

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/324050254>

Multi-agent Model for Domotics and Smart Houses

Conference Paper · January 2018

DOI: 10.5220/0006757202230230

CITATIONS

4

READS

754

3 authors, including:



Guillaume Guérard

Pôle Universitaire Léonard de Vinci

30 PUBLICATIONS 150 CITATIONS

SEE PROFILE



Hugo Pousseur

Université de Technologie de Compiègne

10 PUBLICATIONS 11 CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:



Context-free Smart Grid Model [View project](#)

Multi-agent Model for Domotics and Smart Houses

Guillaume Guerard, Loup-Noé Levy and Hugo Pousseur

Pole Universitaire Léonard de Vinci, Research Center, Paris La Défense, France

Keywords: Multi-Agent System, Microgrid, Smart House, Home Automation, Demand-Response.

Abstract: Most of the demand-side management programs focus on the interactions between an aggregator and its users. Moreover, renewable energy production being irregular, increasing their number implies to predict consumption and energy storage or discharge in real time. This is why the consumption patterns of every device connected to the grid must be organized in order to optimize the global consumption of the grid. Studying the smart grid through modeling and simulation provides us with valuable results which cannot be obtained in the real world due to time and cost related constraints. In this paper, we focus on a multi-agent model to simulate a microgrid and domotics through automaton and energy consumption scheduling.

1 INTRODUCTION

Our society is electrically dependent. The Power Grid supplies energy to households, businesses, and industries. Nevertheless, disturbances and blackouts are becoming common. With the pressure from ever-increasing energy demand and climate change, finding new energy resources and enhancing energy efficiency have become the priority of many nations in the 21st century.

The classical electric power infrastructure that has served us sufficiently to a certain extent, also known as the grid, is rapidly running up against its limitations. Our lights may be on, but systemically, the risks associated with relying on an often overtaxed grid grow in size, scale and complexity every day. The Power Grid is evolving into a Smart Grid, where power systems, information and communication technologies meet in order to generate, transport, distribute and consume energy in a more efficient manner.

A Smart Grid is defined as following (Amin, 2011): it is capable of adapting, predicting and communicating with the different agents it is interacting with (production, consumers, weather...) to optimize production, transport and consumption of energy. It can be seen as a complex system optimizing efficiency, reliability and robustness of the electrical grid. It is made of intelligent nodes interacting autonomously to deliver power to consumers by integrating advanced control and communication techniques.

A smart grid must allow customers to make informed decisions about their energy consumption, adjusting both the timing and quantity of their electricity use. Such technologies detect the need for a load shedding, communicate the demand for participating users, schedule load shedding, and verify compliance with the grid.

From 1980s, many technologies have emerged. Automatic meter reading was used for monitoring loads from important customers, and evolved into the Advanced Metering Infrastructure, whose meters could store how electricity was used at different times of the day. Monitoring and synchronization of wide area networks were revolutionized in the early 1990s when the Bonneville Power Administration expanded its smart grid research with prototype sensors that are capable of very rapid analysis of anomalies in electricity quality over very large geographic areas.

By the late 1990s, home automation was commonly used. Automation describes any system in which informatics and telematics were combined to support activities at home. Security, privacy, reliability and robustness are important aspects concerning power grid operations. According to the Federal Energy Regulatory Commission, demand-response (DR) is defined as:

The changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when

system reliability is jeopardized.

Because a Smart Grid evolves through time and architecture, a multi-agent model is needed to understand its complex behavior. A centralized point of view is unsuitable to solve every problem in a Smart Grid; where a distributed or systemic approach gives tools to model, to understand and to simulate various agents with their own behaviors in interaction.

The paper presents a simulation of a microgrid with random devices in a context of Smart Grid. By the way, the goals are to reduce peak demand, to smooth the consumption curve and to adapt devices' behavior in function of the local requirements and the overall system.

This paper is organized as the following: in the second section demand-response is introduced in order to define a generic model for home automation following by some examples in section 3. Section 4 presents a multi-agent model in a smart grid context. First results are shown in section 5. A discussion about the model and how to enhance it forms the last section.

2 GENERIC MODEL FOR HOME AUTOMATION

Demand-Response includes all intentional modifications to consumption patterns of electricity to induce customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption (Albadi and El-Saadany, 2007).

A Smart House is composed of many devices. They are divided into two categories: those that includes DR programs and those that don't. In our model, demand-response programs are based on price. For further details about price-based programs, we recommended the following articles by Albadi et al. and Cappers et al. (Albadi and El-Saadany, 2008; Cappers et al., 2010).

We classify devices thanks to simple rules about their process and the DR programs they can follow in the following article (Guérard et al., 2017).

A device is defined by a set of four categories, it picks one element of each category:

1. The device is cyclic (i.e. washing machine) or acyclic (i.e. freezer).
2. The device has or doesn't have batteries.
3. Which data are used: external (i.e. heater in the room) or internal (i.e. internal temperature of the refrigerator) or both.
4. The device consume, or produce, or both.

Then, a device gets a set of parameters. They are input values that determine how and when a device will consume or adjust its consumption following a DR program. The set includes:

Internal data : they correspond to internal data of the machine, collected by internal sensors.

External data : they correspond to external data of the machine, in its environment collected by sensors.

Consumer's preference : these parameters are the most important. Because the user should not be hampered in his daily life, its preferences are the bounds that devices have to reach.

Price : consumers, as described in (Kirschen et al., 2000), consider both current prices and the prices of one step into the future. To perform shifting, devices have to know how to schedule their consumption. In our model, we use current prices, prices of one step into the future and price trend. The last two are calculated from derivative function, norms and a pricer.

There are four general DR programs (QDR, 2006; Sezgen et al., 2007; Valero et al., 2007):

Reducing Power: customers can reduce their electricity usage during critical peak periods when prices are high without changing their consumption pattern during other periods.

Shifting: customers respond to high electricity prices by shifting some of their peak demand operations to off-peak periods.

Spinning Reserves: customers use local batteries and distributed generation combined with loads' management.

Emergency Cut: when the peak demand is still active even after the first three actions, an emergency cut is operated.

For each combination of category-parameters-program, an automaton is created. A device is an aggregation of various automaton that describes its behaviors in function of time, consumer preference and real-time price.

3 EXAMPLE OF HOME AUTOMATION

As an example, we will present a cyclic, consumer, without batteries, with internal parameters' device: a dish-washer. In this automaton, a letter of its alphabet

is read every 5 minutes. In order to have a more accurate automaton, we can discretize time in more steps. Those works will be shown in a further paper.

Depending on the dirtiness of the dishes, the dishwasher cycle will require heating the water a different number of times and for different times as shown in Figure 1. However the states "cleaning" and "rinsing" (with a consumption respectively at 2100W and 40W) remain the same. Thus, the automaton makes it possible to model all the cycles with only three states representing its consumption: StandBy, 2100 and 40 (Figure 2).

It allows a large number of arrangements. Indeed, according to the conditions (C_iV) the automatons will create a stack of alphabets elements (L_i) describing the succession of the stages of the cycle. The automaton will unstack from one element to another until the end of the cycle.

For example, to model the *test1* consumption the automaton take the following stack:

$L_1 = 40, 2100, 2100, 40, 40, 2100, 40, 40, 40, 40, 40, 40, 40, 2100, 2100, 2100, 40, 40, 40$

And to model the *test2* consumption the automaton take the following stack:

$L_2 = 2100, 2100, 40, 40, 2100, 40, 40, 2100, 40, 40, 40, 40, 40, 40, 2100, 2100, 2100, 2100, 40$

The presented automaton has a problem in the case where the average consumption during 5min is in fact neither 2100W nor 40W. It is then necessary to either round to the nearest state as done for the 35min-40min section of the red curve, or to create an automaton with more states in order to be more accurate to the real curves, and to take a better discretization of time (each 2min for example). Another automaton for the dishwasher is shown in Figure 3).

The following stack represents consumption of *test2*:

$L_{2bis} = 2100, 2100, 40, 40, 2100, 40, 40, 600, 40, 40, 40, 40, 40, 40, 2100, 2100, 2100, 2100, 40$

The model can be refined to the point of representing any consumption's curve. It is then possible, according to the discretization of the time, to estimate the various actions of the automaton. In our example, the input stack is fixed, so there is only one possibility of consumption.

For another automaton, we obtain a prefix tree of the form presented in Figure 4. It is important to note that from a prefix tree, it is also possible to build the associated finite state automaton as shown in Figure 5, so building an automaton for a device can be done by machine learning.

4 MULTI-AGENT MODEL

A system which consists of large populations of connected agents, or collections of interacting elements, is said to be complex if there exists an emergent global dynamic. This behavior results from the actions of its parts rather than being imposed by a central controller. That is a self-organizing collective behavior that is difficult to anticipate from the knowledge of local behavior (Boccaro, 2004). The complex system approach is described in the following articles (Ahat et al., 2013) and (Amor et al., 2014).

Computer modeling and simulation have proven to be a useful tool, if not essential, to help decision making in studying and designing complex artificial systems (Molderink et al., 2009). Any change in a Smart Grid involves millions or billions of Euros. Thus, any change needs a deep study and some simulations to integrate or to understand all the consequences and any kind of new behaviors, disruptions in the new grid.

A Smart Grid presents a shared resource among multiple actors, with divergent interests. A multi-agent system (MAS) modeling presents the global dynamic of the system from individual components and explores emergent properties associated with this dynamic. However, it should be noted that MAS have a major drawback: one model run does not allow to conclude about the relationship between model and results (Weiss, 1999). We will present in the next section some results, but previously let us expose our first model.

Our model focuses on microgrid. A microgrid is a broader view of local consumers, it is a tree structure representing an eco-district bounded by the upstream substation. Its goal is to distribute energy from a substation to consumers. It orders an amount of energy from the T&D network to local consumers.

A local consumer supports the consumption of energy, which is the distribution of energy among devices under its responsibility. In other words, a local consumer is defined by the area under the control of a smart meter or other automation/management controller. Those devices may also produce energy or storage energy.

The goals of any microgrid are to limit using external sources of energy, to avoid brutal changes in its consumption curve. The consumption of each device from each house has to be adapted accordingly to the microgrid's behavior. For the first simulation, we take four houses for one microgrid.

In each of the houses there are a number of devices: some have batteries others do not, some are cyclic other are not etc. These devices will turn them-

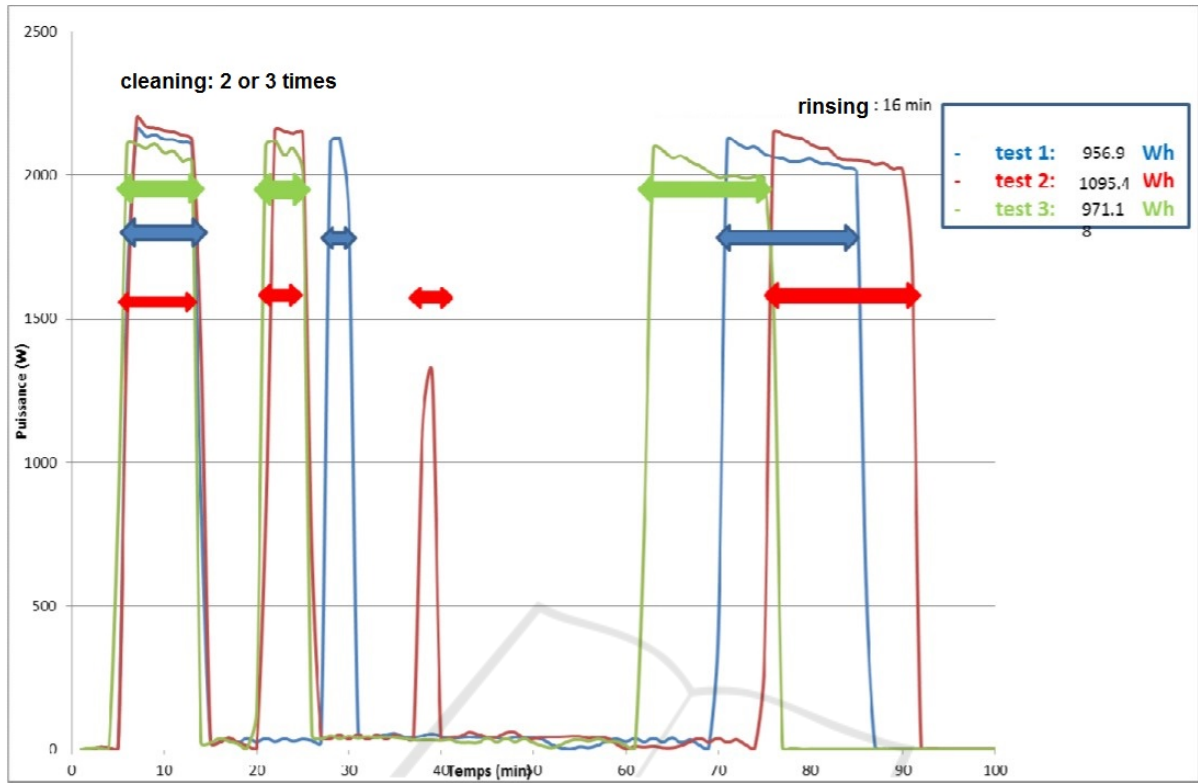


Figure 1: Consumption's curve for a dishwasher.

selves *on* or *off*, or will reduce/increase their consumption according to their automaton. Their behavior will depend on global variables of the microgrid as well as on local variables according to the previous section.

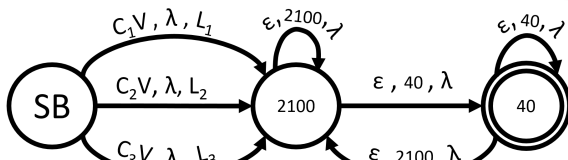


Figure 2: Automaton for a dishwasher.

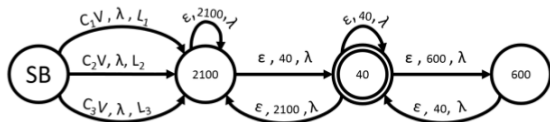


Figure 3: Automaton for a dish-washer (more accurate).

Each agent represents a device with its parameters and values. The device will choose a consumption scheme according to his situation. The devices with a battery can choose to charge or to discharge their batteries. The devices may choose to defer their consumption if they can. This way each device, in func-

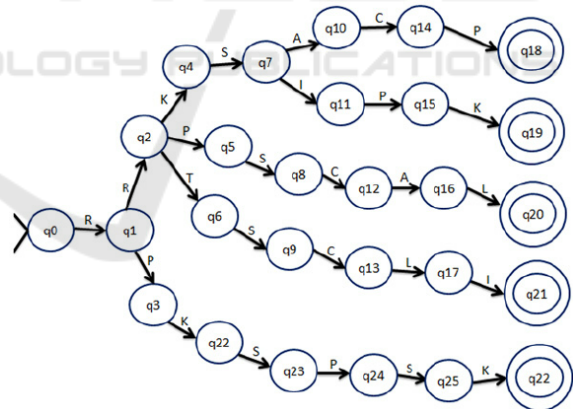


Figure 4: A prefix tree automaton (Datta and Mukhopadhyay, 2015).

tion of its automaton, has a variety of schemes it can choose to adopt.

On the UML diagram (see Figure 6) we can see how the internal and external parameters influence the behavior of the devices, whether it is by activating the battery or delaying consumption.

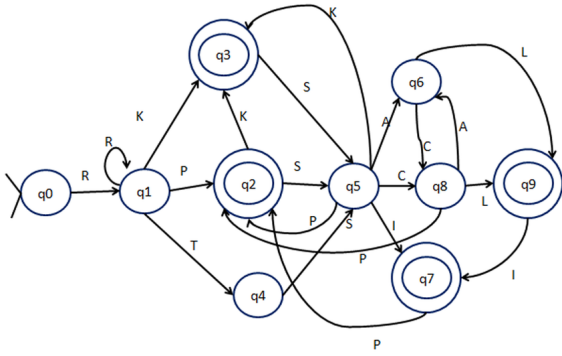


Figure 5: The finite state automaton associated to Figure 5 (Datta and Mukhopadhyay, 2015).

5 FIRST RESULTS

When the regulation is activated in the microgrid, the devices with a battery try to regulate the system using one principle: if the global consumption goes beyond the average value plus a tolerance value that is specific to each device, then the devices will set itself on battery mode in order to get the global value to get closer to its average value. This way, important variations are avoided. But if for every device the threshold tolerance value was the same, then they would all react at the same time, leading to important peaks in the global consumption (see Figure 7). Therefore, the variation of the threshold value must be adapted to the system to stay stable. The same principle is applied to the deferrable devices and with a load shifting program.

The global consumption is approximate to a cyclic curve. The consumption is higher in the evening and decreases rapidly after midnight. The model has been studied running in three different ways, first without any regulation, second with a well-adjusted regulation and third with a poorly adapted regulation. A day is divided in 144 time units.

The figure 7 represents the consumption in function of the time during a day without regulation.

On figure 8 we can see how the amplitude of the peaks are lower with a well-adapted regulation than with no adaptation. The consumption of the grid stays closer to its average.

On Figure 9, even though the consumption-mode-changing-threshold-value (the consumption value of the grid that makes the device change his mode of consumption) is different for each device, the response of the devices is not adapted to the grid. The distribution of the threshold values are not adapted to the variation of the consumption. This gives an overactive microgrid and therefore an unstable sys-

tem. Here, all the devices react the same way at a small decrease in consumption leading to an important rise of consumption, to which the devices react with an even greater decrease, leading the system of balance. The cause of this problem is the bad distribution of the consumption-mode-changing-threshold-value. The solution to this problem was the creation of a process in which the consumption-mode-changing-threshold-value of the device is regularly updated based on the historic of global consumption. This way the devices can adapt to a change in the grid.

On the figure 10, the regulation began after 140 ticks (unite of time). The system went off balance, but once the regulation activated, the devices adjusted their threshold values according to the historic of consumption and managed to find balance again.

6 DISCUSSION AND FUTURE WORKS

The simulation of this paper is based on NetLogo. NetLogo is a language and an IDE (integrated development environment) focused on MAS, allowing to easily create graphs, animations 2D/3D. The main reason to choose NetLogo is the simplicity for creating a prototype allowing fast results.

One of the disadvantages of NetLogo for our work is that the centralization of information about the device consumption cannot be done. In the last simulation, each device had to take decisions alone, only based on the global consumption. The best way to centralize information would be to create an agent with such a role. JADE allows the attribution of more specific tasks for each agent, with a more important consumption monitoring, and more interactions between devices. This representation is more realist, it's easier to implement a device controller than to implement a controller on each device.

Table 1: Comparisons between JADE and Netlogo.

Features	JADE	NetLogo
Utility	Post Prototype	Prototype
Open source	Yes	Yes (since v5)
Development	complex, longer	simply,fast
Task	Multi-threads	Only one
Synchronization	asynchronous	synchronous
Object Oriented	Yes	No
Ontology	Yes	No
Programs	Several	Only one
Service Notion	Yes	No
Language	Java	NetLogo

This table shows the principal differences between

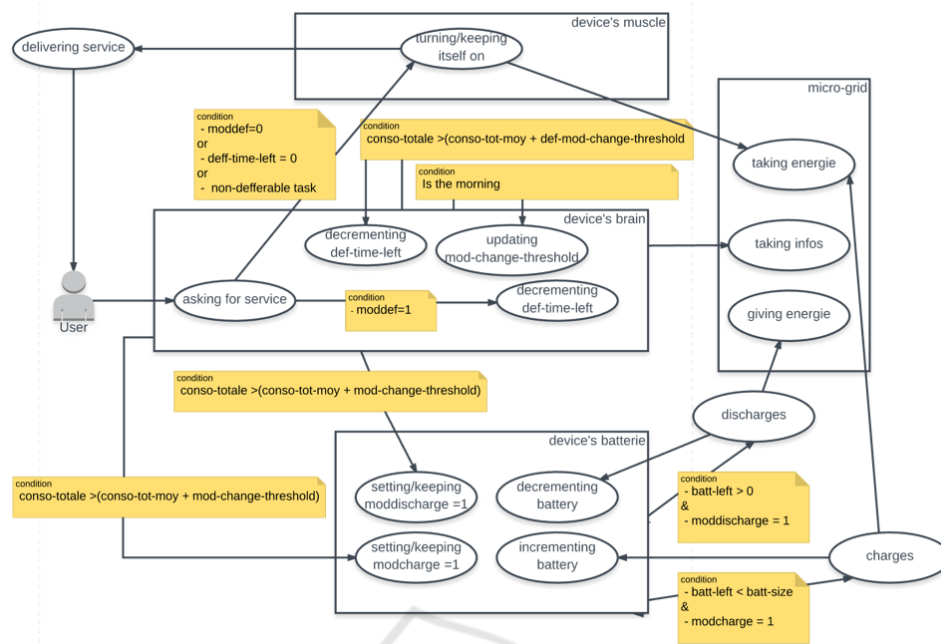


Figure 6: UML diagram of a device with a battery and shifting abilities.

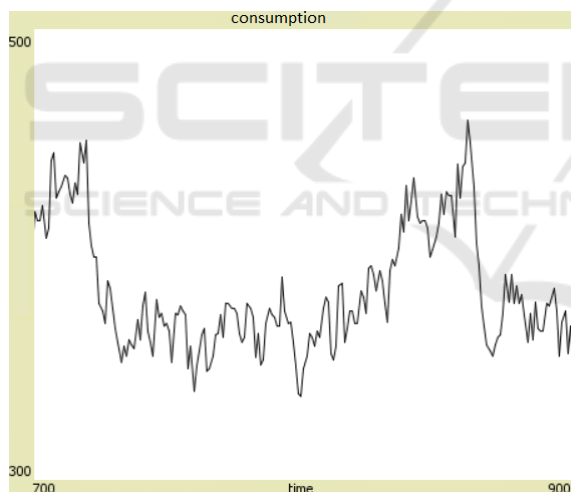


Figure 7: Curve with no regulation.

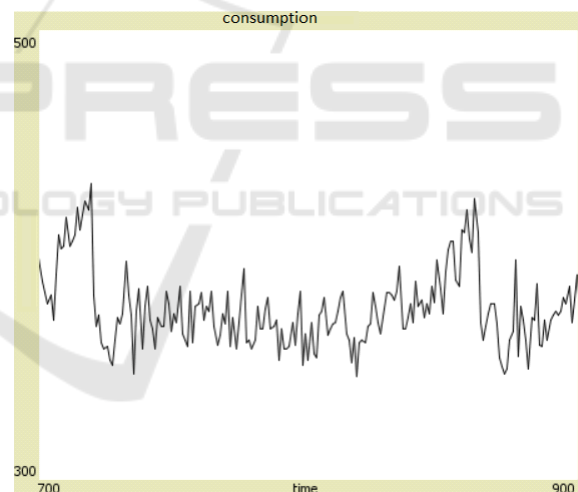


Figure 8: Curve with well-adapted regulation.

JADE and NetLogo

On the figure 11, the **control agent** analyzes the current global consumption. This analysis gives the best distribution strategy improving the optimization, taking into account:

- User parameters (each home gets difference consumption).
- Weather (outside and inside).
- Electricity market price (current price compared with the average price).
- The devices list already launched.

This agent can launch a device, ask a device to switch off (only if this device is an acyclic device). During a device execution, the control agent can change its consumption, but this change has an impact on the execution time.

Each consumer device is represented by an agent, at each creation, an agent begins by declaring himself at the directory agent and waits for an order gave by the control agent.

- A cyclic device executes the order until the task is finished.

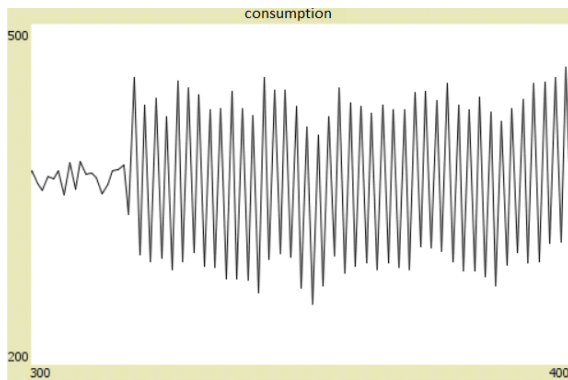


Figure 9: Curve with ill-adapted regulation.

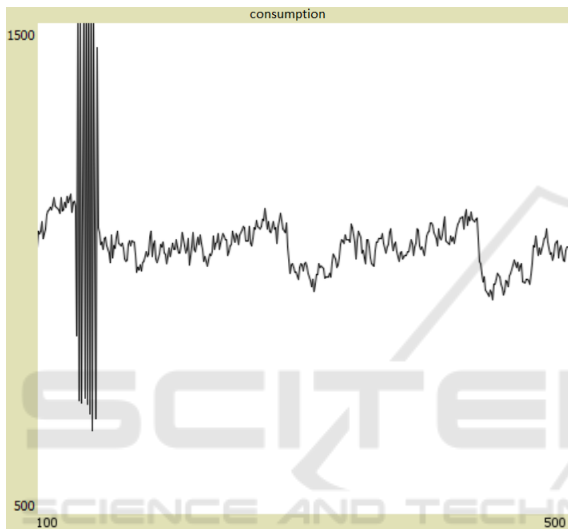


Figure 10: Curve with autoadapted regulation.

- An acyclic device executes the order until the control agent asks to stop.

When a device stops, the agent returns to the control agent the electric consumption used. After using an agent can be replayed.

Each edge represents interaction between two agents. The AID is an object of JADE, representing the agent address. The control agent needs to have the device AID for sending a launch request.

The JADE model will replace the NetLogo model in order to provide more results. The JADE model will be based on a real microgrid near Paris, France, named Le-Perray. This project aimed to combine BIM model, MAS model and deep learning process to optimize energy consumption, production and lower the price for all users.

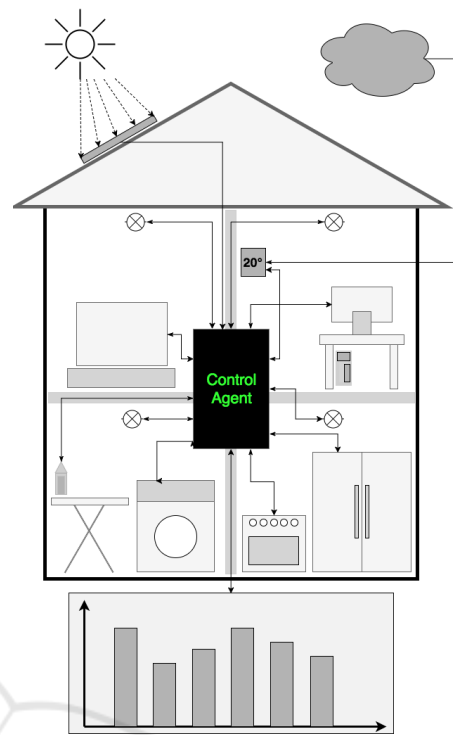


Figure 11: Control agent explication.

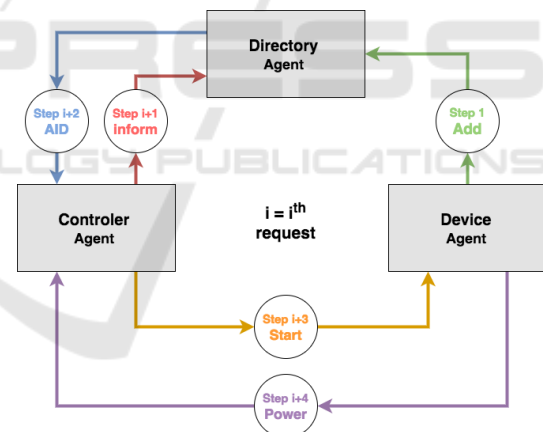


Figure 12: Interaction between home agents.

ACKNOWLEDGEMENTS

Two of the authors are in second and last year in an engineering school (France, the same degree as Msc). They work in a half-time curriculum with an associated professor about their subject (respectively a multi-agent model and a generic automaton model for smart devices). This paper concludes their first year in this curriculum.

REFERENCES

- Ahat, M., Amor, S. B., Bui, M., Bui, A., Guérard, G., and Petermann, C. (2013). Smart grid and optimization. *American Journal of Operations Research*, 3:196–206.
- Albadi, M. H. and El-Saadany, E. (2007). Demand response in electricity markets: An overview. In *2007 IEEE power engineering society general meeting*.
- Albadi, M. H. and El-Saadany, E. (2008). A summary of demand response in electricity markets. *Electric power systems research*, 78(11):1989–1996.
- Amin, S. M. (2011). Smart grid: Overview, issues and opportunities. advances and challenges in sensing, modeling, simulation, optimization and control. *European Journal of Control*, 17(5-6):547–567.
- Amor, S. B., Bui, A., and Guérard, G. (2014). A context-free smart grid model using complex system approach. In *Proceedings of the 2014 IEEE/ACM 18th International Symposium on Distributed Simulation and Real Time Applications*, pages 147–154. IEEE Computer Society.
- Boccaro, N. (2004). *Modeling complex systems*. Springer Verlag.
- Cappers, P., Goldman, C., and Kathan, D. (2010). Demand response in us electricity markets: Empirical evidence. *Energy*, 35(4):1526–1535.
- Datta, S. and Mukhopadhyay, S. (2015). A grammar inference approach for predicting kinase specific phosphorylation sites. *PloS one*, 10(4):e0122294.
- Guérard, G., Pichon, B., and Nehai, Z. (2017). Demand-response: Let the devices take our decisions. In *Proceedings of the 6th International Conference on Smart Cities and Green ICT Systems*, pages 119–126.
- Kirschen, D. S., Strbac, G., Cumperayot, P., and de Paiva Mendes, D. (2000). Factoring the elasticity of demand in electricity prices. *IEEE Transactions on Power Systems*, 15(2):612–617.
- Molderink, A., Bosman, M., Bakker, V., Hurink, J., and Smit, G. (2009). Simulating the effect on the energy efficiency of smart grid technologies. In *Winter Simulation Conference (WSC), Proceedings of the 2009*, pages 1530–1541. IEEE.
- QDR, Q. (2006). Benefits of demand response in electricity markets and recommendations for achieving them. *US Dept. Energy, Washington, DC, USA, Tech. Rep.*
- Sezgen, O., Goldman, C., and Krishnarao, P. (2007). Option value of electricity demand response. *Energy*, 32(2):108–119.
- Valero, S., Ortiz, M., Senabre, C., Alvarez, C., Franco, F., Gabald, A., et al. (2007). Methods for customer and demand response policies selection in new electricity markets. *IET generation, transmission & distribution*, 1(1):104–110.
- Weiss, G. (1999). *Multiagent systems: a modern approach to distributed artificial intelligence*. The MIT press.