings, tailored house

Creature of habit	Initial value [0]	Smart programmable thermostat		Smart thermostat with learning algorithm	
		Value	Δ	Value	Δ
Q [kWh/year]	4,442	3,948	-494	3,212	-1,230
G [m³/year]	552	491	-61	400	-153
CO_2 [kgCO_2/year]	902	801	-100	652	-250
V [€/year]	386	343	-43	279	-107

Table 9: “Unpredictable life” savings, tailored house

Unpredict. life	Initial value [0]	Smart programmable thermostat		Smart thermostat with learning algorithm	
		Value	Δ	Value	Δ
Q [kWh/year]	2,555	2,190	-365	1,866	-689
G [m³/year]	319	273	-46	233	-86
CO_2 [kgCO_2/year]	519	445	-74	379	-140
V [€/year]	222	191	-32	162	-60

A “creature of habit” profile – with a smaller house if compared to §5.1 – can save from 10% to 27% on energy consumption. Payback times of the investments become longer, i.e. almost 5 years for the smart programmable thermostat and 3.5 years for the other solution. In a “unpredictable life” profile, energy saving is instead expected to vary from 15% up to 28%. In both the solutions, payback times are around 6 years.

6. Discussion

Among the two analysed solutions, the smart programmable thermostat is the one allowing the lowest savings: savings vary from 5% to 15% depending of the user profile. By implementing instead a smart thermostat with learning algorithm, savings reach almost the 30% if compared to the starting situation. Users’ profile strongly influences the result: the more unpredictable the behaviour, the higher the savings. Indeed, the so called “family profile”, which is characterised by high predictability and by the highest expected number of hours spent at home, reaches the lowest savings (i.e. from 5% to 17%). Anyway, the payback time of the investments in the two solutions is another aspect to be considered. Considering the same user profile (e.g. “unpredictable life”), a bigger house allows reaching the breakeven point in a shorter time – about 3 years in the 150 m² house, and about 6 years in the 70 m² one. The present work attempts to overcome two main gaps found in the literature. On the one hand, the developed model allows to consider specific features (e.g. type, age, location) of the dwelling for which savings are evaluated. On the other hand, this work focuses on – and allows assessing benefit of – specific smart solutions for heating instead of integrating numerous devices for multiple purposes.

7.Conclusions

The present study provides insights about the savings – both from the environmental and the economic perspectives – that the employment of heating smart devices can bring. In particular, two typologies of solutions are considered, i.e. the smart programmable thermostat and the smart thermostat with learning algorithm. The starting situation from which savings are evaluated is the case of a house with a heating system programmed to run for a certain number of hours every day. Savings arise from the fact that a smart thermostat allows the heating system to run for a lower number of hours. Time spent at home is indeed what reflects the user profile. Three profiles are considered in the study, the so called “family life”, “creature of habit” and “unpredictable life”.

Although the developed model brought to useful results, it presents some limitations and displays space for future improvements. The main limitation of the model is related to the estimation of the number of hours actually spent at home by the occupants. This is not a result from empirical testing, but it is derived from a theoretical reasoning. As a consequence a first element to further investigate is the application of the model by empirically acquiring data on users’ habits. Other further improvements are instead related to enlarging the scope of the model. First, the only baseline scenario with the programmable thermostat is considered (i.e. first hypothesis of the model, §4): the baseline scenario of the thermostatic valves – present in houses with the central heating – could be explored. In this regard, other smart heating solutions, e.g. smart valves, can be investigated. Second, being the focus of the present work on heating, other domestic utilities could be investigated. The computation could be indeed expanded and adapted to also include electricity or water consumption. Third, after having analysed the other utilities, it would be interesting to explore the benefits arising from the integration of different devices – but without losing the single perspective, which is the value of this work. Last, an additional upgrade to the model could be made by exploring more in depth the users' profiles, since they significantly impact the results.

This work is valuable for both academics and practitioners. On the one hand, it provides literature with a model and insights on savings that the employment of single smart devices can bring. On the other hand, it provides a useful tool for final users, IoT solutions providers and energy authorities. Users would easily evaluate the smart devices most suitable to their houses. IoT vendors can use the results to better illustrate the benefits enabled by their solutions. The energy authorities can better define policies intended to obtain energy savings.

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Appendix A

Characteristic	Value
Floor area/heated usable area [m²]	144,1
Total apartment area [m²]	150
Number of rooms [#]	7
Number of radiators [#]	8
Number of front windows [#]	6
Ceiling height [m]	2,7
Place of residence	Reggio nell'emilia
Fuel types	Methane
Nominal power of the boiler [kW]	31,12