Impact of eco-feedback on the behavior of campus users

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Abstract— **We propose a review of articles dealing with the behavior change of users due to the setting-up of an eco-feedback system on university campuses. The main building types studied are dormitories. Results show that feedback is necessary but it needs to be borne by human actions such as social influence, peer comparison, or competition to induce sustainable behaviors. A multidisciplinary solution is given to improve the impact of the eco-feedbacks on users.**

Keywords— Sustainable campuses; eco-feedback; occupant behavior; monitoring; dynamics correlation; Adaptive Multi-Agent System

I. CONTEXT

Due to their size, users and mixed activities, university campuses can be considered as districts or small cities. The students living there are away from their parental home, usually for the first time. Studies show that this may be the best time to give them good consumption habits [1]. Moreover, as students often pay fixed fees for energy consumption, they are a good study group to evaluate the impact of the feedback on their behaviors, independently of a financial motivation [2]. This article reviews diverse studies run on university campuses, the main objective being to reduce the energy consumption based on eco-feedback.

Scientists have shown with 95% certainty that human activity is the dominant cause of global warming, mainly due to GHG (greenhouse gas) emissions [3]. In order to reduce these emissions, a lot of efforts are made to develop energy saving technologies and to improve energy efficiency in buildings: they are called smart buildings. However, there are concerns over the long-term effectiveness of these improvements because of the “take-back effect” [4]. This effect occurs when a building user adopts a bad consumption behavior that could reduce or invalidate the energy gain associated with the improvement of the building. Moreover, behavior-based strategies to cut down energy use are among the most cost-effective on the market [5].

One of the biggest problems encountered by users attempting to reduce their energy consumption is the invisibility of energy. This leads to an ignorance of the real energy consumption and a misunderstanding of the distribution of energy use. For example, householders frequently underestimate their heating bills while they overestimate their lighting and various appliances consumption [6]. Furthermore, it is difficult to maintain efforts to cut down energy use when the results of these efforts are not known or seen. From these elements, it appears that an eco-feedback (information that helps to visualize energy consumption) is a necessary but eventually not sufficient condition to change behavior.

II. STUDIES AND METHODOLOGY

This synthesis reviews the works of J.E. Petersen et al. (2007) [2], T. Chiang et al. (2014) [7], A. Emeakaroha et al. (2014) [8], R.K. Jain et al. (2013) [9], H.-M. Chen et al. (2012) [10], V.L. Chen et al. (2014) [11], P.M. Johnson et al. (2010) [12], and M.J. Bekker et al. (2010) [13]. Results are summarized in Table 1. The studies all focus on university campuses, and mainly on dormitories. They have different objectives: showing that feedback can induce a behavior change, testing different elements of feedback (display, units, resolution) and testing different strategies to decrease energy consumption (competition, peer influence, rewards).

From these studies, a global methodology can be established: set-up of the feedback architecture (hardware and software), establishing a baseline (without informing participants), data recording, data analysis and eventually a survey to determine participants’ feelings about the feedback.

Feedback architectures. Various architectures are presented in these studies; they all monitor the electricity needed for lighting and plugs. They exclude HVAC systems because they are often centralized and students don’t have control over them. However, one of these studies presents a simple way to monitor HVAC energy consumption by setting up thermistors in order to determine when the system is on or off [11].

Baselines. Establishing a baseline from historical data (i.e. data from past years) has been rejected in all the studies because there is no clear way to know if the difference between the actual consumption and the baseline is due to the feedback or to the different groups of students: consumption has to be compared within a same student group [7]. All the baselines are therefore recorded just before the experiments (the baseline duration varies between 1 and 4 weeks). In order not to be influenced by external factors (mainly the weather), different techniques are set up. Authors check that if there are no important differences in temperature and natural lighting between the baseline and the experiment, then external factors are not the cause of the decrease in consumption [2]. Some of the studies also compare change in energy use between a tested group (with feedback) and a control group, but each groups' consumption is compared to its baseline [7-9]. Finally, they create a floating baseline (adjusted baseline) to take external factors into account [10].

Data access. Information security and privacy are taken into account. Students can check their consumption mostly through a personal code or card. As a code can be hacked, data are not identifiable (a set of data can't be linked to a user). A common way to interest users is sending them personalized emails [8,9,11]. Other additional incentives can be proposed such as rewards, competition or peer influence.

III. RESULTS

The work of J.E. Petersen et al. [2] appears to be a reference work. They carried out a two-week experiment by setting a "real-time feedback" in college dormitories. Among 22 dormitories, two had feedback updated every 20 seconds (high resolution), and the others had feedback updated every week (low resolution). A reward (ice-cream party) was proposed for the best group in energy conservation. Results show that the students who had high-resolution feedback reduced their energy consumption by 55%, whereas those who had low resolution cut their energy use by 31% on average. An unexpected result is that exclusively freshmen dormitories had a much greater reduction than exclusively upperclassmen dormitories (46% and 2% of average reduction respectively). Authors suggest that freshmen dormitories could develop a strong sense of community as their habits are not totally developed yet. Moreover, few winning students went to the ice-cream party, suggesting that they were motivated by something else than reward.

T. Chiang et al. [7] compared different eco-feedback designs: numerical, analogue dials and ambient faces design. They settled eco-feedback in 6 shared kitchens of a student residence. The daily average reduction reported is 8% without a statistical significance difference between the different designs. Furthermore, the authors found that students paid most attention to the ranking component of the display (based on their total energy consumption from the start of the experiment) and they found that the high-ranked student group had a greater tendency to take sustainable actions, probably in order to stay on top of the ranking. In contrast, the low-ranked group lost interest for the challenge and were unmotivated to improve their behavior. In addition, a discussion about self-relative ranking (comparison with own baseline) or other-relative ranking (comparison with others' consumption) suggests that both could be efficient but not for the same type of people. Self-relative comparison would be better for people who have high energy consumption whereas other-relative comparison should be more efficient for people with energy-efficient lifestyle.

In their study, A. Emeakaroha et al. [8] introduced the concept of energy delegates. Energy delegates are volunteer students who have to motivate other students, send them email alerts, interpret real-time readings and meet with other delegates to compare results. The experimental group had real-time feedback and energy delegates whereas the control group had real-time feedback and email alerts. Results show that the experimental group reduced its energy consumption by 37% and the control group reduced it by 3.5% whereas they had feedback, which confirms that feedback is not sufficient to change behaviors.

The experiment of R.K. Jain et al. [9] took place in an urban residential building located on a campus. They tested two different unit types within two student groups. Both had a weekly personalized email including tips for reducing energy consumption (e.g. reducing standby power, turning off lights, adjusting refrigerator cooling settings). Results showed that users preferred environmentally-friendly units (here, the equivalent number of trees required to offset CO_2 emissions associated with their electricity consumption) to kilowatt-hours (kWh). This is consistent with previous studies [14,15] showing that people have a limited understanding of kWh due to its abstract nature (hard to visualize).

H.-M. Chen et al. [10] tested an eco-feedback represented by a digital aquarium. Energy consumption was depicted by a dynamic ecosystem, where the healthier the ecosystem, the better the behavior. They set up this feedback in two adjacent

Author(s)	Building type	Additional incentive	Experiment duration	Participants	Energy savings	Location
J.E. Petersen et al. (2007) [2]	Dorm.	Competition & goal-setting reward	2 weeks	1600 students	31-55%	USA
T. Chiang et al. (2014) [7]	Dorm.	Competition & goal-setting reward	6 weeks	42 students	2.5-8%	UK
A. Emeakaroha et al. (2014) [8]	Dorm.	Energy delegate	4 weeks	1600 students	37%	UK
R.K. Jain et al. (2013) [9]	Dorm.	Peer comparisons	4 weeks	80 students	10%	USA
H.-M. Chen et al. (2012) [10]	Students office	Peer comparisons	8 weeks	40 students	10%	Taiwan
V.L. Chen et al. (2014) [11]	Dorm.	Peer comparisons	7 months	100 students	20%	USA
P.M. Johnson et al. (2010) [12]	Dorm.	Competition	1 month	750 students	10%	USA
M.J. Bekker et al. (2010) [13]	Dorm.	Goal-setting reward	3 weeks	190 students	10%	New Zealand

Table 1
Energy savings using information feedback

graduate student offices in order to allow users to compare their results and to encourage a social comparison. A 10% reduction in energy use was reported.

V.L. Chen et al. [11] proposed a feedback architecture to monitor separately HVAC, lighting and wall socket electrical energy. They found that 80% of dashboard activity was generated by 25% of students. Moreover, a behavioral study associated with this experiment [16] compared private to public information effectiveness. Private information was given as a personalized energy dashboard associated with weekly emails, whereas students in the public information group had stickers visibly highlighted. For a room, a green sticker meant this room was above the average consumption of similar rooms whereas a red sticker indicated the contrary. Results show that the students who had their consumption publicly displayed reduced their energy use by 20% whereas those who had private information about their consumption didn't succeed in decreasing their energy use.

P.M. Johnson et al. [12] proposed a residential hall energy competition on the campus of the University of Hawai'i called the "Kukui Cup". In the first edition (2011), 3 freshmen dorms were in competition. They had access to sub-minute feedback through personalized pages. One of the main purposes of this competition was to improve student energy literacy.

IV. Real-Time Eco-correlation detection

In order to improve his energy saving, one should precisely understand the consequences of his actions so as to be motivated to change his bad energy consumption habits accordingly. As a basic example, keeping the shutters closed and turning the lights on when the sunlight can light up the room causes a pointless energy consumption.

Our aim is to provide a computer system able to find, in real time, better-meaning correlations between users action and energy consumption (eco-correlation) from huge amounts of data (Big Data), generated by a network of sensors and connected devices (Internet of Things or *IoT*), and therefore present meaningful eco-feedback (focus on relevant correlations) to help the users find where and how they can minimize their consumption. To process these big data our system relies on a bio-inspired collective artificial intelligence (Adaptive Multi-Agent Systems) that uses a new analytical tool (Dynamics Correlation), described in the following.

For a better understanding of our system, let us take a toy study case of a student's room heated by an electric heater. See in Figure 1 the normalized data collected for that room from simulated sensor captor, the temperature (A) and the electricity consumption (B).

A. Collective Artificial Intelligence

The spread of the Internet of Things (sensors and connected devices) has led to the Data Flood, the exponential growth of ambient data. As a result, the conventional data analytic techniques require more storage capabilities and computing power, to keep up with the data flood, by reason of their centralized architecture. In centralized systems, a single unit or entity process all the data. Therefore, like its biological equivalent, the brain, a centralized system suffers from cognitive overload when the number of the external signal or perceptions reaches the system's limit. The cognitive overload causes, in the best case, a loss of information and can break down the whole system, in the worst case.

Nature gives us several examples of decentralized systems that thrive in harmful and highly dynamic environments, which have led to the family of bio-inspired collective artificial intelligence.

This subsection presents the fundaments of one of these artificial intelligences, the Adaptive Multi-Agent Systems (AMAS), used to design our system.

Emergentism vs Reductionism. One way of designing a decentralized system we could think about is to use a divide and conquer strategy. We split the main objective of the system into sub-objectives easier to reach and split these sub-objectives into smaller ones. We repeat this process until no more split is possible since the objectives of the lowest level can be realized with elementary actions. This is known in philosophy as Reductionism [17]. But as a matter of fact, this strategy results in a decentralized design process, not in a decentralized system. Indeed, in software engineering, all of the classical development processes rely on reductionism and we refer to them as Top-Down approaches.

In contrast to Reductionism, Emergentism has an opposite view of complex systems. Aristotle said: "*The whole is more than the sum of its parts*" [18]. We define this "more" as the interactions between the components (sub-parts) of a system hence the need to start designing a decentralized system from its components, with the purpose of including the interactions mechanisms in the design process. This gives rise to the Bottom-Up approaches.

Multi-Agent Systems. A Multi-Agent System (MAS) [20] is defined as a macro-system composed of autonomous agents which pursue individual objectives and which interact in a common environment to solve a common task. It is often viewed as a paradigm to design complex applications. The autonomy of an agent is a fundamental characteristic: an agent is capable of reacting to its environment and displaying pro-activity (activity originating from its own decision). As such, it is the building brick of a paradigm which can be used to model a complex reality in a bottom-up way, relying only on a limited and localized knowledge of the environment for each agent. And indeed, agents have been used in a great variety of fields, a fact which can contribute to explain the difficulty to produce a unified definition of the concept.

Emergence and Adaptation. Reductionism does not fully describe complex systems, given its lack of interactions modeling. Reductionism suffers from another issue, the need of a clear global goal, wherein emergentism such a global goal is not considered at all and the global function of the complex system arises from the interactions of its components, which is defined as Emergence [18]. One example of emergence, taken from nature, is the ability of ants to always find the shortest or the easiest way between the food source and the anthill, despite the absence of an ant leader that knows the location of each ant and gives them, accordingly, the direction to follow.

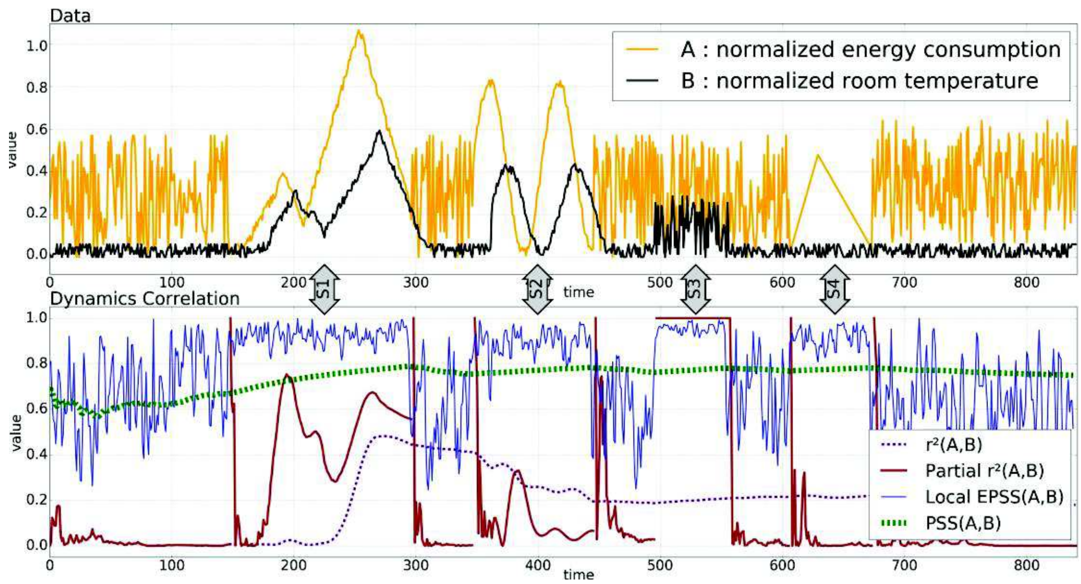

Figure 1 – Illustration of data (top) and their dynamics correlation (bottom)

An interesting result of the emergence phenomenon is the adaptation of the system to its dynamic environment, which means the reorganization of the system, caused by a perturbation, to remain in a well-functioning state. For example, if we put an obstacle on the foraging path, the ants will find a new shortest or easiest path to get back food efficiently.

The difficulty here is to give the system's agents the right behavior in order to get the right global function and a good adaptation capability since there is no formal process, which translates the behavior of the components and their interactions into a well-defined global function.

Adaptive Multi-Agent Systems. While it is not true for all MAS, some interesting properties can be achieved when taking advantage of the autonomy of the agents. This autonomy, coupled with an adequate behavior of the agents, can lead to systems able to adjust, organize, react to changes, etc. without the need for an external authority to guide them. These properties are gathered under the term *self-* capabilities* [21] (self-tuning, self-organizing, self-healing, self-evolving...).

A MAS relying strongly on self-* properties is an Adaptive Multi-Agent System (AMAS) [22]. A designer following this approach focuses on giving the agent a local view of its environment, means to detect problematic situations and guidelines to act in a cooperative way, meaning that the agents will try to achieve their goals while respecting and helping the other agents around them as best as they can. The fact that the agents do not follow a global directive towards the solving of the problem but collectively build this solving, produces an emergent problem solving process that explores the search space of the problem in original ways.

B. Analytical tools

The AMAS is a generic technique that relies on domain specific concepts to produce a domain adapted system. In this case, our system should rely on a new analytical tool, designed from conventional analytical tools, so that it can handle big data.

Correlation coefficient. The most spread analytical tool is a statistical one, the correlation coefficient r [23], defined as follows: $$r_{A,B} = \frac{\sum_{i=1}^{n}(a_i b_i) - n\bar{A}\bar{B}}{n\sigma_A\sigma_B} \quad (1)$$

Where, A, B are two variables (data features).
$\bar{X}$ is mean of X.
σ_X is the standard deviation of X.
n is the number of data points (values).

In statistics, if $r_{A,B} > 0$, A and B are positively correlated, then A's values increase as B's. If $r_{A,B} < 0$, A and B are negatively correlated, then A's values increase as B's values decrease. If $r_{A,B} = 0$, A and B are not correlated (independent). The higher the coefficient is, the stronger is the correlation and usually we use the correlation magnitude ${r_{A,B}}^2$.

This statistical correlation has two downsides. First, if $r_{A,B} = 0$, it does not necessarily mean that A and B are independent. For example, if $\mathrm{A} = \mathrm{B}^2$ then $r_{A,B} = 0$ but the two variables are in fact correlated. Second, when two variables are time shifted, such as $\sin(x)$ and $\sin(x + {}^{3\pi}/_{2})$ (both are sinusoidal functions that takes the same argument, but they are time shifted with a ${}^{3\pi}/_{2}$ delay), which leads to a null or very low correlation coefficient (illustrated as situation *S2* in Figure 1), and therefore a loss of relevant information. Especially in our application domain, where usually the effects of users actions are observed after a given amount of time like *S1* and *S2* in Figure 1, when the student turns the heater on its electricity consumption is immediate but the heat is sensed after a little time. Symmetrically when the student turns the heater off its consumption stops but the heat remains for a little time, inducing the time shift.

Phase Space Similarity. Another analytical tool, used in physics, called *Phase Space* [24] overcomes the downsides of the correlation coefficient thanks to its focus on the behavior of a single variable over time. The Phase Space is a collection of points, whose coordinates are calculating as follows:

$$\left(psx_{A_i}, psy_{A_i}\right) = (A_i - A_{i-1}, A_{i+1} - A_i) \quad (2)$$

So, one point of the Phase Space needs three successive values of the variable (A). For example, the Phase Space of a sinusoidal function represents an ellipse attributable to the cyclic nature of the sinusoidal function. Moreover, all the time shifted variables have the same or a similar Phase Space.

Like the correlation coefficient, we define the Phase Space Similarity (*PSS*) metric for an automatic comparison between two Phase Space, as follows:

$$PSS_{A,B} = \left(1 - \frac{\sum_{i=2}^{n-1} \sqrt{\left(psx_{A_i} - psx_{B_i}\right)^2 + \left(psy_{A_i} - psy_{B_i}\right)^2}}{(n-2)}\right)^2 \quad (3)$$

Put it simply, *PSS* is the squared complement to 1 of the mean Euclidean distance between each couple of points taken from each phase space. However, if the data aren't normalized (have the same scale) their phase spaces will have different scales and the *PSS* will, probably, be negative although they have the same dynamics, then the mean Euclidean distance should be divided by $\sqrt{2}$ after normalizing the data, otherwise by the maximal Euclidean distance:

$$\sqrt{\left(\max_{2\le i\le n-1} psx_i - \min_{2\le i\le n-1} psx_i\right)^2 + \left(\max_{2\le i\le n-1} psy_i - \min_{2\le i\le n-1} psy_i\right)^2} \quad (4)$$

Another drawback of *PSS* is when one variable has a well-defined dynamic (a phase space with a clear pattern like situation *S4* for data *A* in Figure 1) and the other one has a nondescript dynamic (a chaotic phase space), like a randomly generated variable (see *B-S4*, Figure 1), the *PSS* will be higher than it should, leading to confusions.

Dynamics correlation. Both of correlation coefficient (r) and Phase Space Similarity (*PSS*) have intrinsic limitations and unique features. So, to overcome their drawbacks we associate them into a new analytical tool by, first, using the *PSS* to identify situations of interest (S), data segments with high *PSS*, then computing r^2 of each segment (*Partial* r^2) to detect dynamics correlations. The use of the dynamics correlation is described in our system architecture.

C. AMAS for real-time eco-correlation

We presented in the previous subsections a collective artificial intelligence theory, able to cope with massive and dynamic environments, and a new analytical tool for a better data correlation study. Now let's see how we can combine them with the purpose of designing an Adaptive Multi-Agent System for dynamic eco-correlation detection.

The agents: system architecture. The system is composed of two types of agents: "*Percept*" and "*Correlation*".

- **Percept:** a *Percept* agent represents a sensor data stream. It receives the data, normalize them, send them with the newest phase space points, computed with equation (2), to its associated *Correlation* agents and links itself to other *Percepts* by creating common *Correlation* agents, in order to study the dynamics correlation, on the fly. Also, the percept helps other percepts to find dynamics correlations between them.
- **Correlation:** a *Correlation* agent is associated with two *Percept* agents and applies (implements) the dynamics correlation tool following this procedure:

1- For each new couple of data values (A_i, B_i), their corresponding phase space points $\left(psx_{A_i}, psy_{A_i}\right)$ and $\left(psx_{B_i}, psy_{B_i}\right)$ received from its Percepts A and B, compute the *local PSS*, meaning the *PSS* given only the last phase space points received:

$$LPSS_{A,B} = \left(1 - \sqrt{\left(psx_{A_i} - psx_{B_i}\right)^2 + \left(psy_{A_i} - psy_{B_i}\right)^2}\right)^2 \quad (5)$$

2- When the *local PSS* comes very close to 1, it is the beginning of a data segment called a situation of interest (S), like *S1* to *S4* (see Figure 1), then compute the correlation coefficient r^2 of this segment (*Partial* r^2) incrementally, using equation (1) where the mean and the standard deviation are updated as follow:

$$\overline{A_i} = \frac{S_i}{i} \; with \; S_i = S_{i-1} + A_i \, , S_0 = 0.$$

$$\sigma_{A_i} = \frac{Q_i}{i} - \overline{A_i}^2 \; with \; Q_i = Q_{i-1} + A_i^2 \, , Q_0 = 0.$$

3- When the situation of interest ends, meaning the local PSS moves away from 1, and the last value of the *partial* r^2 is higher than 0, then the data have a high dynamics correlation. Moreover, if the *partial* r^2 is near to 1 the data are statistically correlated, variating similarly (*S3* Figure 1), else they are time-shifted (*S1* and *S2* Figure 1).

4- Otherwise, when the *partial* r^2 equals or is close to 0 (see for example *S4* in Figure 1), it still is a situation of interest and needs the cooperation of the agents to find a percept which is correlated.

Cooperative behavior & Interactions. Cooperation is the engine of the self-organization processes taking place in the system and the heart of our bottom-up method. Cooperation is classically defined by the fact that two agents work together if they need to share resources or competences. We describe the cooperation mechanism of our Adaptive Multi-Agent System as follows:

1- Initially, when the system starts, each data stream is *agentified*, in other words, a dedicated *Percept* agent is created to represent and handle the stream.

2- A new *Percept* first builds a random neighborhood, which means it links itself to random *Percepts* by creating common *Correlation* agents.

3- As soon as a *Correlation* agent finds a situation of interest, the agent sends it back to its *Percepts*.

4- Then these percepts update their mutual correlation and spread it through their neighbors if the situation of interest represents a dynamics correlation.

5- Otherwise, the *Percept* with the well-defined dynamic tries to find a correlation with another neighbor for this data segment (active search) and the other *Percept* puts in contact the former with *Percepts* that have a well-defined dynamic for the same segment as well (passive search).

6- If after a long time the *Correlation* agent doesn't find any situation of interest, the agent becomes useless and signals it to its *Percepts* in order to launch an inquiry into a potential anomaly (sensors malfunction). Then the agent destroys itself.

7- Likewise, when a *Percept* doesn't receive new situation of interest or doesn't help other (5-passive search) anymore, it expands its neighborhood randomly to find new correlations. If this doesn't work the *Percept* raises an anomaly alert of uselessness.

8- Also, according to the openness property of the AMAS theory, when a new *Percept* agent is created, it will build a small random neighborhood and each of its neighbors suggests to it other interesting percepts.

9- Finally, when a *Percept* is not computing (it has free time) it expands its neighborhood by selecting the neighbors of its neighbors that have similar situations of interest.

This system is currently being developed and to sum up, the aim is to have the system explore a huge data space efficiently in order to detect eco-correlations and raises anomalies in real time. Thus, it can be used to choose which data to display for the users via the eco-feedback to increase the impact on them. In our example, the system point out to the student erratic use of the heater, which lead to a better eco-feedback.

V. CONCLUSION

Through these different studies appears a global methodology to test the impact of eco-feedback on students' behavior. The eco-feedback is a necessary condition to be aware of the real time consumption and to see positive consequences of behavior change, but it is not sufficient. It appears that every time there is a competition, a peer influence or a process involving human beings, results in energy consumption reduction improve. The main limits of these studies are the duration of the experiment which is often too short to determine if a change in behavior is sustainable, and the number of participants which is too low to obtain reliable statistics. As the impact of eco-feedback on human behavior is a complex subject associating different fields (e.g. psychology, sociology, computer sciences, human-computer interaction, educational sciences), more multidisciplinary work is necessary in order to find the best mechanisms to sustainably modify behaviors.

One example of such multidisciplinary work is the design of a collective artificial intelligence that uses statistics and physics to find correlations between actions of the users and their effects on energy consumption. Ultimately, there is a new need for a human expertise (the users) to interpret the eco-correlations and extract data relations, like cause and effect relations, between actions and energy consumption. A further work is to improve the eco-feedback by including those relations. For this purpose, we add to our system a dynamic relation detection ability using a new reasoning mechanism inspired from logic (Inference to the Best Explanation) and epidemiology (Hill's criteria of causation).

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