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Fabrice Crasnier, Jean-Pierre Georgé, Marie-Pierre Gleizes. Real-Time Learning of Power Consumption in Dynamic and Noisy Ambient Environments. 11th International Conference on Computational Collective Intelligence Technologies and Applications (ICCCI 2019), Sep 2019, Hendaye, France. pp.443-454, 10.1007/978-3-030-28374-2_38 . hal-02397445

HAL Id: hal-02397445

<https://hal.science/hal-02397445>

Submitted on 6 Dec 2019

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Official URL

DOI : https://doi.org/10.1007/978-3-030-28374-2_38

To cite this version: Crasnier, Fabrice and Georgé, Jean-Pierre and Gleizes, Marie-Pierre *Real-Time Learning of Power Consumption in Dynamic and Noisy Ambient Environments*. (2019) In: International Conference on Computational Collective Intelligence Technologies and Applications (ICCCI 2019), 4 September 2019 - 6 September 2019 (Hendaye, France).

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Real-Time Learning of Power Consumption in Dynamic and Noisy Ambient Environments

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Abstract. The usual approach to ambient intelligence is an expert modeling of the devices present in the environment, describing what each does and what effect it will have. When seen as a dynamic and noisy complex systems, with the efficiency of devices changing and new devices appearing, this seems unrealistic. We propose a generic multi-agent (MAS) learning approach that can be deployed in any ambient environment and collectively self-models it. We illustrate the concept on the estimation of power consumption. The agents representing the devices adjust their estimations iteratively and in real time so as to result in a continuous collective problem solving. This approach will be extended to estimate the impact of each device on each comfort (noise, light, smell, heat...), making it possible for them to adjust their behaviour to satisfy the users in an integrative and systemic vision of an intelligent house we call *QuaLAS: eco-friendly Quality of Life in Ambient Sociotechnical systems*.

Keywords: Ambient intelligence · Multi-agent systems · Complex systems · Collective learning

1 Introduction and Context

Miniaturization of technologies has gradually transformed our living spaces into pervasive environments with a sufficient level of perception to seamlessly interact with them, and where people now expect intelligent automation of their comfort. An ambient environment is made up of a multitude of heterogeneous devices, some measuring its physical characteristics while others act on its physical properties. Knowing how to operate such a complex and interconnected system is a first level of learning that is often left to experts in the field, as it currently requires specific modelling frameworks.

On the contrary, we propose to use an autonomous and local multi-agent adaptation approach so as to provide ambient sociotechnical systems immersed

in dynamic environments with real-time learning capacities. The main gap with existing techniques is the broader idea that, to fully understand and control a real-world complex systems, it is necessary to use an Artificial Intelligence approach that is itself a complex system [3]. We illustrate this concept with electrical consumption, which is similar to all other forms of learning about impacts of devices (on temperature, noise, light, smell...) with some slight modifications.

Below, after defining the concepts of the intelligent ambient environment, we explain why we decided to base our work on intelligent housing using a multi-agent approach. In Sect. 2, we present the multi-agent system allowing us to consider the self-modelling and simulation of electricity consumption by ambient socio-technical devices. Section 3 details some experiments and analyses them.

1.1 The Ambient Environment

As early as the 70's, home automation was described [6] as consisting of knowing and then controlling an environment using a number of detectors such as thermometers, hygrometers, radars and all kinds of electronic systems. In this representation, electronic devices are omnipresent in the environment but an operator remains in control of the execution of all tasks that act for his personal comfort. With technological developments, advances in information technology and in particular network interconnections, this vision evolved towards ubiquitous computing: computer devices are omnipresent, to such an extent that they gradually disappear to become one with the host environment. *"The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it"* [7].

In recent years, the number of connected objects in our personal and professional environment has increased steadily, in particular for *Industry 4.0* and *Smart Cities*. Figures of nearly 50 billion connected objects are announced for the beginning of 2050 with a spread within the new habitats averaging 250 home automation objects per household.

Research using ambient environments continues today with the advent of *smart-**¹. A particular interest is the focus on user *comfort* and environmental impact. Research such as [2] aims at determining the influence of the behaviour of the occupants on the thermal and visual comfort of this environment, as well as the impact on the energy performance of the building. To carry out these experiments, four offices were instrumented with sensors to detect environmental physical variables, as well as operations on blinds and windows.

[4] shows the difficulty of observing a highly dynamic environment with humans at the centre of the activity and designs a system capable of observing the recurrent actions of users so as to establish in which contexts these actions are performed in order to supplant the user if a similar situation arises.

[5] focuses on human activity in relation to residential power consumption. His approach is based on the SMACH platform [1] to simulate human behaviour

¹ Cities, grids, homes, environments...

in the habitat, which makes it possible to simulate the daily activity of households. It is defined as a set of inhabitants, tasks and electrical appliances. The central element is the notion of task. These tasks involve the use of energy-using household appliances, which are predefined in an environment for residents to use. This model, although scalable, requires a knowledge of the characteristics of the devices that will be added to the environment.

1.2 The Intelligent Ambient Environment

The combination of ubiquitous computing and artificial intelligence has given rise to a new field of research, that of ambient intelligence (AmI). The idea is that it is possible to continuously analyze the environment, learn about the user-environment interaction and model their activities. This provides an ability to discern situations, contexts or problems and dynamically adapt to them. It is noteworthy that, probably given the growing maturity of technology, there was a rapid interest from the industry in a domestic setting, as can be seen with the Philips HomeLab² inaugurated in 2002.

The European Commission, through ISTAG (Information Societies Technology Advisory Group) has been promoting the concept of ambient intelligence and providing guidelines for a unified vision of AmI. In 2001 the group imagined four illustrating scenarios³, showing different situations of use but all four integrate in depth the relationship between human needs and comforts, and their intelligent environment. ISTAG defends the idea that ambient intelligence should be attentive to the specific characteristics of each individual, adapt to the needs of users, be able to respond intelligently to spoken or gestural indications, and even engage in dialogue. It must be non-intrusive and most often invisible. Finally, it should not involve a long period of learning for the user and should be usable by ordinary people.

The purpose of our research is to enable an intelligent house to learn its *eco-citizenship function*, enabling it to minimize consumption costs when making decisions while remaining within the constraints imposed on it. But like Smart Grids, learning how to use electricity in a Smart Home (that can be integrated into Smart Buildings) is not a naive subject as current devices do not (or seldom, or not reliably) provide their own instantaneous consumption. It is also unreliable to estimate that the manufacturer's indications will be sufficient to predict the power consumption of each device in real time. It is also unrealistic to suppose that a device is always constant without degradation. Moreover, providing a complete set of new fully integrated devices would have a strong monetary and resources consumption impact. This is not eco-friendly, at a time when devices are being reconditioned to give them a second life.

Our work aims at showing how it is possible to take an existing environment with its devices and enhance it with artificial intelligence so as to have sufficient

² <https://www.noldus.com/default/philips-homelab>.

³ Scenarios for ambient intelligence in 2010 (ISTAG 2001 Final Report) (2001) by K. Ducatel, M. Bogdanowicz, F. Scapolo, J. Leijten, J. C. Burgelma.

elements to perceive, decide and produce adequate actions. In this context of activity, we assume that the main electricity meter provides the overall electricity consumption of the house and each device has only the ability to provide its operating condition as on/off (or it can be deduced, or the user has to indicate this). This minimalist information, which can be integrated at low cost into the habitat, has to still enable devices to learn their electricity consumption in order to participate in the function of minimizing habitat consumption.

1.3 Why a Multi-agent Approach?

In a real and evolving ambient environment, devices appear according to needs, operate intermittently over time, and disappear according to their obsolescence. Learning their power consumption can be seen as the resolution of a simple linear system. As shown in Fig. 1, to perform these calculations, it is necessary to create a linear system composed of p non-collinear equations p_i with n unknown variables d_k , where p_i represents a perception of the environment at a time t and d_k the power consumption of a device. Each perception p_i forms an equation where the consumption of each device is weighted by 0 or 1 corresponding to their operating state (on/off) at a time t and where the total consumption is known. This results, to be solvable, in an invertible square matrix ($p = n$) of rank n .

Perception \ Devices	Devices			Power consumption (Watts)
	1	2	3	
p[1]	ON	ON		352
p[2]		ON	ON	542
p[3]	ON		ON	925

$$S = \begin{cases} 352 = d1 + d2 \\ 819 = d2 + d3 \\ 925 = d1 + d3 \end{cases} \quad M = \begin{pmatrix} 1 & 1 & \square \\ \square & 1 & 1 \\ 1 & \square & 1 \end{pmatrix} \begin{pmatrix} 352 \\ 819 \\ 925 \end{pmatrix}$$

Fig. 1. Environmental perception set

As the overall consumption of the environment is equal to the sum of the devices in operation, the equation allowing us to solve the problem can be expressed as:

$$GlobalConsumption_t = \sum_{k=1}^n DeviceState_{k,t} * DeviceConsumption_{k,t}$$

Unfortunately, the formal solution of a system of linear equations is possible only in an ideal theoretic situation as it does not meet several of the requirements of a realistic ambient socio-technical system: (1) supporting dynamics⁴;

⁴ Adding devices, changing or removing some.

(2) supporting noisy data⁵; (3) proposing a solution at any time⁶; (4) having an acceptable resolution time for the studied environment⁷.

The Adaptive Multi-Agent Systems (AMAS) approach we propose enables the design of decentralized systems whose objective is to solve complex, incompletely specified problems, and for which there is no acceptable algorithmic solution already known [3]. According to this approach, the designer defines the local behaviour of each of the agents composing the system so as to obtain a global organization of these agents that produces an *adequate collective function*⁸. This organization between agents results from interactions between the multi-agent system and its environment, and by continuously and locally adapting to its dynamics, it is thus able to manage (and learn from) unforeseen events. The increasing complexity of ambient environments with the appearance of billions of devices favours the design of decentralized intelligent systems with self-* properties⁹. These systems consist of a set of autonomous and interacting agents, leading to the emergence of a collective behaviour. Thanks to their self-* properties, these systems are capable of adapting to and managing dynamics due to endogenous and exogenous changes. This approach has already shown interesting results in Ambient Intelligence [4].

2 A Power Consumption Estimation MAS

Our research aims at enabling each device in an ambient environment to continuously estimate its own power consumption. The multi-agent consumption system model presented in Fig. 2 shows the environmental perception capabilities, i.e. the overall electricity consumption of the environment as well as the operating states of the actual devices (roller shutter, radiator, ceiling lamp, loudspeaker...). It is composed of an *Estimation agent* and *Device agents*. An Estimation agent processes the perceived data and solicits the Device agents representing real ambient socio-technical devices within the MAS in order to obtain an estimate of their electricity consumption.

The Consumption MAS achieves this objective by minimizing the observed error between the overall consumption and the sum of the electricity consumption estimates provided by the Devices agents. The evolution of the system is carried out by comparing the successive situations provided by the environment. A *situation* consists only of a perception of the overall consumption of the environment as well as the operating states of the actual devices (on/off).

2.1 The Estimation Agent

The Estimation agent is responsible of minimizing this power estimation error. To achieve its objective, the Estimation agent constantly cooperates with the

⁵ Due to imprecise or low-quality sensors.

⁶ Even partial or imprecise, possibly linked with a certainty coefficient or trust.

⁷ The solver has to start learning in real time and not wait for a specific data set.

⁸ Result or behaviour of the system considered satisfactory by an external observer.

⁹ Self-stabilizing, self-organizing, self-observation, self-optimizing, self-managing...

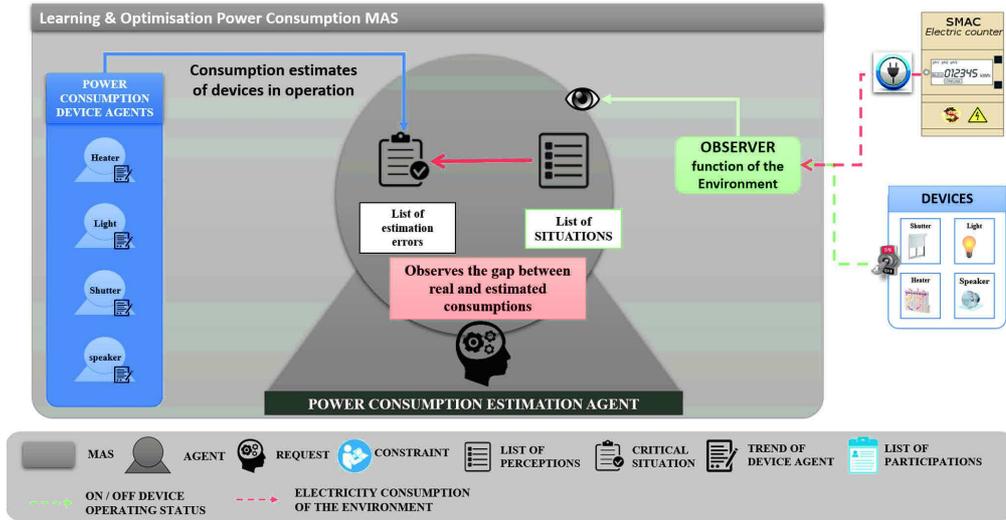


Fig. 2. Model of the multi-agent consumption system

Device agents by providing them with the necessary elements to improve their consumption evaluation (i.e. feedback). It receives new data from the environment whenever changes occur.

At time t , the Estimation agent perceives information from the ambient environment that we will call a *situation* S_i (see Fig. 3). It simply consists of the overall power consumption of the environment as well as the operating states (on/off) of the actual devices.

Devices \ Situations	Devices										Power consumption (Watts)
	1	2	3	4	5	6	7	8	9	10	
S[1]	ON					ON	ON	ON			741
S[2]	ON		ON	ON				ON	ON		1113
S[3]	ON			ON		ON		ON			953
S[4]	ON			ON		ON	ON	ON		ON	1392
S[5]		ON	ON					ON	ON	ON	1207
S[6]		ON				ON		ON	ON	ON	1372

Fig. 3. Footprints of the environment called *situations*

The Estimation agent calculates the estimation error, which represents all the errors made collectively by the Device agents at the time of their power consumption estimation:

$$Error = \sum_{k=1}^n (EstimatedDeviceConsumption_k) - GlobalConsumption$$

This is done for each situation (Fig. 4). The red/left bars indicate the overall power consumption of a situation and the blue/right bars represent the sum of the power consumption estimates made by the Device agents.

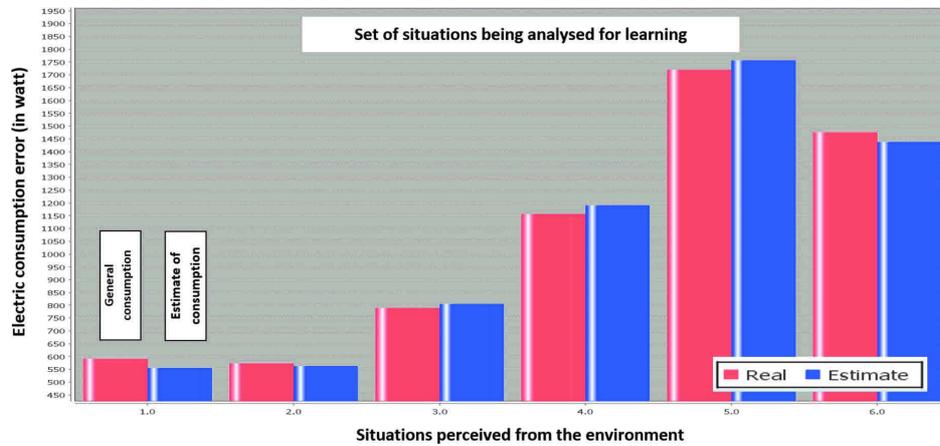


Fig. 4. Real versus estimated power consumption (Color figure online)

The Estimation agent consecutively memorizes the situations as the environment changes, thus forming a knowledge base of situations (Fig. 5). If the error is positive, the devices have collectively overestimated the value of the consumption and if the error is negative, they have underestimated it.

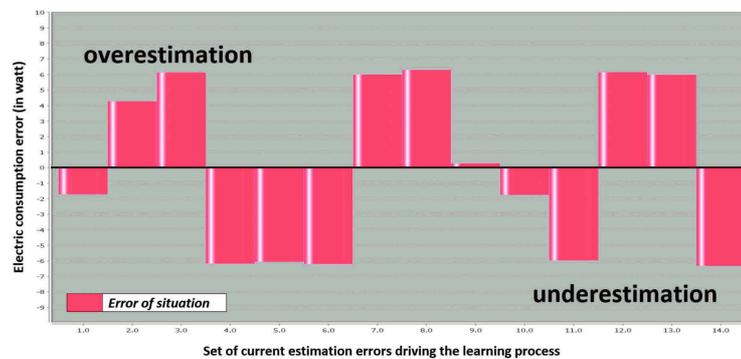


Fig. 5. Representation of errors in a knowledge base of 14 situations

In addition, the Estimation agent evaluates the convergence of consumption errors after each addition of a situation in the knowledge base (representing a *learning phase*), its approach to zero indicating that a collective solution is found. It is important to note that this solution, although already interesting for the user, is not necessarily indicating the exact real consumption of the devices, as a sufficient number of different situations is needed to have a unique mathematical solution. Nevertheless, its approach to zero indicates that the Estimation agent

is ready to integrate a new environmental situation in the knowledge base, as it is no longer sufficient to progress.

As long as the convergence of the maximum error is not close to zero, the Estimation agent requests of the Device agents to re-evaluate their consumption estimates. At each learning step¹⁰ of the agents, the Estimation agent provides the Device agents with all the errors for the situations in which they are involved.

Once the convergence of the maximum error is close to zero (Fig. 6), a learning phase ends and the Estimation agent integrates a new environmental situation (if it is available, else it waits for a change in the environment). The latter disrupts the balance of errors if the solution previously found was not exact. A new learning phase begins until there are no more disruptions in the errors observed, indicating that all device estimations are exact.

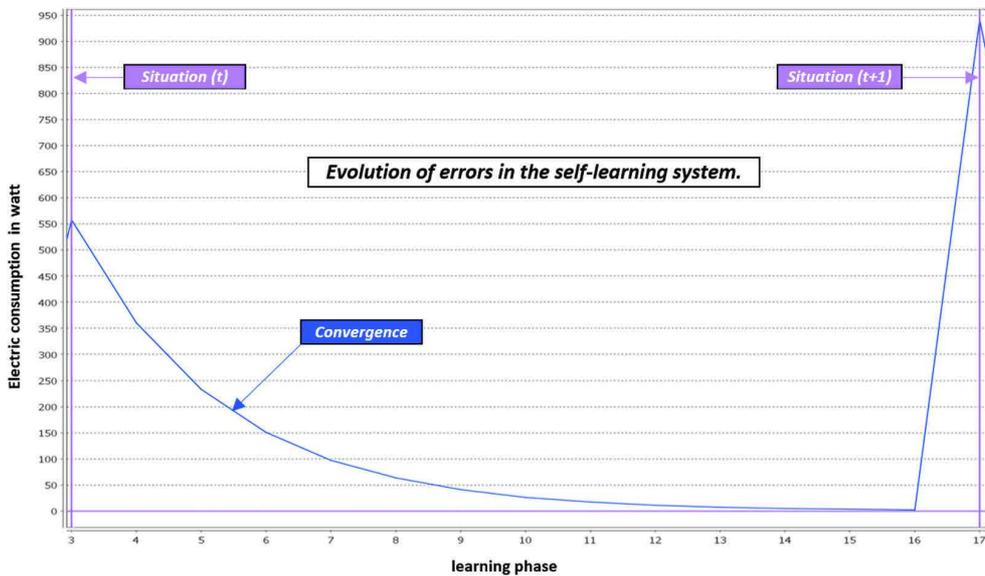


Fig. 6. Convergence between two perceptions

2.2 The Device Agent

The Device Agent is the virtual representation of an ambient socio-technical device of the environment within the Consumption MAS. Its nominal behaviour (its goal) is the learning of its power consumption and its cooperative behaviour is to help the Estimation agent to solve the consumption errors it observes.

The Device agent perceives the data provided by the Estimation agent, containing the estimation errors for all the situations in which it is active. As we indicated (Fig. 5), this information consists of positive and negative errors, and the Device agent will determine the maximum overestimation $C+$ and underestimation $C-$ errors. Its goal is then to minimize these *critical situations* but it can not usually do it by itself: changing its power consumption estimation will

¹⁰ Or life cycle of the agents: perceive, decide, act.

either increase both C_+ and C_- or decrease both, and the other active devices are also responsible of the error. Thus, it will mainly equilibrate them (trying to reach $C_+ + C_- = 0$) by calculating a value α allowing the balancing of these situations, such that:

$$(C_+ + \alpha) + (C_- + \alpha) = 0, \text{ which is: } \alpha = -\frac{1}{2}(C_+ + C_-)$$

Figure 7 shows an example for a Device agent analyzing 4 situations. The Device agent calculates the equilibrium point between the two extreme situations in order to obtain a maximum minimization (M) while collectively reducing their difference (E).

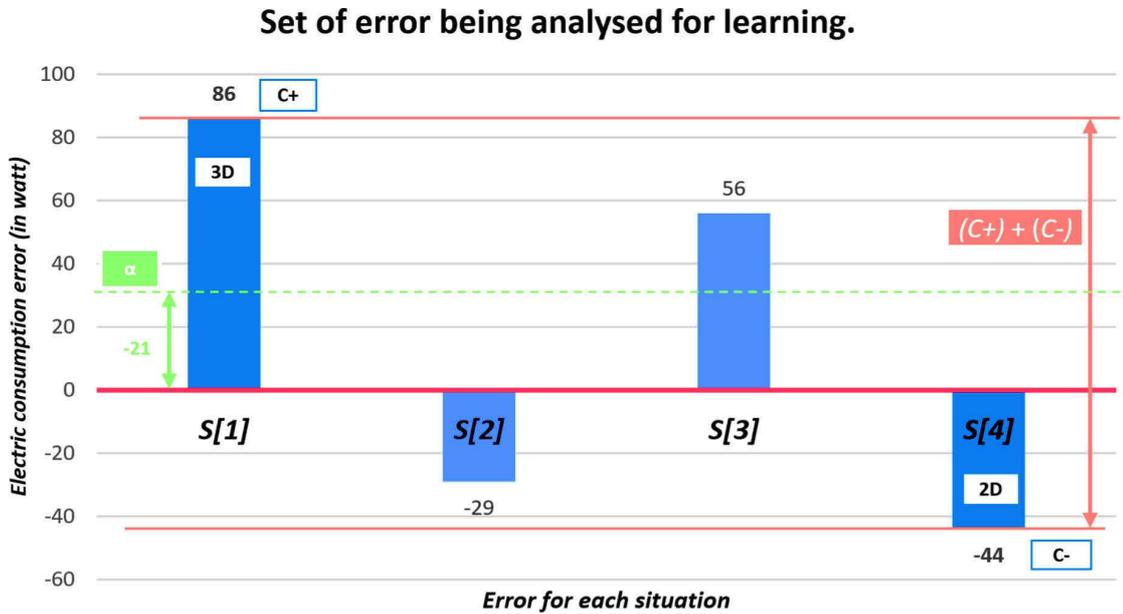


Fig. 7. Example of a minimization function.

The Device agent is able to determine the number of participants in the most critical situation that will possibly¹¹ help. Since it shares the problem solving with them, it can adjust its participation as follows:

$$\alpha = -\frac{1}{2}(C_+ + C_-)\frac{1}{k}, \text{ with } k = \text{numberOfParticipatingAgents}$$

The agent Device modifies its electricity consumption estimation at each learning cycle by adding the result of its minimization function, and transmits the new estimation to the Estimation agent. He also creates a history of his previous estimates to determine if he has a cyclical behaviour, thus indicating his inability to improve his estimation. It also transmits this information to the Estimation agent.

¹¹ It is uncertain as some agents may be part of other more critical situations.

3 Experiments and Results

We subjected our power consumption learning model to various non-noisy and noisy environments consisting of 5, 10, 20, 20, 30, 30, 40, 50 ambient devices respectively in order to observe its ability to pass certain scales (Fig. 8). We consider that the problem is solved if all devices have reached a learning error of less than 1%. Each learning scenario is repeated 10 times to obtain an observation average that reflects reality. Indeed, since perceptions of the environment are random, in some cases, some perceptions do not serve any useful purpose in learning and even disrupt the system, but they are part of the perceptions generated by the environment. It is therefore important to show the system's ability to take this disruption into account. We can study the average number of perceptions of the environment necessary to solve the problem as well as its average speed of learning.

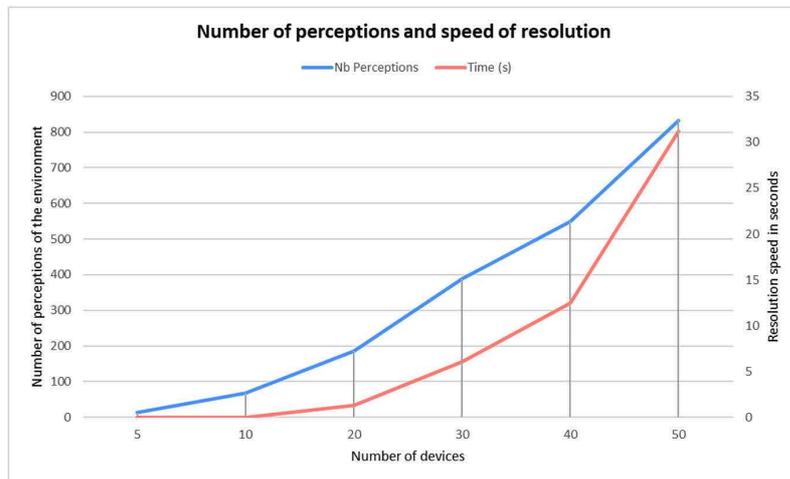


Fig. 8. Number of perceptions and speed of resolution

We can observe in real time how an agent adjusts its estimation. In Fig. 9 with 10 devices for instance, an agent appears in the environment as soon as the multi-agent system is started and progresses towards a limit of about 350 watts, which is its real power consumption.

With 15 devices, we show that the worst device error converges both in a non-noisy (Fig. 10) and a noisy (Fig. 11) environment.

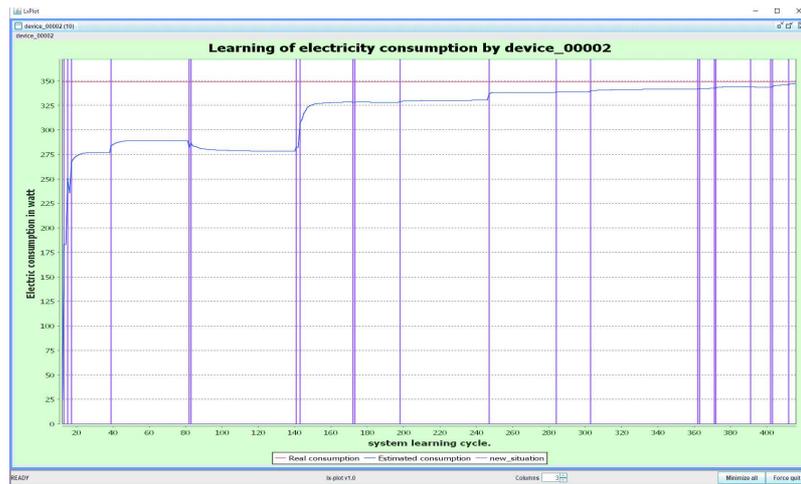


Fig. 9. Learning of electricity consumption by a device

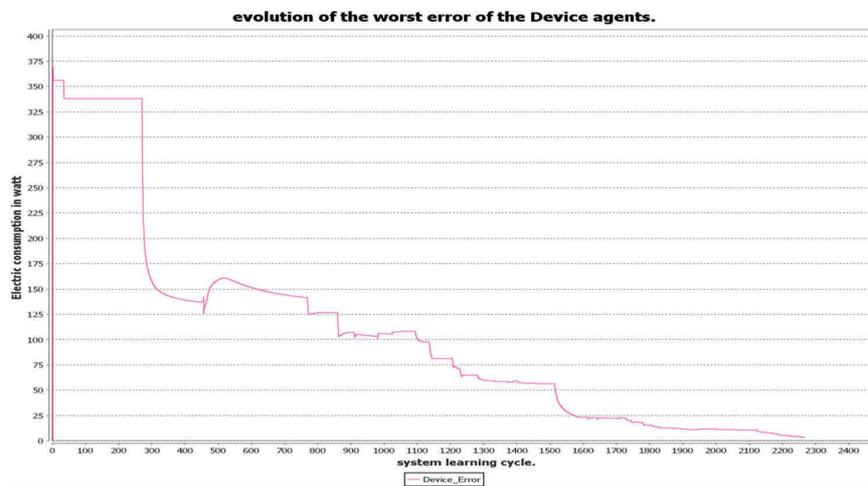


Fig. 10. Evolution of the worst error of the device agents without noise

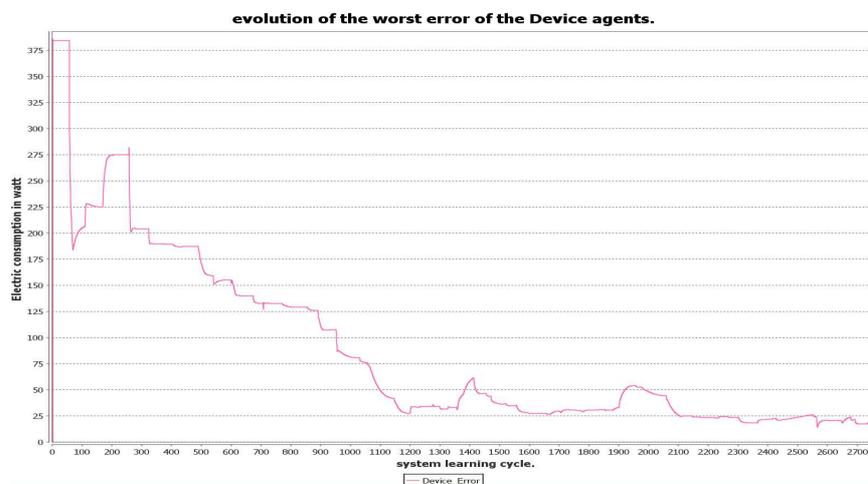


Fig. 11. Evolution of the worst error of the device agents with noise

4 Conclusion

We presented a multi-agent learning system for dynamic and noisy intelligent ambient environments and illustrated the concept on estimating power consumption of electric devices. Research on ambient habitat has generally focused on the study of human behaviour and most often relies on an expert knowledge of the characteristics of socio-technical devices. This type of data is currently not available in real environments (and seems generally unrealistic with all the new devices appearing all the time), so we propose a learning model with minimal resources, that can be deployed in any environment.

Thus, the self-adaptive multi-agent system we described seeks to achieve this objective by using only the overall power consumption and operating status of the devices. The Estimation agent observes the environment in real time as it changes and requests new estimates from Device agents until real and estimates match. The learning of the power consumption of each Device agent emerges as a result of the collective adjustments of the estimates of all the agents, as they try to correct the errors in each situation.

The next step is to use this learning model on the impacts of each device on physical comforts of the surrounding environment: how much a device consumes power or how much it produces heat, or light, or noise is quite similar. This integrative and systemic vision of an intelligent house, called *QuaLAS: eco-friendly Quality of Life in Ambient Sociotechnical systems*, will be a system of systems that responds to eco-citizen behaviour while satisfying people living in an ubiquitous environment. The various self-adaptive multi-agent systems (one for each consumption or comfort) will have to coordinate to best meet all the objectives of well-being and eco-responsibility.

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