Strategies for Domestic Energy Conservation in Carinthia and Friuli-Venezia Giulia

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***Abstract*—Households account for a significant fraction of overall energy consumption. Energy usage can be reduced by improving the efficiency of devices and optimizing their use as well as by encouraging people to change their behaviour towards a more sustainable lifestyle. In this study, we investigate patterns of domestic energy use in Carinthia (Austria) and Friuli-Venezia Giulia (Italy). In particular, we report the results of an online survey about electrical devices and their use in households. We outline typical scenarios in the two regions and discuss possible strategies to reduce the consumption of energy in these regions.**

Keywords: energy consumption analysis, electricity use, energy efficiency, household appliances, survey, smart energy

I. Introduction

Worldwide electricity consumption is constantly increasing, especially in developing countries, which has led to an increase in overall carbon emission. Between 1999 and 2004, residential energy consumption in the EU-25 grew by 10.8% [1]. Optimizing energy production requires tracking of the amount of energy users are consuming. Statistics of Austria for the years 2003 to 2010 [2] show that thermal use accounts for 40% of the total energy consumption broken down to water heating (16%), space heating (14%) and cooking (10%). For the 60 % non-thermal use, refrigerators and freezers account for the largest part (12%), followed by the other large household appliances (9%), lighting (8%), consumer electronics (7%), small appliances (4%) and standby (4%). Smart meters act as sensing units that provide producers with feedback about energy demand. Users can also make their demands more flexible, by postponing the use of certain energy-greedy appliances and avoid operating appliances in periods of peak demand. Therefore, households and their inhabitants play an important role in the grid. To effectively engage users, dynamic pricing mechanisms (e.g., critical peak pricing and real-time pricing) and persuasive interfaces have been introduced.

However, socio-economic parameters, such as number of inhabitants, their age and occupational status tend to affect the use of energy. For instance, [3] shows that the consumption produced by the washing machine, dryer and lighting is affected by the age of inhabitants, whereas the use of refrigerator and freezer is less affected by these factors. Since elderly people tend to live alone and spend more time at home, power consumption is 42% higher in such households. New and renovated properties with efficient appliances tend to be inhabited by young individuals who might be more aware or sensitive to energy conservation.

To successfully design energy management systems it is necessary to take regional differences into account. Low urbanized areas often have a less developed network of natural gas and district heating, which can lower the use of electrical energy for cooking and heating purposes. [3] shows that households in rural areas (i.e., Burgenland and Carinthia) tend to consume 21% more power than the ones in urban regions like Vienna. The costs of energy for water heating and cooking are 106% and 73% higher respectively in rural areas, while space heating is on average 172% higher in rural areas than in urban regions. Indeed, rural regions tend to have a higher proportion of semi-detached and detached houses, as well as larger living spaces (on average 118m^2 rather than 78m^2). These types of dwellings tend to have a higher energy consumption than appartments in large buildings, and, therefore, show a higher potential for saving energy. Moreover the lower density also facilitates the installation of alternative energy, especially photovoltaics, together with nearly Zero Energy Buildings.

This paper presents early results from the MONERGY[1] project. Our objective is to propose solutions to reduce energy consumption in the Austrian region of Carinthia and the Italian region of Friuli-Venezia Giulia. To this end, we intend to highlight commonalities and differences in circumstances and lifestyles that might affect the overall energy profiles of the households. In particular, we carried out an analysis of the devices that are most responsible for residential energy consumption. The objective of this study is to investigate patterns of energy use and outline typical scenarios in the two regions. Consequently, we will identify solutions to involve customers in saving energy and supporting the international reduction goals.

The remainder of the paper is organized as follows. In Section 2, we report previous work in classifying households according to specific characteristics of the building and the building's inhabitants. We then describe the approach undertaken in our study in Section 3 and analyze our findings in Section 4. In Section 5 we discuss potential strategies that could be employed in order to reduce energy consumption. Finally, we conclude the paper by outlining possible future directions of our project.

[1]MONERGY is a research project co-funded under the INTERREG IV Italy – Austria programme through the European regional development fund (ERDF) and national public resources. More at: http://www.monergy-project.eu/

II. Related work

The problem of determining the performance of households based on characteristics of the building and the behaviour of its inhabitants has already been widely addressed in previous studies. In [4], analysis of survey data is used to discover heating habits of recently built houses in the Netherlands. Exploratory factor analysis was used to identify a number of factors denoting the underlying relationships among observed variables. The five factors ('use of appliances and space', 'energy-intensive', 'ventilation', 'media', and 'temperature comfort') accounting for most of the variance were then used to extract behavioural patterns in the data. Finally, four user profiles were determined by correlating the factors to characteristics of inhabitants and the building. Nevertheless, the progressive installation of smart meters is paving the way for automatic methods that can extract habitual behaviour from the overall energy consumption of the household. In [5], electricity readings are sampled every 15 minutes and are analyzed in the frequency domain to extract specific features. The data is organized in days so that it is possible to apply principal component analysis and detect daily recurring behaviors. Moreover, the authors used interviews to interpret the activities performed by the users in their routines. Non-intrusive load monitoring (NILM) [6] can be applied to disaggregate the power profile of attached loads from the overall household consumption. In this way, information of devices responsible for the events detected can be used to annotate the energy use with higher accuracy. In [7], data collected from almost 8000 customers in Finland was analyzed using self-organizing maps [8]. The map is useful to discover which features are more expressive for the classification, since households with the same feature and mapped to the same cluster can be represented by that property. In addition, the authors computed the optimal number of clusters and applied the K-means algorithm to obtain them. In this way, they were able to group users and provide the users with an informative comparison to other profiles in the geographical neighborhood. The approach was also applied to metering data in the UK [9] and Republic of Ireland [10]. In [11], interviews with energy providers were used to collect a set of features to characterize customers. The authors analyzed consumption traces from more than 3000 households using a self-organizing map. The result of the analysis is a set of features that are more easily inferable from the metering data.

III. Research Question and Approach

Determining commonalities and differences in scenarios and lifestyles is necessary when planning strategies to lower energy consumption. This study is based on the following research questions:

- **Is there difference in the amount of electrical devices used in the two regions?**
  Due to the highly developed gas distribution network in Italy, we expect households in Friuli to exploit this resource rather than electricity. To test this hypothesis, we look for differences in terms of energy-greedy devices such as the ones used for space and water heating, as well as for cooking.
- **Is there difference in the diffusion of renewable energy sources between the two regions?**
  To answer this question, we look at the number of households that exploit renewable energy for producing electricity and heating water.

A. Experimental design

In order to define an exhaustive characterization of the scenarios we conducted a small study in which we ran a web-based survey on our project website. We studied characteristics of households (e.g., size and ownership), type of devices used and occupant behaviour, as they all affect the energy use. Our target population consists of people older than 18 living in one of the two regions. The survey was offered only in Italian and German. To collect a random sample of participants and ensure a correct distribution of respondents, the survey was simultaneously announced to families and via mailing lists to universities and various companies across the two regions. The validity of collected responses is determined by demographic data. Moreover, to cross check critical aspects we duplicated certain questions and placed them in the survey with different phrasings. In addition, we ensured anonymity and also that each respondent could complete the questionnaire only once. The survey required about 15 minutes to be completed and consisted of 43 questions grouped in 5 different sections:

1) Household information
2) Use of electric devices
3) Sensitivity towards energy consumption and renewable energy generation
4) Sensitivity and expectations towards technology
5) Demographic information

B. Pre-processing and feature extraction

After collecting data using the survey, we screened the dataset to remove any anomalies that might compromise the data. We paid particular attention to data entered by participants manually. For instance, we cross checked the number of floors with respect to the household size, and we bounded numerical fields. In a few other cases (e.g., type of education not matching with any given option), it was not possible to fix errors and we treated them as missing values in the analysis. In order to analyze the dataset and address our research questions, we defined a list of properties of interest (Table I). In this way entries can be described by specific metrics and the dataset can be partitioned into groups with similar characteristics. Feature vectors were automatically extracted from the pre-processed entries using the R statistical environment. To ease the analysis stage, we transformed nominal variables (e.g., type of dwelling) into multiple binary variables and we assigned a numerical meaning to each ordinal variable (e.g., frequency of use of air conditioners).

C. Analysis

Although we are carrying out a confirmative study, as the first step of our analysis we performed pairwise correlation to look for potential relationships in the dataset. In particular, we used Pearson correlation for quantitative data and Spearman rank-order correlation for categorical data. We then used the correlation matrix to perform principal component analysis (PCA), a variable reduction method which constructs a number of linearly uncorrelated principal components from observed

Factor	Variables
Household information	Ownership[a] Type[d], Size[c] Floors[b], Number of inhabitants[b] Daily time spent at home beside sleeping[b]
Laundry	Laundry times per month[b] Use of dishwasher[a], drier[a], washing machine[a]
Kitchen appliances	Presence of electric hob[a] Presence of electric oven[a]
Lighting	Switched to energy-saving light bulbs[a] Habit to leave lights on with no one[c]
Media	Number of consumer electronic devices[b] Habit to leave devices in standby[c]
Comfort	Use of electrical heaters[a] Number of air conditioning units[b] Use of air conditioner in summer[c] Number of electric boilers[b]
Sensitivity to energy conservation	Replaced devices in the last 4 years[a,b] Presence of photovoltaic plant[a] Presence of solar plant[a] Presence of wind generator[a] Presence of geothermal generator[a] Absence of tariffs promoting energy shifting[a] Devices would use in lower-price periods[b] Devices used in lower-demand periods[a,b] Average monthly energy bill[b]
Sensitivity to technology	Knowledge of Home Automation[d] Ownership HA system[a] Willingness to purchase[a] Usefulness of energy awareness[a]

[a] Binary variable
[b] Quantitative variable
[c] Ordinal variable
[d] Nominal variable

TABLE I. FEATURES USED FOR THE ANALYSIS

variables. This allowed us to map the high-dimensional dataset collected by the survey to a two-dimensional space defined by the two components accounting for most of the variance in the dataset. In the second part of the analysis we addressed the research questions by comparing the two regions according to the types of energy-greedy devices used and the number of renewable energy sources exploited. For this purpose, we used the non-parametric Mann–Whitney–Wilcoxon U test.

IV. RESULTS

We collected 340 full responses out of 397 participants, with an overall completion rate of 85.64%. More specifically, we received 186 responses from Carinthia (96 female and 90 male) and 139 from Friuli-Venezia Giulia (63 female and 76 male). However, the survey is self-selected, which means that people are invited to participate rather than selected using a probabilistic sampling method such as random sampling. Therefore, the results cannot be considered representative of the population, although we can analyze the data to possibly discover patterns [12], [13]. We report some demographic information of respondents in Table II.

A. Scenarios in the two regions

In order to outline typical scenarios, participants were asked to provide information of their household and the type of devices used. A first view of the dataset is given by the biplot produced by the principal component analysis (Fig. 1). As noticeable, certain features are particularly discriminatory for representing the two regions. Carinithians' use of electric hobs, heaters and boilers accounts for a greater share of their energy profile being accounted for by these devices but this is

Occupant Variable	Carinthia	Friuli-V.G.
Age 18 - 35	37.1%	59.71%
Age 36 - 45	29.57%	17.27%
Age 46 - 65	31.18%	20.14%
Age > 65	2.15%	2.88%
Primary school	0%	0%
Secondary school	1.61%	3.60%
High school	23.66%	33.81%
Bachelor's degree	4.84%	7.19%
Master's degree	35.48%	38.13%
PhD	29.03%	14.39%
Other	5.38%	2.88%

TABLE II. RESPONDENTS

less apparent in F.V.G. as a greater proportion of residents use gas-powered devices (and so these devices appear less frequent as part of their energy profile). On the other hand, people from Friuli tend to have more air conditioners. A further difference is given by the availability of adaptive tariffs, which is prevalent in Italy. This makes sense, as Italy has already completed the rollout of smart meters. Therefore, households can already exploit multiple tariff plans (e.g., day/night and weekday/weekend). In Carinthia, certain households use a night meter to manage the main electrical boiler using a cheaper tariff. Differences will be discussed in greater detail by reporting the results of the survey. Given a confidence level of 95%, the Spearman's ρ for the number of residents and the average monthly electricity bill is 0.408 for Friuli and 0.308 for Carinthia. The resources used for space heating and cooling are shown in Table III. The values Mdn and IQR represent respectively the median value and the first and third quantiles. Since users might simultaneously use various sources, we let users select multiple possibilities. In Friuli, the higher use of gas results from a more developed gas distribution network, whereas in Carinthia we can observe the presence of district heating, especially in urban areas. Concerning the amount of cooling units, a different climate might be the cause of the higher penetration of air conditioners in the italian region. To

Device	Carinthia	Friuli-V.G.
Electric heaters / heat pumps	10.22%	6.47%
Gas	9.14%	63.31%
Oil	21.51%	8.63%
Wood	11.29%	14.39%
Pellet	7.53%	3.60%
Coal	0%	0%
District heating	30.65%	0%
Solar plant	2.69%	2.88%
Geothermal plant	6.99%	0%
Air conditioner	2.16%	45.19%
Number of units	Mdn=1, IQR=1-1.25	M=2, IQR=1-2
Frequency of use	Mdn=2, IQR=1.75-2.25	Mdn=2, IQR=1-3

TABLE III. SPACE HEATING AND COOLING

find the frequency of use of air conditioners we assigned 1 to the frequency value "not every day", 2 to "less than two hours per day" and 3 to "more than two hours per day". Since it is an ordinal variable we found that the median value is 2, which corresponds to using air conditioners for less than two hours per day in the warm period of the year. As shown in Table IV, the availability of gas in Friuli results in a lower usage of electricity for water heating. The availability of gas affects also the type of cooking facilities, particularly electric hobs (Table V). Concerning the laundry frequency, we noticed that it is proportional to the number of inhabitants ($\rho = 0.488$ with $p < 0.05$ and $N = 322$). However, the difference between the two regions is less noticeable when observing the diffusion of

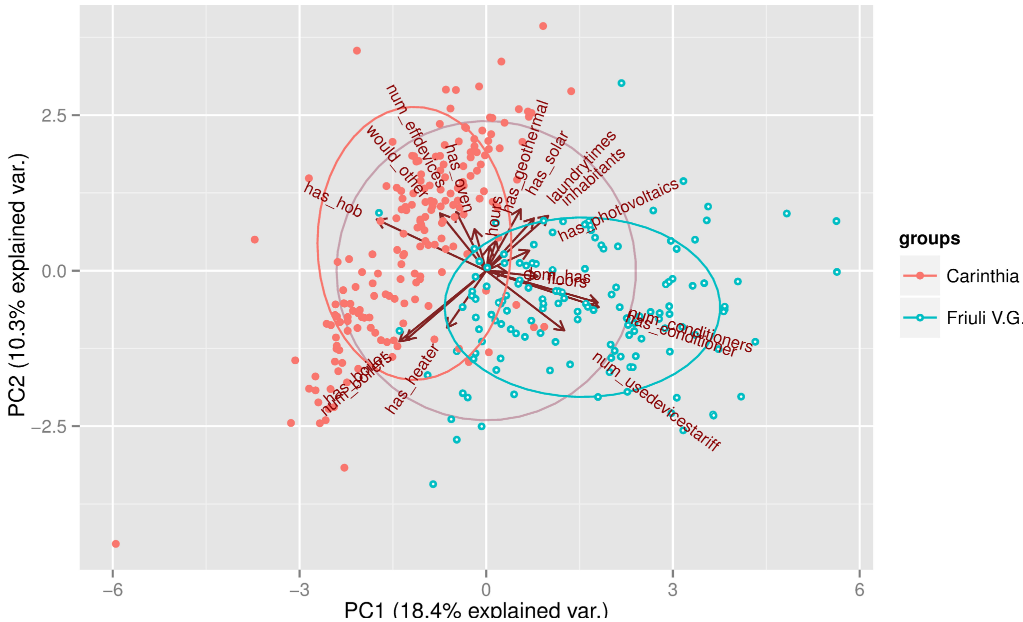

Fig. 1. Biplot of the principal component analysis

Device	Carinthia	Friuli-V.G.
Electric boiler	41.40%	12.23%
Gas	6.99%	82.01%
Oil	22.04%	6.47%
Wood	6.45%	2.88%
Pellet	6.45%	0.72%
Coal	0%	0%
District heating	17.74%	0%
Solar plant	15.59%	12.95%
Geothermal plant	7.53%	0%
Number of boilers	Mdn=1, IQR=1-2	Mdn=1, IQR=1-1

TABLE IV. WATER HEATING

Variable	Carinthia	Friuli-V.G.
TV	85.48%	89.21%
DVD/BlueRay player	69.35%	69.78%
Home Theater	7.53%	12.95%
Game console	34.41%	28.06%
HiFi stereo	63.44%	53.96%
Cordless phone	31.72%	66.91%
Computer	96.24%	97.84%
Printer and/or Scanner	73.12%	79.86%

TABLE VII. CONSUMER ELECTRONICS

Device	Carinthia	Friuli-V.G.
Hood	69.89%	82.73%
Dishwasher	84.95%	68.35%
Hob	98.92%	82.73%
Oven	95.70%	95.68%
Microwave oven	60.75%	61.15%
Fridge	98.92%	99.28%
Freezer	40.86%	27.34%
Electric hob	98.37%	5.22%
Electric oven	100%	87.97%

TABLE V. KITCHEN DEVICES

laundry equipment (Table VI) and consumer electronics (Table VII).

Variable	Carinthia	Friuli-V.G.
Laundry frequency (monthly)	Mdn=8, IQR=4-12.75	Mdn=8, IQR=5-17
Washing machine	92.47%	87.05%
Dryer	27.96%	5.76%
Washing machine with dryer	4.84%	7.91%
Iron	74.73%	76.98%

TABLE VI. LAUNDRY

B. *Energy-greedy devices*

To observe differences in terms of energy-greedy devices, we collected information related to the types of appliances used for: water heating (presence of an electric boiler), space heating (use of electric heaters), space cooling (use of air conditioners) and cooking facilities (presence of an electric hob and an electric oven). We could not quantify the use of certain devices such as electric hobs and ovens, so we compared the regions according to whether these devices are used. In particular, we ran a one- and two-tailed Wilcoxon U test. We first tested the null hypothesis that the observations collected on the two regions mean the same distribution. We then tested if the number of greedy devices in Friuli is greater than Carinthia. The null hypothesis was rejected in both cases with a $p < 0.05$ (Fig. 2). This indicates that the number of different energy-greedy devices used in Carinthia is higher than in Friuli. Although the

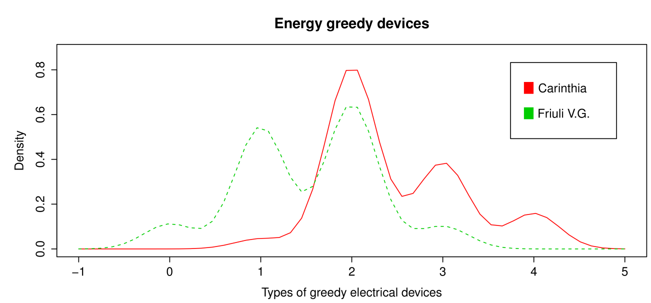

Fig. 2. Density plot for the types of greedy devices

higher amount of electrical devices represents a high energy saving potential in Carinthia, the absence of smart meters and time-dependent tariffs does not allow for the exploitation of classic demand-response strategies. In the survey, inhabitants from Carinthia expressed the willingness to exploit this kind of tariffs for operating the washing machine (48%), the electrical boiler (23%), and the dryier (20%). The 67.20% of users from Carinthia declared to have replaced an electrical device during the last 4 years to reduce the consumption at home. Among those, energy-efficient light bulbs (51%), washing machines (32%), televisions (19.89%), electrical hobs (15%), refrigerators (13.44%) and dryers (9.14%) account for most of replacements. On the contrary, households of Friuli usually can exploit multiple pricing conditions. Users declared to consider the current cost of electricity when using their washing machine (62.59%), lights (24.46%), iron (22.3%), electric oven (21.58%), dryier (10.79%), conditioner (10.07%) and dishwasher (9.35%). Similarly to Carinthia, lights (38.85%), washing machines (17.99%) and televisions (9.35%) are the most replaced devices.

C. Renewable energy sources

To observe differences in the penetration of renewable energy in the two regions, we counted the number of renewable sources exploited per household. In the survey we asked for the presence of: photovoltaic plants, solar thermal plants, geothermal plants and wind energy plants. We then ran a Wilcoxon U test with a confidence level of 95%. The null hypothesis that the observations are drawn from the same distribution was accepted with $p = 0.96$ (i.e. $p > 0.05$). Fig. 3 reports the density plot for the two distributions. In particular we noticed a very low penetration of geothermal heating, with just a person per region declaring to use it at home. Moreover, it is interesting to notice that in Friuli the number of photovoltaic plants is higher than Carinthia, with 7.91% and 2.69% respectively. However, the situation is opposite when looking at the solar-thermal heating, accounting for the 16.67% in Carinthia and 13.67% in Friuli.

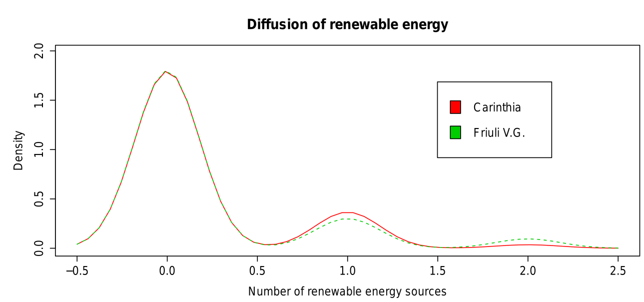

Fig. 3. Density plot for the number of renewable energy sources exploited

V. Strategies

Energy conservation strategies are implemented as feedback mechanism informing users of their consumption. Billing can be seen as simple example where consumption information is returned in terms of overall cost. However, the problem with classic billing mechanisms is that the actual use of energy is invisible to the user. The user receives a too coarse-grained information with significative delay to affect his decision making. Prepaid billing is a simple way to increase energy awareness, leading to average savings of 11% regardless of disconnections from the grid [14].

Pricing schemes can be used to incentive users operate in periods of the day in which the demand and cost of energy is lower. However, to effectively provide awareness of the energy available in the grid, tariff plans should dynamically consider the offer of energy, so that users can allocate the energy necessary for their activities by bidding it on a real-time manner [15].

Persuasive interactive systems are required to support users in understanding their use of energy, to make them responsible and induce a long-term change in their behavior and lifestyle. The work presented in [16] classifies feedback in *indirect* and *direct*. Displaying consumption in real time has been shown to raise user awareness and effectively lead to a reduction in energy use up to 15%. On the other hand, indirect information, such as analytics and trends are necessary to enable learning mechanisms, and consequently, long-term change. [17] identifies *antecedent* and *consequent* strategies. Antecedent strategies aim at preventing users to take a certain behaviour, by using information and tips, goal setting and commitment strategies. In consequent strategies feedback is returned to the users as consequence of their behavior, by displaying the amount of energy used. This information is often enhanced by positive feedback, such as a reward, which can be monetary or social when the consumption is compared to other people within a community. Energylife [18], [19] is an application defined within the European project BeAware [20]. It consists of a carousel of cards showing the consumption of individual appliances and the saving over the last seven days. In addition, it exploits this information to offer daily advices (e.g., devices consuming more or less than other days) and present a quiz every three days. Users can therefore collect rewards by saving electricity and actively participating in the application, i.e. reading advices and answering to quizzes. When certain conditions are satisfied, the lighting system is used as ambient interface to notify users about the current consumption. Nevertheless, studies have also shown that in spite of awareness, the effectiveness of these systems in making people responsible depends on their sensitivity and motivation [21]. The analysis in [22] assesses 36 studies performed between 1995 and 2010 to show that real-time feedback strategies using disaggregated information (i.e. consumption information down to the device level) generate the highest energy savings (see Fig. 4). This can be achieved by manually annotating the power profile [23], using Non-Intrusive Load Monitoring to automatically detect events from meter data [6], [24], and monitoring each device with multiple sensing units. Knowing which devices the user

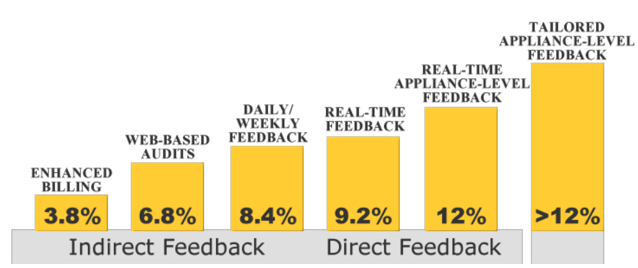

Fig. 4. Effectiveness of feedback [22], [25]

is interacting with allows applications to extract a model of the user's behavior from usage data. Applications can hence offer tailored services, such as personalized recommendations. According to [25], exploiting energy consumption patterns can lead to more effective energy conservation strategies, with estimated energy savings of around 20%.

VI. Conclusions and future work

This paper presented results from a web-based survey study with the goal of analyzing different scenarios in the region of Carinthia and Friuli-Venezia Giulia. We reported about possible strategies that might be considered when aiming to lower energy consumption. Driven by our findings, we are setting up a monitoring system consisting of distributed sensing units, which will provide a testbed for specific conservation strategies. In our current research, we seek to combine disaggregated consumption information with prepaid billing so as to turn appliances in pay-as-you-go devices. The presence of a virtual wallet tracking the expenses of residents might already provide savings in the absence of an advanced metering infrastructure, especially in Carinthia. From a wider perspective, we consider the household as a data space where devices are consumers and producers of events. Streams of collected events can be analyzed to extract frequent reoccurring episodes, for which it might be useful to propose specific control strategies. Episodes describe typical patterns of user behaviour, and as such, they represent valuable information that can be used to predict next activities and act beforehand. Indeed, tailoring strategies to residents has been shown to improve the effectiveness of sustainable living programmes.

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