Chapter 17
Less Automation More Information: A Learning Tool for a Post-occupancy Operation and Evaluation

Chiara Tonelli, Barbara Cardone, Roberto D'Autilia, and Giuliana Nardi

Abstract Climate change and the pandemic generated an urgent need to have an efficient urban habitat that includes technological innovations to deal with the ecological and digital transitions. Italy counts about 14 million buildings, 12 of which are houses, responsible for more than 40% of final energy consumption, most of which is ascribable to users' behavior and lifestyle. The increase in buildings' energy performance is strongly related to a smart management of the demand and self-consumption, as well as a more effective and active involvement of the occupants: it is, therefore, pivotal to come up with user-friendly tools to measure and monitor the performance of the buildings and users' habits. Tools to encourage the choices toward the environment's comfort, rather than automation technologies, allowing the occupants and information systems to move in the direction of ecological transition. The aim is to create an aware "energy citizenship" for people living in efficient buildings. The proposal is a system that uses IoT technology and provides a global evaluation of the state of the house, from which can be extracted suggestions for better and virtuous behavior. The overall ecological footprint is measured based on five "cycles": energy; environment; water; waste production; food. Collected data create an urban database that, along with big data, constitutes a set of boundary conditions that are crossed with single units' data. The measures related to single units can be applied to a wider network in order to create a smart city, involving dwellers in a serious game on their homes' performance. The proposal is part of the research on post-evaluation occupancy, in the belief that even the best model-houses perform worse in use, rather than the predictions expected on paper.

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17.1 Introduction

The recent pandemic highlighted some housing inadequacies with respect to the morphology, the comfort, and the health of people. The architectural research identified the need for more compact and flexible solutions to face different climatic conditions as well as new needs for the living space (Rode et al. 2014). The minimum size paradigm derived from hygienic criteria[1] should be replaced by a new one that takes into account sustainability, health, and energy efficiency. At the same time, people's awareness of the impact of their actions should be improved.

Emergencies such as climate change and the pandemic also urged the need for efficient urban habitats and technological innovations to encourage the ecological transition. Italy counts 14 million buildings, 12 of which are residential, responsible for more than 40% of final energy consumption, most of which is ascribable to users' behavior and lifestyle (Fig. 17.1).

The improvement of the buildings' energy performance and the reduction of the environmental impact depends on the smart consumption and user involvement to

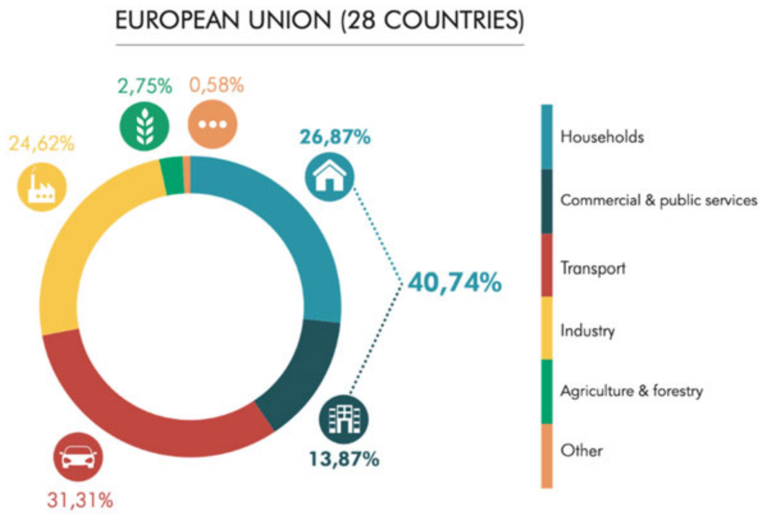

Fig. 17.1 Final energy consumption, EU28, Eurostat 2021 (2019 data)

[1] See the Italian Ministerial Decree: DM 5 Luglio 1975, Modificazioni alle istruzioni ministeriali 20 giugno 1896, relativamente all'altezza minima ed ai requisiti igienico-sanitari principali dei locali di abitazione. Last accessed 23/05/2022: https://www.gazzettaufficiale.it/eli/gu/1975/07/18/190/sg/pdf.

keep the environment healthy. It is therefore essential to have efficient tools to monitor the performance of the buildings together with the inhabitants' behavior acting on their daily habits and, more generally, improving the "Energy Culture" (Stephenson et al. 2010).

The relationship between energy and culture has long been a focus of cultural anthropology (White 1943): it is possible to trace the history of civilization through the availability, distribution, and use of energy (Smil 2018). The three interrelated components: norms, practices, and material culture interact with the social institutions to create the energy culture (Stephenson 2018) (Fig. 17.2).

Habitus is a long-term thinking pattern shaped by a particular cultural environment that influences modern social behavior (Bourdieu 1980). The study of energy culture aims to change habits by promoting new practices, attitudes, and behaviors (Rau et al. 2020). The technology, the buildings, and other assets that influence energy use are referred to as material culture. The norms are common ideas, the individual and collective expectations and goals regarding material activities and culture. Daily actions and the selection and acquisition of assets are examples of practice.

Over the past forty years, much literature considered the interaction between humans and buildings, but no standard way has emerged for comparing the results of different studies (Dong et al. 2018; Hong et al. 2015). The technologies related to the Internet of Things (IoT) offer the possibility of measuring the overall behavior of a living space. In order to improve the models in literature, which deal, in general,

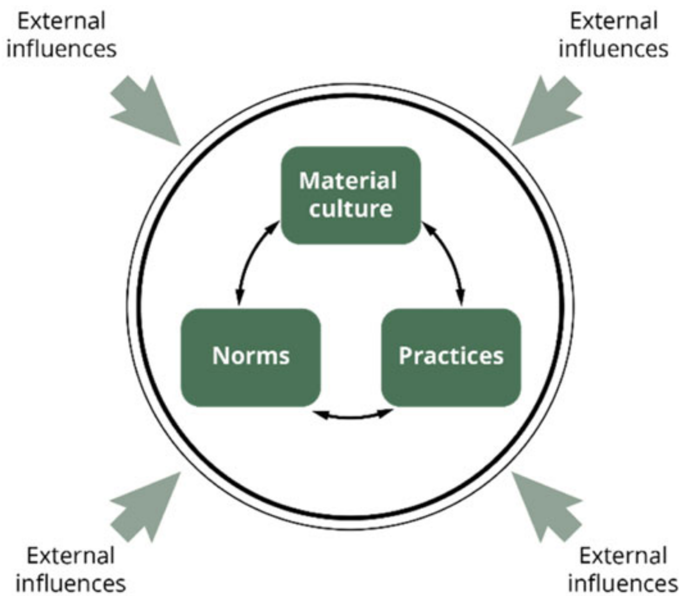

Fig. 17.2 An energy culture framework (adapted from Stephenson 2018)

with the monitoring of single environmental variables, we try to calculate the overall impact of different variables taking into account their interdependence.

The aim of this paper is to develop a machine learning tool to increase the environmental awareness and to help the residents to optimize the energy consumption together with the environmental impact (Tonelli and Converso 2014). The tool is also intended for the planning analysis and, at the same time, to trigger a process of gamification among the tenants.

17.2 Materials and Methods

We propose a machine learning algorithms that can be trained by data coming from sensors that measure the environmental data, as a tool to improve the (Tonelli et al. 2019) "smart citizenship" and to optimize the environmental quality of life at home. This strategy is related to the "architecture of choices" (Johnson et al. 2012; Scheibehenne et al. 2010), and it is derived from scientific insights originating from "neurological" models together with the possibility of having a large amount of data available. The tool is designed to make people aware of the quality of the environment in which they live, but not to prescribe behaviors.

Rather, it is continuous monitoring that can induce a change in individual behavior.

Quoting the Italian Research Plan[2] "*Digital technologies have, in turn, a function which, although ancillary, is of crucial importance for achieving the reduction of energy consumption and, consequently, of the environmental impact: (…) must favor the virtuous behaviour of users by providing clear and understandable information in real-time (feedback) on the state of the building and on consumption and, at the same time, guaranteeing adequate support in the decision-making process (…)*".

The monitoring tool helps to optimize consumption and calculate the ecological footprint. The specific goals are as follows:

- to monitor the ecological footprint of the house and the behavior of the inhabitants by showing these data in a simple and intuitive way;
- to predict future scenarios based on user choices and external data;
- to estimate the long short-term consequences of behavior in terms of consumption and ecological footprint;
- to suggest best practices to improve the ecological footprint;
- to allow the planning of actions to achieve personal goals.

Finally, the tool is designed for a single housing unit but can be integrated into a larger network to build an urban database. The collection of this data on an urban scale, together with data on traffic conditions, weather, and external pollution, constitutes the set of boundary conditions that the machine learning system intersects with the internal data of each unit.

[2] Last accessed 23/05/2022: https://www.mur.gov.it/sites/default/files/2021-05/PNR2021-2027.pdf.

17.2.1 The Neural Network Architecture

The purpose of the algorithm is to return a habitability index k based on a given number N of environmental variables $x_1, x_2, \ldots, x_N$

$$[0, 10] \ni k = k(x_1, x_2, \ldots, x_N) \tag{17.1}$$

The x_i variables are in general strongly correlated random variables, feature that make it very difficult to guess the functional form of $k(.)$.

Our purpose is to build a machine that provides a home habitability index on a scale ranging from 0 to 10. There are of course several constraints that can easily be turned into algorithms. For example, if the value of variable x_n is above a danger threshold, then $k = 0$ for any value of the other variables x_i with $i = n$. However, there are other variables whose behavior and correlation with the others is more difficult to guess, such as the availability of household appliances or the presence of possible smokers.

We observe that by means of "natural intelligence," a good planner is able to estimate the value of k based on its experience. Our aim is therefore to create a machine giving the same answers as an experienced planner, and for this purpose, we train an artificial intelligence system.

One of the most difficult problems in machine learning is known to be the choice of the optimal network topology. The most expensive sectors in terms of energy, economy, and environment are precisely that of neural architecture search (Strubell et al. 2020).

We proceeded in a simpler way, choosing four possible neuronal architectures and comparing the reliability of their responses. The four networks are linear regression, a network with nearest neighbors interactions, a convolutional neural network, and a random forest. In Goodfellow et al. (2016), a detailed description of the four architectures can be found.

To train the networks, we generated 10,000 data records and submitted them to the human evaluators who assigned a score from 0 to 10 to the environmental configuration. A subset of these records are used to train the networks, and the remaining was used to verify their efficiency. By providing the neural network with the tables whose scores we know, we were able to assess whether the response was reliable, and we can compare the responses of the four networks.

17.2.2 The Environmental Variables

The algorithm processes the environmental data and outputs the result. The input variables are classified into five categories:

- the geographic position of the building (Table 17.1);

Table 17.1 Outdoor conditions

Variable	Code	Unit of measure
Summer temperature	T	°C
Winter temperature	T	°C
Relative humidity	RH	%
Altitude	SLM	m s.l.m.
Wind	W	km/h

Table 17.2 Outdoor pollution

Variable	Code	Unit of measure
Atmospheric particulate matter	PM10	$\mu g/m^3$
Atmospheric particulate matter	PM2.5	$\mu g/m^3$
Nitrogen dioxide	NO_2	$\mu g/m^3$
Ozone	O_3	mg/m^3
Carbon monoxide	CO	mg/m^3
Sulfur dioxide	SO_2	$\mu g/m^3$
Benzene	C_6H_6	$\mu g/m^3$
Benzo(a)pyrene	$C_{20}H_{12}$	ng/m^3
Arsenic	As	ng/m^3
Cadmium	Cd	ng/m^3
Nickel	Ni	ng/m^3
Lead	Pb	$\mu g/m^3$
Noise (day)	dB	Decibel
Noise (night)	dB	Decibel

- the variables related to the buildings' geographic location, such as the outdoor pollution (Table 17.2);
- the buildings' shape, based on their estimated occupancy rate (Table 17.3);
- the presence of facilities and appliances (Table 17.4);
- the indoor pollution (Table 17.5).

These variables may be strongly statistically correlated. Moreover, the variables are also heterogeneous, being both qualitative and quantitative in nature. For this reason, artificial intelligence is particularly useful.

Table 17.3 Indoor condition

Variable	Code	Unit of measure
Square meter	A	mq
High	H	mt
Volume	V	mc
Inhabitants	P	Number

Table 17.4 Facilities and appliances

Variable	Code	Unit of measure
Cooling system	–	Boolean
Heating system	–	Boolean
Domestic hot water	ACS	Boolean
Washing machine	–	Boolean
Dishwasher	–	Boolean
Refrigerator	–	Boolean
Computer	–	Boolean
Photocopier	–	Boolean
Television	–	Boolean

Table 17.5 Indoor pollution

Variable	Code	Unit of measure
Tobacco smoke	ETS	$\mu g/m^3$
Carbon disulfide	CS_2	$\mu g/m^3$
Sulfur oxide	SO_x	$\mu g/m^3$
Carbon monoxide	CO	mg/m^3
Ozone	O_3	$\mu g/m^3$
Atmospheric particulate matter	PM10	$\mu g/m^3$
Atmospheric particulate matter	PM2.5	$\mu g/m^3$
Benzene	C_6H_6	$\mu g/m^3$
Formaldehyde	CH_2O	$\mu g/m^3$
Microbiological agents—bacteria, viruses, endotoxins and mycotoxins	–	Boolean
Indoor allergens—mites, epidermal derivatives of pets, cockroaches, fungi	–	Boolean
Mold	–	Boolean
Radon	Rn	Boolean

The geolocation provides data on temperature, relative humidity, and site altitude, quantities that influence the global air quality and the users' sense of comfort.

The outdoor pollution rate adds up to the indoor pollution rate, and it is in general higher than the outdoor rate, as shown by the data of the European Environment Agency.[3]

[3] Last accessed 23/05/2022: https://discomap.eea.europa.eu/map/fme/AirQualityExport.htm.

The main environmental pollutants are listed according to the national set of rules which ensures that the limit values and reporting period for calculating the concentration of pollutants in the air are given.

The shape of the rooms influences indoor health conditions when considered in relation to the number of occupants. Allometric relationships have been studied for urban spaces, assuming a relationship between population density and the extent of inhabited land similar to the one between body mass and metabolism in biology (D'Autilia and D'Ambrosi 2015). Extending to the analysis of residential land, this approach could lead to the identification of a "natural law" that takes into account other parameters as well as subjective and cultural constraints (Cardone and D'Autilia 2018). The allometry method makes it possible to identify a mathematical law based either on the variables normally used to define the living spaces or on different variables such as the sharing of common spaces. The law is expressed in a formal way and makes it possible to simulate different scenarios, providing an efficient analytical tool for studying and forecasting different urban contexts.

The presence of facilities and appliances (e.g., cooling and heating systems, one or more televisions, etc.) results in a given level of noise pollution, radiation, and consumption. This also affects the perception of the comfort of living.

The indoor pollutants come from a variety of sources. Human factors that contribute to indoor pollution include tobacco smoke, the combustion process of oil, gas, paraffin, coal, and wood. Man-made pollutants come from cleaning products and the use of household appliances and tools such as printers and plotters. Other important indoor pollutants come from the building materials and furniture materials such as chipboard or pesticide-treated cabinets, carpets, and paneling.

The indoor pollutants can be grouped into 3 main categories:

- chemical pollutants: nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), airborne particulate matter (PM10, PM2.5), benzene (C_6H_6), formaldehyde (CH_2O), polycyclic aromatic hydrocarbons (PAHs), environmental tobacco smoke (ETS), asbestos;
- physical agents: radon;
- microbiological contaminants (indoor allergens): mites, animal allergens, molds and fungi, outdoor allergens.

Outdoor pollutants infiltration can be due to ventilation systems and vents. Air-conditioning systems can easily become a breeding ground for molds and other biological contaminants and can spread pollutant agents throughout the building. In Tables 17.1, 17.2, 17.3, 17.4 and 17.5, the considered variables are reported together with the range and the units.

Once the levels and parameters to be correlated had been defined, the next step was to create a database of case studies. Based on the case studies created and their evaluation, the machine was trained to evaluate general indoor health, taking into account the previously defined environmental, architectural, and shape parameters.

17.3 Results

Once the four models were trained on the data, we tested their validity by means of test data. From the statistical analysis of the results, it can be seen that convolutional neural networks are the ones that work best (Figs. 17.3, 17.4, 17.5 and 17.6).

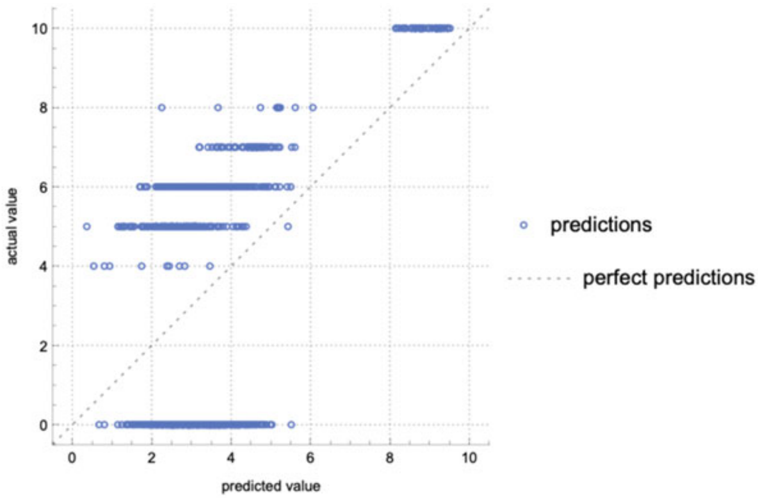

Fig. 17.3 Comparison of the perfect prediction with the linear regression model

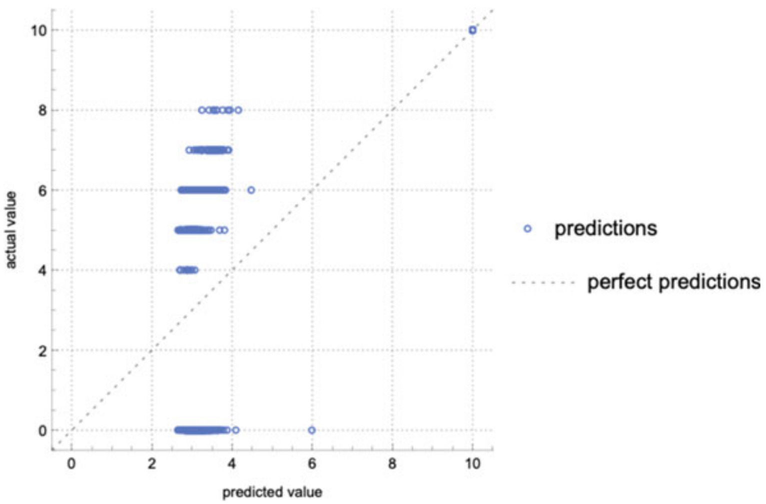

Fig. 17.4 Comparison of the perfect prediction with the nearest neighbors model

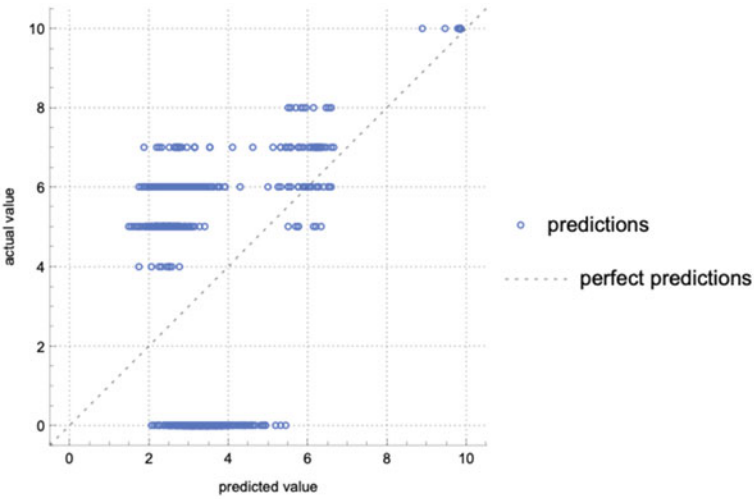

Fig. 17.5 Comparison of the perfect prediction with the convolutional neural network model

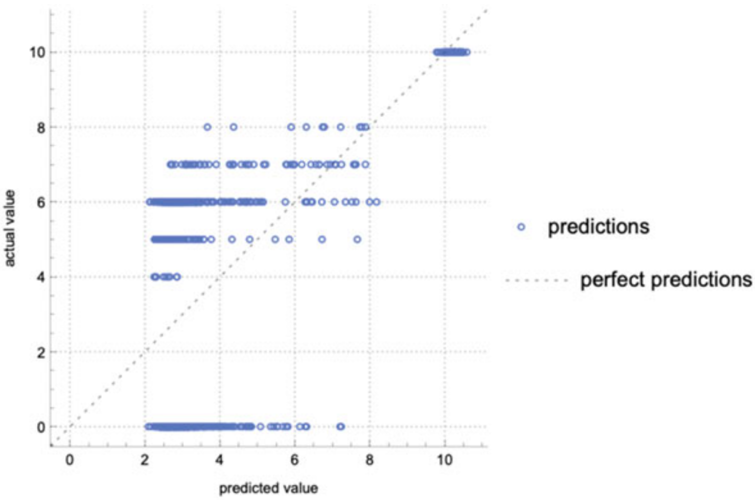

Fig. 17.6 Comparison of the perfect prediction with the random forest model

This result is somewhat unexpected because convolutional neural networks are very efficient for the recognition of images or in general of data arranged on a grid. The high level of correlation of the variables and their inhomogeneity has a correspondence with the distant characteristics of the images, such as the nature of the edges of a figure and its color.

The algorithm obtained is able to provide a habitability index as a function of the chosen variables. This means that, connected to environmental indicators, it provides a single number that could be visible on the "dashboard" of an apartment to inform the inhabitants of the level of domestic pollution. This instrument does not prescribe the actions to be taken, but, like a sort of speedometer, it informs people of the environmental situation, increasing their awareness, and the possibility of interventions. The algorithm can continue to learn as the available data increase, thus improving its reliability. Finally, the AI system can communicate with similar systems in the neighboring apartments, increasing its efficiency, and creating a global environmental map.

17.4 Conclusions

The described tool simulates a sort of awareness on the home governance, so that people can act in a specific way knowing that each choice has an impact in terms of environmental footprint. The predictor increases the precision of the calculations and the accuracy of the results as the number of cases analyzed increases.

In order to develop a more effective tool, it would be advisable to build a dataset based on measures related to more effective situations where all parameters are known. The final assessment should be carried out by a pool of experts on different topics, so that the conditions can be studied not only from an architectural and urban planning point of view, but also from a health and psychological point of view. In addition, the configurations studied can be labeled starting from the diseases that affect the residents. The creation of an effective predictor would make this possible:

- in-depth knowledge of the current situation concerning existing indoor environments' healthiness;
- widespread availability of an effective evaluation tool preparatory to the development of a sole and complete indoor environment health certification, which is lacking at the moment;
- estimation and production of effective solutions to renovate unhealthy environments;
- creation of a design tool to address the construction of suitable indoor environments;
- widespread and accessibility to in-depth knowledge of these topics;
- introduction of policies aimed at increasing healthiness in indoor environments;
- opportunity to educate users to a virtuous behavior, aimed at improving the healthiness in indoor environments.

The system's output is a dashboard, a sort of digital-control panel which allows the users to follow in real time the parameters related to their own consumption of energy and resources, through the connection with devices such as smartphones, tablets, and PCs. The overall ecological footprint is measured based on energy, environmental, water waste, and food "cycles."

The system uses IoT technology and processes the data collected by the sensors with artificial intelligence and provides a global assessment of the state of the house (a number), from which partial assessments and suggestions for better and more virtuous behavior can be derived. The final goal of such a system is to be connected with similar system to create a network of real-time information about the ecology of the indoor habitat.

The resulting tool does not deal with automation technologies to control the indoor spaces' comfort, but addresses tools able to make choices that allow occupants and information systems to learn together. The fine-tuning of these tools is enabled by the availability of parametric modeling software, jointly with opportunity to develop artificial intelligence models to calculate the connection among variables.

The development of devices to convert the large, heterogeneous, and variable amounts of data into information enables the development of a resilient and adaptable planning methodology based on the complex interactions between structural and technological systems, between spaces and functions, between social and economic factors. The machine learning system combines this data with indoor data from various sensors that calculate consumption, environmental parameters, and the behavior of people in each unit.

The final aim is to create a conscious "energy citizenship" living in energy-efficient buildings. Energy and functional issues were, and remain, one of the driving factors for sustainable strategic development, and the strength of the smart approach lies in its ability to promote a holistic vision. The measures related to single units can be applied to a wider network in order to create smart districts and smart cities, involving dwellers in a serious game on their homes' performance. The European Framework Program identified Smart Cities as one of the answers to the energy and environmental problems highlighted by the Strategic Energy Technology Plan.

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