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A Low Energy Consumption Wireless Cellular Network

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Abstract

In this paper, the SOGREEN project is presented, its aim is to study a new telecommunication network in which energy and wireless communications are jointly managed. We introduce reinforcement learning and the Hierarchical and Distributed Cognitive Radio Architecture Management (HDCRAM) which are respectively used for the energy management of the telecommunication network and as the network management architecture. We also show that the energy efficient network studied can be used for the smart grid and more precisely as a communication architecture or as a reserve for frequency support.

Introduction

Within the Framework of French ANR program, the SOGREEN project aims at studying a new telecommunications Network with very low energy consumption. For that purpose the main idea of this project consists in connecting very closely the cellular network with the smart grid.
Europe targets to develop a low-carbon economy through the 2020 roadmap. On the other side, forecast on ICT industry states a continuous increase in global CO2 emissions pushed by the exponential increase in data traffic that characterizes wireless networks. Hence, there is a strong request to reduce the overall footprint and to improve the energy efficiency of cellular networks. In the past, some progress has been made to increase the efficiency of single network components; however, to reduce the energy consumption of the system as a whole, we need to emphasize the interconnection of the power grid and cellular network. Accordingly, SOGREEN proposes a holistic Smart Energy system based on intelligent devices interconnected by means of communication networks. Through the tight integration of smart grid and wireless network and following a multidisciplinary approach, we expect to dramatically improve the energy usage.
Designing off-grid small cells and communication protocols to enable utilization of renewable energy in cellular networks is a promising paradigm for reducing the on-grid energy consumption of Next Generation Mobile Networks while satisfying the ever-increasing demand for high data rate services. Accordingly, SOGREEN aims to investigate a novel framework where green energy powered small cells and wireless backhaul equipment are interconnected to form small micro-grids, where radio and power resources are pooled and jointly optimized (see Figure 1). We envision a management system, provided by machine learning capabilities, which is able to observe its environment, predict its future status, and autonomously take decisions that optimize the system performance both in terms of data-services and energy consumption. However, optimizing the behavior and consumption of each of these individual cells does not necessarily guarantee overall network-wide optimality. Therefore, in order to tackle this aspect, besides the management of each cell, in SOGREEN we investigate possible system-wide synergies between the two infrastructures, i.e., electrical and cellular networks. This is becoming possible with the emergence of the smart grid and the decentralization of energy generation.
This paper is organized as follows: in the first section the concept of a green small cell connected to the smart grid is presented. Afterwards, the decision making algorithms based on reinforcement learning that are used in the management of a green small cells are described in section 2. The third section provides some insights on the possible services that the two networks can provide to each other and, in section 4, a Cognitive Radio Manager, named HDCRAM for Hierarchical and Distributed Cognitive Radio Architecture Management, is applied to this new mixed paradigm of cellular networks and smart-grid. Section 5 concludes the paper.

1. SOGREEN Small Cell Architecture

We propose an *innovative architecture* where small cells equipped with solar panels and storage capabilities are interconnected to a smart energy grid, where ICT provides the "intelligence and communication" vehicle to allow consumer, producer, and distributor to control and manage energy resources in real time.
Figure 1 shows the innovative framework proposed in SOGREEN. Three types of network are depicted: the first one is the classical communication wireless network; the second one is the Smart Grid network (or power system), which provides

electricity and thus enable mobile services. These two networks are very nested as it can be seen in Figure 1. The last one, often forgotten, is the communication network associated to the Smart Grid. Indeed, in order to be managed efficiently, the Smart Grid must have a communication infrastructure to exchange control information between all entities that it is composed of (smart meters, phasor measurement units, etc.). For instance, the communication between a small cell and a power system utility could be performed via a smart meter installed on the small cell, where a smart meter is a meter device equipped with communication ability. This last communication network may use the classical communication network to achieve these communications between entities, it also may use some advances Cognitive Radio techniques.

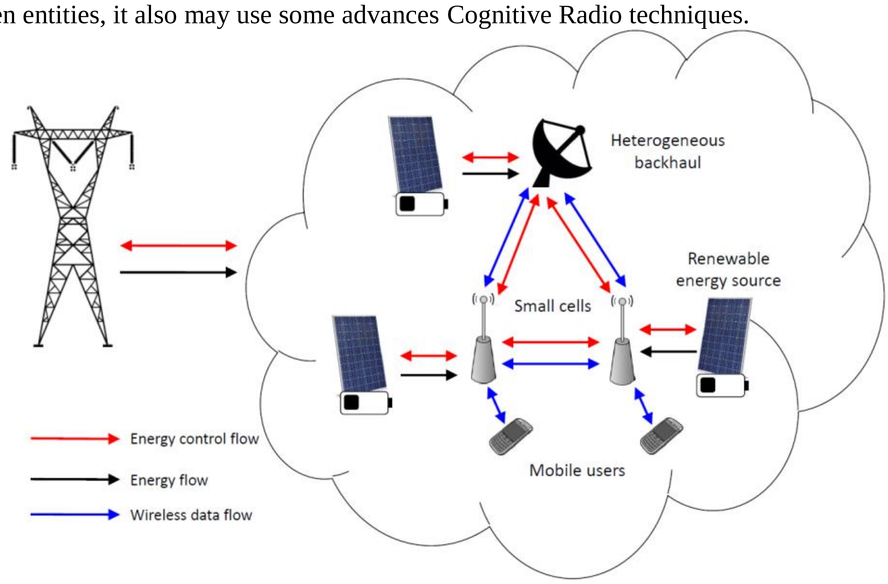

Figure 1 : proposed framework for joint optimization of wireless network and associated power grid

2. Energy Management of Green Small Cells

In the proposed architecture illustrated in Figure 1, the green small cells, deployed to offer high data rate services to local mobile users, are powered by two sources of energy: the smart grid and the renewable energy. From the perspective of mobile networks operators, this scheme offers several benefits compared with a classic grid-powered cellular network such as long-term cost savings and reduced carbon emissions. However, the variety of energy resources and the flexibility offered by local storage require planning and control for an efficient utilization, especially given the difficulty associated with integrating renewable sources due to their inherent intermittence. Additionally, in a large scale deployment scenario, the price framework (real time pricing) of the smart grid, the local production, and the energy demand of the small cells are likely to change profoundly, which makes the energy management more complex.

To this end, machine learning, and more precisely reinforcement learning, represents a powerful tool to operate a whole green cellular network in the most efficient way. In fact, the latter acquires the capability to dynamically optimize itself to meet the requirements in terms of Quality of Service (QoS) as well as optimizing the energy and environmental footprints. The learning process is achieved through continuous interaction with the environment which allows dynamic reconfiguration whenever it is needed. In case where preliminary knowledge of the environment behavior is available (for example, in cooperative learning between new green small cells and their already deployed neighbors), the learning phase is accelerated. But in general, the green cellular network can still reach the best performances in a plug and play situation.

To solve the problem of learning from interaction, reinforcement learning relies on the agent-environment framework illustrated in Figure 2. The latter is composed of an agent that corresponds to the decision-maker and an environment that represents all the factors that are likely to influence the decision making.

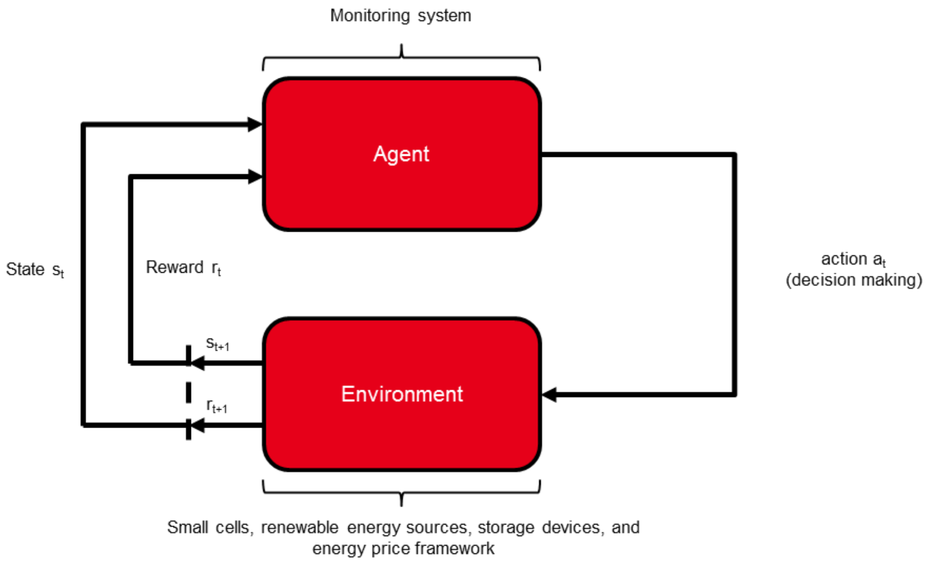

Figure 2: The agent-environment interaction in reinforcement learning [1].

At each time step t, the agent receives a representation of the environment's state $\vec{\mathbf{s}}_t \in S$, where S is the set of possible states, and selects an action $\mathrm{a}_t \in A$ accordingly, where A is the set of possible actions. As a consequence of its action, the agent receives in the next time step a numerical cost $c \in C$, and perceives a new state $\vec{\mathbf{s}}_{t+1}$.
Each pair state-action can be defined by its Q-value $\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a})$, which represents the expected total discounted cost counting from the state-action pair $(\vec{\mathbf{s}}, \mathrm{a})$, over an infinite time

$$\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a}) = \mathrm{E}\{\sum_{t=0}^{\infty} \gamma^t c(\vec{\mathbf{s}}_t, \mathrm{a}_t) \ \textit{such that}\ \vec{\mathbf{s}}_0 = \vec{\mathbf{s}}\ , \mathrm{a}_0 = \mathrm{a}\ \}$$

where $\gamma \in [0,1]$ is the discount rate that determines the current value of future costs. In other words, the Q-value estimates in the long-term how good it is for the agent to choose a particular action in a given state.
During the learning process, the agent visits a finite number of states and collects the cost each time an action is taken. The objective is to find an optimal policy, i.e., a state-action mapping that minimizes the expected cumulative cost of the agent when visiting the state space. More specifically, in the Q-learning algorithm, the Q-values are first arbitrarily initialized, and then the optimal Q-values are computed in a recursive method. In each iteration, after the execution of an action a in a state $\vec{\mathbf{s}}$, the agent receives an immediate cost, perceives a new state $\overrightarrow{\mathbf{s}'}$, and updates the value of $\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a})$ as:

$$\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a}) \ \leftarrow\ \mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a}) + \alpha \cdot \Delta\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a})$$

$$\Delta\mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a}) = \mathrm{c}(\vec{\mathbf{s}}, \mathrm{a}) + \gamma \min_{a' \in A} \mathrm{Q}\left(\overrightarrow{\mathbf{s}'}, \mathrm{a}'\right) - \mathrm{Q}(\vec{\mathbf{s}}, \mathrm{a})$$

where $\alpha \in [0,1]$ is the learning rate, a' is the next state optimal action, and $\mathrm{Q}\left(\overrightarrow{\mathbf{s}'}, \mathrm{a}'\right)$ is the next state Q-value.
Watkins et al. [2] have proven that if each admissible state-action pair is visited infinitely often and the learning rate is decreased in a suitable way, then the Q-value will converge to an intermediate minimal $\mathrm{Q}^*(\vec{\mathbf{s}}, \mathrm{a})$ with probability 1. Therefore, we can determine the optimal action a^* with respect to the current state such that $\mathrm{Q}^*(\vec{\mathbf{s}}, \mathrm{a})$ is minimal

$$\mathrm{a}^* = \underset{a \in A}{\operatorname{argmin}}\, \mathrm{Q}^*(\vec{\mathbf{s}}, \mathrm{a})$$

Finally, the optimal state-action pairs are stored into a look-up-table, which is used for the optimal control of the system.
It is noteworthy that the goals pursued by the agent can be various such as energy cost minimization, carbon emission reduction, and QoS enhancement. Consequently, the learning settings (e.g., states, actions and cost evaluation) are adapted in a way the energy management fulfills the chosen objective(s).

3. Possible synergies between the smart grid and the cellular networks

The approach used for the past century for managing the electrical power-system which is based on converting fuel-to-electricity in real-time is no longer sustainable in the modern society. Firstly, the fuel-reserves worldwide are rapidly approaching depletion and secondly there is a lot of pressure from social concerns related to climate change. In Europe, the climate and energy package [3] has set as goals for 2020 a 20% cut in greenhouse gas emissions (from 1990 levels), 20% of EU energy to come from renewable sources, and a 20% improvement in energy efficiency.
In order to achieve these goals, in the past years, the field of power systems has seen a surge of new technologies such as, wind and photovoltaic generators, electric vehicles, distributed energy storage, and smart meters, as briefly summarized in the infographic of Figure 3. All these elements have a direct impact on the way electrical energy is generated, transported, and managed, and the classical hierarchical architecture of the power grid has serious problems handling these challenges. As [4] points out, most probably the new direction will be towards distributed and decentralized energy systems using renewable energy as they can be designed to adapt more quickly to changing energy demands. A similar vision is presented in the two roadmaps for smart-grids drafted by ADEME (the French Environment and Energy Management Agency) [5] and by ANCRE (the French National Alliance for Energy Research Coordination) [6]. Here, decentralized local systems that make optimal use of the available renewable sources in their areas are envisioned together with a central manager that ensures the global equilibrium at a national or even European level.

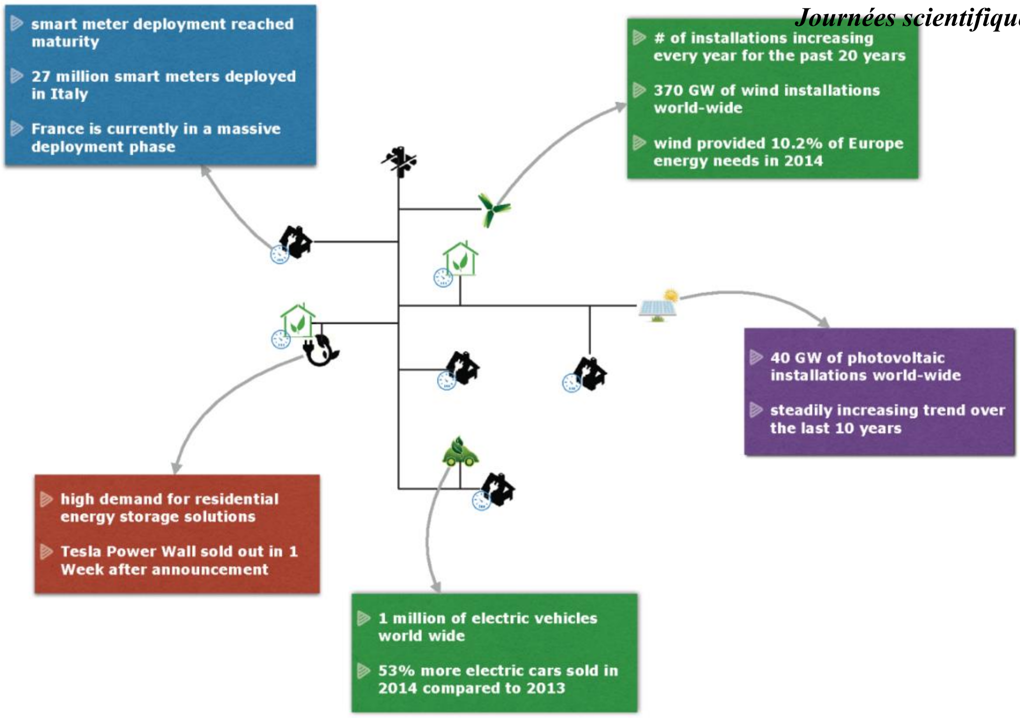

Figure 3 New emerging technologies that pose difficult challenges and require immediate technical and business innovation on several aspects of the grid, such as architecture and system planning, control and management, and resource exploitation.

All these ideas point to the fact that the only suitable alternative for making optimal use of this flood of scattered small power resources is a distributed paradigm that is able to self-coordinate, learn and adapt in order to cope with the various operating modes of the grid.

It is also our vision that a large scale distributed system cannot be efficiently managed by using a centralized perspective. Such an approach is far from being computationally feasible, it has the vulnerability of a single point of failure, and it is impossible to implement when the various actors participating in this scheme refuse to share confidential data between them. Moreover, a centrally managed system severely limits the innovation in the field. In this regard it is interesting to look at the recent lessons provided by the way the internet revolutionized the communication networks and the way we think about data. One can safely asses that such a wave of innovation will not arise in the power system unless the conventional top to bottom, centralized architecture is replaced with some sort of plug-and-play system that allows different parts of the system to emerge and evolve in parallel and finally connect and be able to work seamlessly together. This type of flexibility will allow for new actors to be involved in the energy infrastructure at all its levels: equipment, applications, control, data management, information and communication, and of course business and markets.

The role of the communication network in this envisioned system could be twofold. On one hand it would provide a reliable communication channel between the different nodes of the network. Wireless cellular networks would be far superior to classic methods, such as PLC (power line communications), in their suitability for this task. Small latencies and good data streams are obvious advantages, but even more important is their capability of offering a complete communication graph, i.e., each node is able to communicate with all the other nodes. Moreover, cooperation between the different elements of the grid would not be limited by its electrical connections. This is important, because as we know from [7] the convergence speed of distributed algorithms is proportional to the algebraic connectivity of the communication graph. On the other hand, for the smart-grid, the generators and energy storage embedded in the small-cell architecture proposed in SOGREEN are just additional distributed resources that could be used for different services. For example, in the same way [8] proposes a solution for frequency support by using residential resources, a similar approach might be possible by using the resources of the ICT network. This will impact the management of each green-cell as the involvement of the ICT infrastructure would advance from the simple buying and selling of energy through the smart-metering infrastructure to aggregations of multiple cells being able to aid in providing other services to the electrical-grid, such as load balancing, congestion management, frequency support, or black start.

4. Application of HDCRAM to the SOGREEN network

The green network proposed in this paper is a complex system with distributed intelligence. For this type of system, a management architecture allows to identify how the link between cognitive information, decision making and configuration orders is done.

Hierarchical and Distributed Cognitive Radio Architecture Management (HDCRAM) is a logical architecture developed for the management of intelligent systems. This architecture was first proposed for the management of cognitive radio equipment [9] but can be used for the management of any intelligent system. For example, it has recently been proposed for the management of the Smart Grid [10]. The HDCRAM architecture is shown in figure 3.

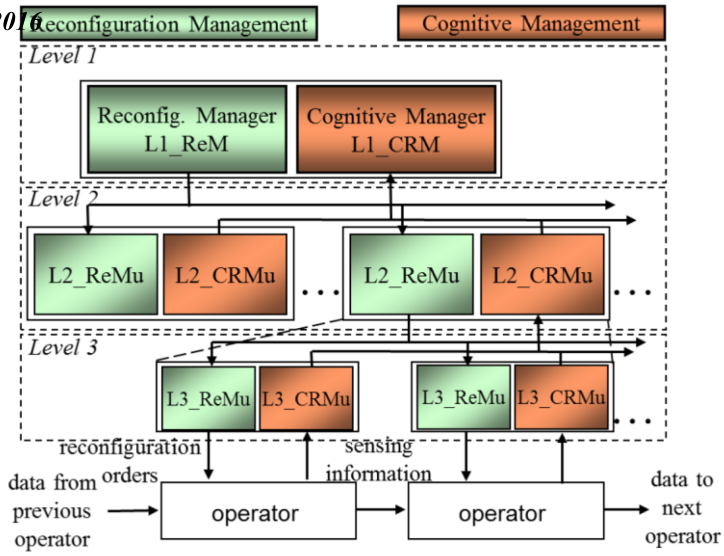

Figure 3 : Hierarchical and Distributed Cognitie radion architecture management

As we can see on figure 3, HDCRAM is a three level architecture. Each operator of the system managed is linked with a level 3 unit which can make local decisions which involve this operator. The level 2 is composed by many units which receive information exchange information (cognitive information or reconfiguration orders) with several level 3 units. As a consequence, a level 2 unit can make decisions involving several operators. The level 1 is composed by only one unit which is the global manager of the system and makes global decisions which involve the whole system. This entity exchanges cognitive information and reconfiguration orders with all the level 2 units of the management architecture.
Moreover, this architecture is composed by two independents paths. The cognitive parts is composed by Cognitive Radio Management units (CRMu) which are intelligent entities and can take decisions. A CRMu receives cognitive information from operators or from a lower level CRMu. Then, if it can make the decision, it sends order to the corresponding Reconfiguration Management unit (ReMu). If not, the cognitive information is transmitted to the higher level CRMu. A ReMu receives orders from the associated CRMu or from a higher level ReMu. If the ReMU is a level 3 ReMu, the corresponding operator is reconfigured. A ReMu of level 1 or 2 transmits the orders to the lower level ReMu.
The operators of the SOGREEN network have different roles, they can act on: the energy flow, the classical communications and the communications for the Smart Grid. As a consequence, HDCRAM shall be adapted before we can use it for this new network.

5. Conclusion

In this paper, the SOGREEN network is introduced. This green network is powered by renewable energy resources and by the smart grid. We propose to use reinforcement learning for energy management and to use HDCRAM as an architecture for network management. We also show that the SOGREEN network and more generally cellular can be used for the smart grid either as a communication network or as a reserve for frequency support.

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References

1- Sutton, Richard S., and Andrew G. Barto. Introduction to reinforcement learning. Vol. 135. Cambridge: MIT Press, 1998.
2- Watkins, Christopher JCH, and Peter Dayan. “Q-Learning.” Machine learning 8.3-4 (1992): 279–292.
3- European Commission, “2020 climate & energy package,” 2015.A
4- Ren21, “Renewables 2015 Global Status Report,” tech. rep., Paris, 2015.
5- ADEME, “Systèmes électriques intelligents - Feuille de route stratégique,” tech. rep., 2013.
6- ANCRE, “Réseaux d’énergie de demain? Les Propositions de L’ANCRE en 2015,” tech. rep., 2015.
7- Olfati-Saber, R. (2005). Ultrafast consensus in small-world networks. In Proceedings of the 2005, American Control Conference, 2005. (pp. 2371–2378). IEEE.
8- "Lebel, G., Kuypers, K., Caire, R., Hadjsaid, N., Bebiou, S., and Glatigny, A. Distributed and coordinated demand response for the supply of frequency containment reserve (FCR). In CIRED 23rd International Conf. on Electricity Distribution."
9- Godard, L., Moy, C. and Palicot, J. An executable meta-model of a hierarchical and distributed architecture management for cognitive radio equipments. In annals of telecommunication. 64 (7-8)(2009) 463-482,
10- Palicot, J., Moy, C., Résimont, B. and Bonnefoi, R. Application of Hierarchical and Distributed Cognitive Architecture management for the Smart Grid, Ad Hoc Networks (2015)