Advanced metering infrastructure backhaul reliability improvement with cognitive radio

Rémi Bonnefoi, Christophe Moy, Jacques Palicot

Advanced Metering Infrastructure Backhaul Reliability Improvement with Cognitive Radio

Rémi Bonnefoi, Christophe Moy and Jacques Palicot
CentraleSupélec/IETR, CentraleSupélec Campus de Rennes, 35510 Cesson-Sévigné, France
Email:{remi.bonnefoi, christophe.moy, jacques.palicot}@centralesupelec.fr

***Abstract*—The monitoring of the smart distribution grid requires a reliable telecommunication system. In this paper, we propose to use cognitive radio to enhance the reliability of smart grid communications. We show that, in case of failure of the primary wireless communication network used for the advanced metering infrastructure (AMI) backhaul, cognitive radio can be used to connect aggregators to a backup network. The chosen backup network can be a cellular network or an IoT (internet of things) network. Then, an analysis of the reliability of the AMI backhaul in an IoT network is done and we show how cognitive radio and machine learning algorithms can be used to enhance the communications reliability.**

I. Introduction

The real time monitoring of the electricity grid allows to reduce the number and the impact of power failures. The distribution grid was first monitored by the Supervisory Control and Data Acquisition (SCADA) system designed for the monitoring of industrial systems. When SCADA is used for the distribution grid, remote terminal units (RTU) and programmable logic controllers are placed all along the grid. These devices send measures and receive orders from a general controller. In a smart grid, the monitoring of the distribution grid is done by the advanced metering infrastructure (AMI), the distribution automation (DA) and the management of distributed energy ressources (DER) [1].

In AMI, a two ways flow of information is used between control centers and consumers. On one way, the meters installed in consumers' homes measure the electricity consumption and send it to control centers. On the other way, smart meters receive information (such as the electricity price) for demand response (DR), this information can be used by the consumer or by smart appliances to adapt their power consumption.

Many Smart Grid applications (such as AMI, DA and DER) require a reliable network for real time communications. Wireless communication networks can be a low cost and reliable way to carry out Smart Grid communications. Indeed, in case of failure of the grid, power line communications (PLC) are no longer usable and wired communications can be damaged by earth potential rises (EPR) [2]. Moreover, cellular networks such as 2G, 3G and 4G are already widely deployed in many country and have a large coverage. They are, consequently, a promising solution for the Smart Grid [3].

The use of cellular networks for the smart grid has already been studies in the litterature. In [4], the authors analyze the throughput and the packet loss ratio of an LTE network used for the Advanced Metering Infrastructure (AMI) and for the remote control of the Grid. In [5], the performance of an LTE network used for data transmission from phasor measurement units (PMU) to control centers is evaluated. In [6], GSM and GPRS base stations are reengineered to be used for smart grid communications. However, the reliability of cellular networks worries distribution system operators (DSO). That is why we propose an innovative solution for the improvement of the reliability of cellular networks used for Smart Grid.

If an element of the smart grid can access to several telecommunication networks, it can use one of them as a default communication network (or primary network) and the others as backup networks used in case of failure of the default network. This increases the reliability of the communications. Moreover, a cognitive radio (CR) [7], [8] can sense its environment and reconfigure itself to fit it. With cognitive radio, a device on the grid can access multiple standards without having multiple communication systems. Reconfiguration is proposed by the Gridman task group to increase the reliability of Smart Grid communications [9]. This task group proposes a reconfigurable backhaul to increase the reliability of WiMAX base stations. In case of backhaul connection break, the base station can reconfigure its backhaul and becomes a relay node to another base station or to a mobile station to avoid data loss.

In this paper, we focus on the use of cognitive radio for the AMI backhaul. PLC or another communication technology can be used between smart meters and aggregators and we suppose that GPRS (General packet Radio Service) is used between the aggregators and the control center. The transceiver of the aggregators is a cognitive radio used to communicate with the control center through the GPRS network. In case of failure of the GPRS network, the cognitive radio chooses one of the available backup standards to communicate. The radio equipment can use another cellular network or can use an existing Internet of Things (IoT) network. When a cellular network, such as UMTS (Unified Mobile Telecommunication System) or LTE (Long Term Evolution), is used, the quality of service (QoS) can be maitained. On the contrary, the insertion of the AMI backhaul in an IoT network (or Low Power Wide Area Network (LPWAN)) can reduce the quality of service of both networks. In this paper, we evaluate the reliability of the AMI backhaul and of the IoT network and we show how cognitive radio and machine learning algorithms can be used to enhance this reliability.

The rest of this paper is organized as follows, the system model is introduced in section II. Reconfigurable aggregators are described in section III. In section IV, we introduce the reliability of the AMI backhaul in an IoT network and in section V we show how cognitive radio can facilitate the insertion of aggregators in an existing IoT network. In section VI some numerical results are presented and section VII concludes this paper.

II. System model

A. Context

We suppose several residential areas in which houses are equipped with smart meters. Each residential area is connected to the distribution grid by a substation in which an aggregator is installed. The aggregator communicates with smart meters through PLC and with a control center using the GPRS network. The system is illustrated in figure 1.

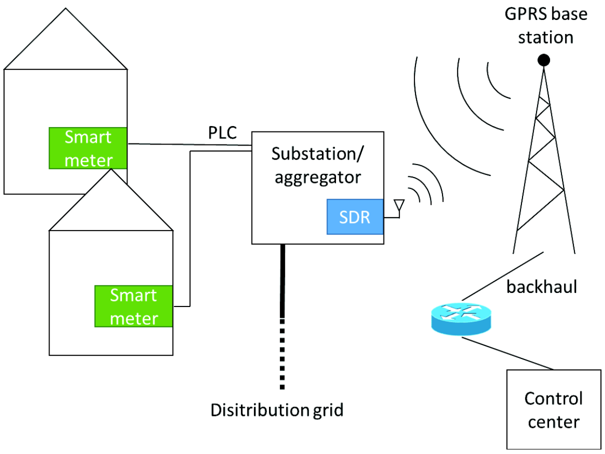

Fig. 1. Communications of the advanced metering infrastructure

The RF transceiver of the aggregator is a cognitive radio which can reconfigure itself and access multiple wireless standards. If the aggregator has difficulty connecting to the primary network, the cognitive radio can be reconfigured and a new communication standard is used to communicate with the control center.

Communications considered for normal operation (PLC and GPRS) are these used by ERDF (Electricité Réseau Distribution France) for the deployment of the French smart metering system. In this country, 35 millions of smart meters and 700 000 aggregators will be deployed by 2021 [10]. Each smart meter makes a measure of the home's power consumption every 10/30 or 60 minutes and sends it to the aggregator. On average, an aggregator is connected to 50 meters. As a consequence, a large number of aggregators will be installed in cities (1000 for a city of 50 000 inhabitants).

We suppose that the aggregator aggregates the data received from smart meters and sends the total power consumption to a control center in a small message (which can be a SMS in a cellular network). After receiving the power consumptions, the control center use them to estimate the state of the distribution grid and to compute the new electricity price. Then, the control centers send back a short message to aggregators. This message (or packet) can contain the new electricity price and can be an acknowledgement to the aggregator.

With this ackowledgement, we can ensure the QoS (reliability) for the AMI backhaul. This quality of service, or reliability, depends on the number of lost packets. In [11], the U.S. Department of Energy recommended a reliability of 99-99.99% for the AMI backhaul.

If the aggregators and the control centers have an ID (e.g. an IP address) they can communicate through any wireless network. In case of failure of the GPRS base station, the aggregator can reconfigure its RF chain to access to other wireless networks. For example, if the aggregator is in the coverage of a UMTS or a LTE base station, it can use them to transmit information.

B. Cognitive Radio

A cognitive radio, is a radio frequency equipment which adapts its communications to its environment. Figure 2 shows the simplified cognitive cycle.

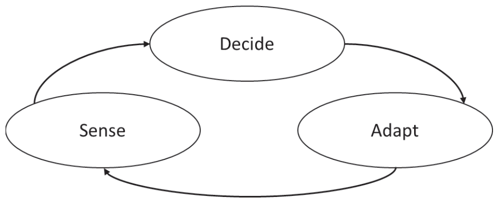

Fig. 2. Simplified cognitive cycle

A cognitive radio has sensors which are used to acquire knowledge of its environment. The result of the sensing is used to make decisions and to reconfigure the radio frequency equipment. Cognitive radio is usually used for dynamic spectrum access (DSA) [12]. In a DSA scenario, secondary users want to access to licensed channels unused by primary users. Before accessing a channel, a secondary user must sense if a primary user uses this channel. With the sensing result, the secondary user decides if it access to this channel or chooses another channel for data transmission.

In this paper, the cognitive radio of the aggregator is mainly used for the selection of the backup standard in case of failure of the GPRS network. During the sensing part of the cognitive cycle, the cognitive radio senses the available and usable backup standards and detects the failures of the standard in use. When a failure occurs, the aggregator decides which standard should be used. Then, during the adaptation phase, the transceiver is reconfigured to use the selected backup standard.

C. Model

In case of failure of mobile networks, aggregators can use an IoT network (or LPWAN) to maintain the communication between aggregators and control centers. In LPWAN, each message is encapsulated in a packet. We suppose that IoT base stations can transmit and receive packets from devices (or connected objects). We also suppose that time and frequency are slotted in the IoT network and that devices randomly access to slots as illustrated on figure 3. We denote T the slot duration which depends on the IoT standard. We suppose that each connected object uses only one channel. Several slots are used by connected objects and others are free. These free slots can be used by aggregators.

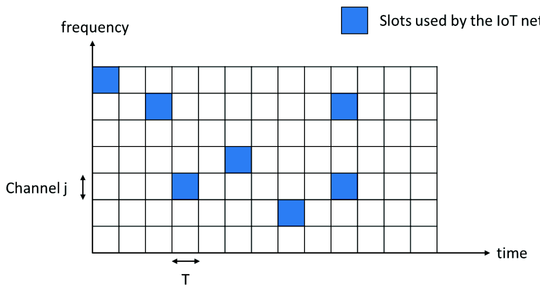

Fig. 3. A slotted IoT network [13]. All the slots unused by connected objects can be used by aggregators in case of failure the primary network

For the analysis of the reliability, we only consider the packets lost because of collisions and we don't considers packets lost because of propagation conditions. We also suppose that the RF transmit power used by aggregators and that used by connected objects have the same order of magnitude. As a consequence, when an aggregator and a connected object send or receive a packet in the same slot, both are lost.

To maintain a certain level of reliability, aggregators should know if a collision occurred. To know it, an aggregator can sense collisions or the base station can send an acknowledgement to the aggregator when the packet is received. If two devices far from one another send a packet in the same slot, it can be difficult to sense the collision. In this paper, we focus on reliability and we suppose that the base station sends an acknowledgement to the aggregator when a message is successfully sent.

In the following section, we introduce the mechanism used for the selection of the backup standard used in case of failure of the GPRS network and we detail scenarios in which backup standards can be used.

III. Multi-standard communications for a better reliability

The reconfiguration of the RF chain can be done efficiently only if the aggregator has knowledge of the usable standards. To acquire this knowledge, the aggregator must sense its environment to detect the available networks. For this detection, aggregators can have a prior knowledge of the available standards or can use blind standard recognition algorithms [14]. Once neighboring standards have been detected, the aggregator can establish a connection with them to evaluate if the available base stations are usable. The available and usable standards are stored in a database.

To update the database of usable standards, the aggregator should detect and connect to usable base stations regularly. For example this update can be done once a week during off peak hour.

The best available standard is chosen according to the criteria of the distribution system operator (DSO). From the DSO point of view, the best choice is to use the cheaper reliable way to exchange AMI information. This justifies the use of GPRS as a default standard. Moreover, since the DSO has a contract with a mobile operator for the use of a GPRS network, this contract can include the use of the UMTS or LTE networks for backup. Others backup solutions such as IoT networks can be emergency solutions used in case of failure of all cellular networks.

The selection of the backup standard is done based on the information sensed and on the information received from the control center. If the aggregator hasn't received information from the control center, it first uses its default network. If the transmission fails, the aggregator selects another standard. The selected backup standard is the best backup standard according to the DSO criteria. If this standard is not operational, the aggregator will choose the next standard in its database and so on.

The standard chosen at the end of the selection process depends on the severity of the failure. We propose to classify failures in three categories, minor, medium and major failures. Table I lists some example of failures.

TABLE I
Possible failures

Failure type	Example of failure	Backup networks
Minor failure	Saturation of the GPRS network	UMTS, LTE
Medium failure	Failure of the GPRS base station	UMTS, LTE or IoT
Major failure	Natural disaster (storm, earthquake) or local failure of all mobile networks	IoT

If the aggregators try to establish a connection with a saturated base station (minor failure), the aggregator can reconfigure its RF chain and use another cellular network. At the next data sending, the base station will try to use the GPRS network and use it if it is not saturated.

In case of medium failure, the aggregator will use the best available backup network. This backup network will be used until the fixing of the GPRS base station. The aggregator will use its cognitive radio to regularly sense if the GPRS base station was repaired.

If a major failure happens, all the surrounding base stations are unusable. For example, this can happen if the backhaul of mobile networks is broken or if the failure of the GPRS network has caused traffic jams. In this case, aggregators will have to connect to more distant base stations. They will use long range communication standards such as SigFox[1] or LoRa [15]. These networks can be good solutions for maintaining the link between aggregators and control centers. It can be noted that, after a natural disaster, the number and the nature of the messages exchanged between control centers and aggregators can change. One of the main issues of IoT networks is their reliability. Indeed, a large number of aggregators can use the IoT network at the same time (100 or 500 if the problem affects a small city). If the AMI backhaul is inserted in a dense IoT network, the number of collisions and the number of lost packets will be high and the reliability of the backhaul will be very low.

In the following section, we define the reliability of the AMI backhaul in an IoT network and we show how cognitive radio can improve the reliability of the AMI communications in an IoT network.

IV. Reliability of the AMI backhaul in an IoT network

We suppose that many connected objects communicate through the IoT network. In this network, time and frequency are slotted. Each object uses only one of the m possible frequency channels of same bandwidth. We suppose that the time is divided in slots of duration T. The slot duration depends on the packet size and on the throughput. For example, in a LoRa network, the packet size can be 50 bytes and the throughput is between 0.293 and 38.4 kb/s thus the time slot can be between 10 ms and 1.365 s.

For the analytical analysis of the reliability in each channel, we suppose that connected objects and aggregators access to the channel following a Bernoulli distribution.

For one of the connected objects, we define the communication probability as the probability that this device uses the channel and we define the occupancy probability of the channel as the probability that at least one connected object uses the channel. In channel j, we denote P_j this probability:

$$P_j = 1 - \prod_{i=1}^{n_j}(1-p_i) \tag{1}$$

Where n_j is the number of devices in band j and p_i the probability that the device i uses the band. We can see that this probability increases with the number of devices and with the devices' communication probabilities.

If n_a aggregators with a communication probability $p_{a,k},\ k \in [\![1; n_a]\!]$ begin to use only the channel j, the probability that at least one aggregator uses the channel is:

$$P_a^j = 1 - \prod_{k=1}^{n_a}(1-p_{a,k}) \tag{2}$$

For the analysis of the reliability in a channel, we use the packet delivery ratio (PDR) which can be defined as the ratio between the number of AMI successful communications and the number of packets sent for AMI backhaul (sent by aggregators or by the control center).

$$R_{AMI} = \frac{\mathbb{E}\{\text{Nb of successful AMI communications}\}}{\mathbb{E}\{\text{Nb of packets sent for AMI}\}} \tag{3}$$

In one temporal slot, we have a successful transmission if there are no collisions in this slot. I.e. if only one packet is sent in the temporal slot and the expectation of the number of successful communications is equal to the probability of successful communication:

$$\begin{aligned} P_{succ} &= \left(\prod_{i=1}^{n_j}(1-p_i)\right)\sum_{l=1}^{n_a} p_{a,l} \prod_{k=1,k\neq l}^{n_a}(1-p_{a,k}) \\ &= \left(\prod_{i=1}^{n_j}(1-p_i)\right)\left(\prod_{k=1}^{n_a}(1-p_{a,k})\right)\sum_{l=1}^{n_a}\frac{p_{a,l}}{1-p_{a,l}} \end{aligned} \tag{4}$$

Furthermore, in one temporal slot, the expectation of the number of packets sent for AMI backhaul is equal to:

$$\mathbb{E}\{\text{Nb of packets for AMI}\} = \sum_{l=1}^{n_a} p_{a,l} \tag{5}$$

This expression of the reliability in channel j can be deduced from equations (4) and (5):

$$\begin{aligned} R_{AMI} &= \left(\prod_{i=1}^{n_j}(1-p_i)\right)\left(\prod_{k=1}^{n_a}(1-p_{a,k})\right)\frac{\sum_{l=1}^{n_a}\frac{p_{a,l}}{1-p_{a,l}}}{\sum_{l=1}^{n_a} p_{a,l}} \\ R_{AMI} &= (1-P_j)(1-P_a^j)\frac{\sum_{l=1}^{n_a}\frac{p_{a,l}}{1-p_{a,l}}}{\sum_{l=1}^{n_a} p_{a,l}} \end{aligned} \tag{6}$$

If we suppose that all aggregators have the same probability to use the channel, we can denote p_a this probability and the reliability of the AMI backhaul becomes:

$$R_{AMI} = (1-P_j)\,(1-p_a)^{n_a-1} \tag{7}$$

We can evaluate the probability of occupancy of an aggregator in a LoRa network. Indeed, an aggregator sends and receives a packet every 10/30 or 60 minutes. If we suppose that time is divided in slots which last between 10 ms and 1.365 s, the probability of occupancy of an aggregator varies between 2.8×10^{-6} and 2.3×10^{-3}.

These numerical evaluations show that $p_a \ll 1$, with a first order Taylor expansion, we can approximate the reliability of the AMI backhaul:

$$R_{AMI} = (1-P_j)\,(1-(n_a-1)p_a) \tag{8}$$

In the same way, we can define the reliability of the IoT network in which the AMI backhaul is inserted:

$$R_{IoT} = \left(\prod_{k=1}^{n_a}(1-p_{a,k})\right)\left(\prod_{i=1}^{n_j}(1-p_i)\right)\frac{\sum_{i=1}^{n_j}\frac{p_i}{1-p_i}}{\sum_{i=1}^{n_j} p_i} \tag{9}$$

[1] www.sigfox.com

Likewise, if all aggregators have the same occupancy probability, (9) becomes:

$$R_{IoT} = (1-p_a)^{n_a-1}\left(\prod_{i=1}^{n_j}(1-p_i)\right)\frac{\sum_{i=1}^{n_j}\frac{p_i}{1-p_i}}{\sum_{i=1}^{n_j}p_i} \qquad (10)$$

Which can be approximated by:

$$R_{IoT} = (1-(n_a-1)p_a)\left(\prod_{i=1}^{n_j}(1-p_i)\right)\frac{\sum_{i=1}^{n_j}\frac{p_i}{1-p_i}}{\sum_{i=1}^{n_j}p_i} \qquad (11)$$

Equations (8) and (11) show that the reliabilities of the AMI backhaul and of the IoT network decrease linearly with the occupancy probabilities of connected objects and with the number of aggregators in the band.

To enhance the reliability of the AMI backhaul, aggregators can send their packets until they receive an acknowledgement. This increases the number of packets sent and leads to a degradation of the reliability of the IoT network.

To maintain the reliability of both the AMI backhaul and the IoT network below a given threshold (required reliability) in each channel, aggregators should use channels with a low P_j. In the next section, we show how cognitive radio and reinforcement learning algorithms can be used to enhance the reliability of both networks.

V. Cognitive communications through an IoT network

In an IoT network, aggregators can use machine learning algorithms for the selection of the least occupied channel. With these algorithms, aggregators will first have an exploration phase during which they will try all the channels to evaluate the occupancy probabilities. After this exploration phase, they can choose the best channel and use it for all transmissions, this is called the exploitation phase. In this section, we propose to use the upper confidence bound (UCB) algorithm to learn which channel has the lower occupancy probability. This agorithm has been proposed in cognitive radio for opportunistic spectrum access [12]. It presents a very low footprint (in memory and processing power) and learns effectively the probability of occupancy of all channels. Moreover, UCB starts exploiting within the exploring phase, so no time is lost.

We denote t the number of data transmission realized by an aggregator and $T_j(t)$ the number of selection of the channel j. When channel j is selected for data transmission, an aggregator considers that a transmission is successful if it receives an acknowledgement and unsuccessful else. We define the reward of the data transmission in channel j as:

$$r_t(j) = \begin{cases} 1 & \text{if the transmission is successful} \\ 0 & \text{else} \end{cases} \qquad (12)$$

To evaluate the average reward in channel j, we use a confidence bound of its sample mean. If we denote a_t the channel selected for transmission t, the sample mean of the reward in channel j after T_j selections is:

$$\overline{X}_j(t) = \frac{\sum_{l=1}^{t-1} r_l(j)\mathbb{1}_{\{a_l=j\}}}{T_j(t)} \qquad (13)$$

Where $\mathbb{1}_{\{a_l=j\}}$ is the indicator function. We define the upper confidence bound algorithm indexes in each channel as [16]:

$$B_j(t) = \overline{X}_j(t) + A_j(t) \qquad (14)$$

Where A_j is an upper confidence bias. With the UCB algorithm, the selected channel is that with the higher upper confidence bound:

$$a_t = \underset{j}{\text{argmax}}(B_j(t)) \qquad (15)$$

For the UCB_1 algorithm, this bias is equal to:

$$A_j(t) = \sqrt{\frac{\alpha \ln t}{T_j(t)}} \qquad (16)$$

Where α is the exploration coefficient. During the exploration phase, $T_j(t)$ is low and $A_j(t)$ is high, as a consequence during this phase, the algorithm will explore all the channels. When t and $T_j(t)$ increases, $A_j(t)$ decreases and the aggregator will transmit most of the time in the channel with the higher empirical reward, this exploiting past experience results.

The duration of the exploration phase depends on the value of α. The exploration phase is longer when α is high. When $\alpha \ll 1$, the exploration phase is very short, this can lead to a bad channel selection. When $\alpha \gg 1$, the exploration phase is very long. This can cause data losses because channels with high occupancy probabilities are used many times.

In an IoT network, the probability of occupancy is often low, but, when many aggregators begin to use the network, the IoT network can become overloaded. Moreover, aggregators use the network only for a few days. As a consequence, they don't have time for a long exploration phase. Then learning fast convergence is of outmost importance.

VI. Numerical results

For simulations, we suppose that several aggregators use an IoT network. All these aggregators have the same probability to send a packet equal to $p_{agg} = 10^{-4}$. If the IoT base station receives a packet from an aggregator during one slot, it sends the acknowledgment in the same channel during the next slot.

Since this acknowledgement is sent only when the packet sent by the aggregator is received by the base station, the probability of occupancy of an aggregator does not exactly follow a Bernoulli distribution with probability $2p_{agg}$. Actually, if the reliability of the channel is not too low and if p_{agg} is sufficiently low, the probability of occupancy of an aggregator can be approximated by a Bernoulli distribution with probability $2p_{agg}$.

We first suppose a band with a probability of occupancy $P = 0.1$ and we show the evolution of the reliability of the AMI backhaul versus the number of aggregators in one channel.

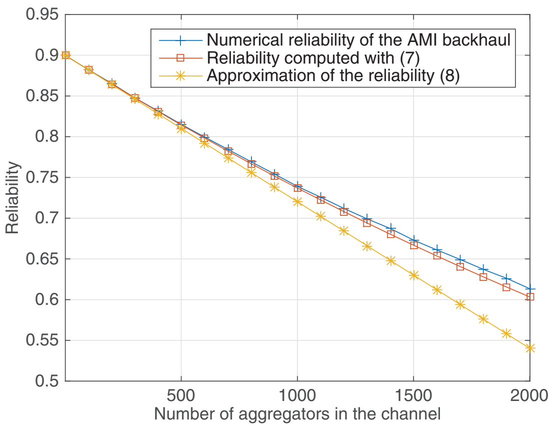

Fig. 4. Reliability of the AMI backhaul in one channel versus the number of aggregators in the channel

Fig. 4 shows that when the number of aggregators is below 500, the reliability of the AMI backhaul can be approximated by equation (8) with $p_a = 2p_{agg}$.

We now suppose an IoT network divided in $m = 10$ channels. Each channel has its own probability of occupancy, without loss of generality, channel are sorted in ascending order of P_j, these probabilities are equal to $P_j = \{0.01\,; 0.02\,; 0.03\,; 0.04\,; 0.05\,; 0.06\,; 0.1\,; 0.13\,; 0.17\,; 0.2\}$.

Fig. 5 shows the evolution of the reliability of the AMI backhaul in the 10 bands versus the number of aggregators.

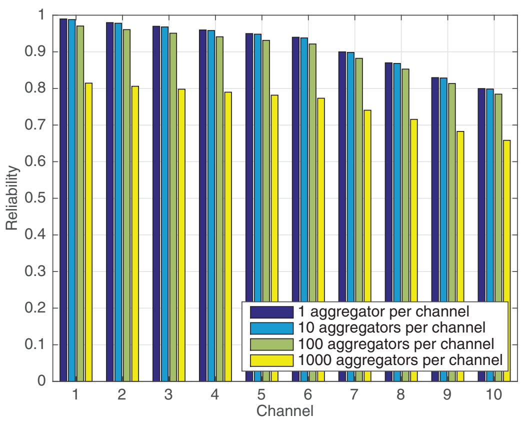

Fig. 5. Reliability of the AMI backhaul in each channel versus the number of aggregators in the channel

We now suppose that 100 aggregators are using the IoT network. Each aggregator uses the UCB_1 algorithm to find the channel with the highest reliability (the lowest probability of occupancy). Aggregators don't use the IoT network for a long time, thus, the learning phase should be short and the exploration coefficient α should be low. We consider 1×10^7 temporal slots (approximately 1 day for time slots of 10 ms) and for all aggregators, $\alpha = 0.3$. We focus on the effect of the UCB algorithm on the reliability and we suppose that aggregators don't resend packets if they don't receive the acknowledgement. Fig. 6 shows the proportion of selections of each channel by aggregators.

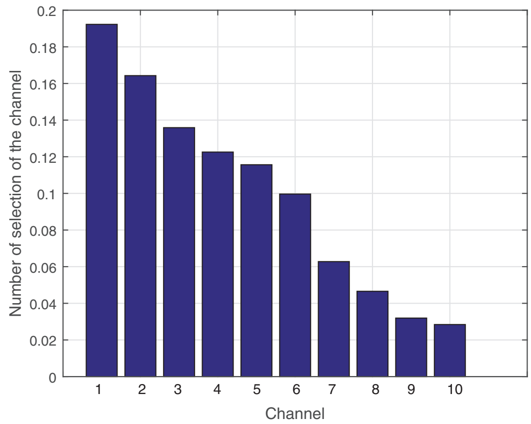

Fig. 6. Proportion of selection of each channel with $\alpha = 0.3$

We can see that the more free is a channel, the more it will be chosen by aggregators. Moreover, most of the communications occur in the channels with a reliability of 95% or more. The whole reliability of the AMI backhaul can be defined as the total number of successful communications divided by the number of packets sent, we can compare the total reliability of the AMI backhaul with and without the UCB algorithm. With the UCB algorithm, this reliability is equal to 95.5% whereas without it we have a reliability of 91.7 %. The average reliability in the IoT network is slightly below the required reliability of 99%. As a consequence, the reliability of the IoT network studied is not sufficient to use it as a default network but it allows to maintain the connection between aggregators and the control center in case of failure of the mobile networks.

When the UCB_1 algorithm is used, the reliability of the AMI backhaul in the IoT network increases with time. During the exploration phase, aggregators use all the channels and the reliability is equal to 91.7%. During the exploitation phase, each aggregator uses only one channel and the reliability is higher. For $\alpha = 0.3$, the reliability of the AMI backhaul after one day of exploration is equal to 96.2%. Figure 7 shows the evolution of the reliability with time for different values of α.

We can see on figure 7 that the lower is α, the higher is the reliability after one day of exploration. When α increases, the duration of the exploration phase increases, this decreases the reliability after one day of exploitation but can increase the long term reliability.

VII. Conclusion

In this paper, we presented cognitive radio as a solution for improving the reliability of Smart Grid communications.

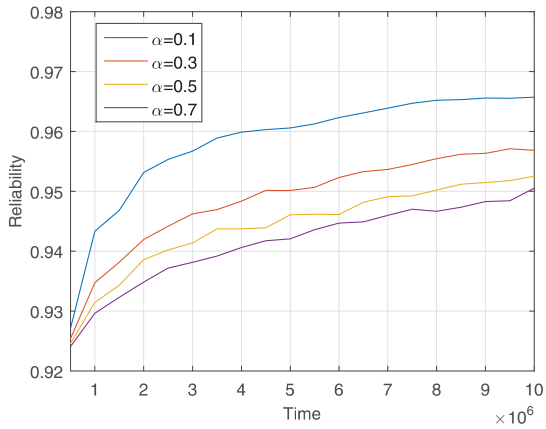

Fig. 7. Evolution of the reliability with time for different values of α

We proposed to use cognitive radio to switch between the primary network (or default network) and backup networks in case of failure. When the backup network is an IoT network, cognitive radio and reinforcement learning algorithms can be used to enhance the reliability of the AMI backhaul and to reduce the impact of the AMI backhaul on the IoT network. We have shown how cognitive radio can be used to enhance the reliability of the AMI backhaul. In future work, we are going to study the use of cognitive radio to enhance the reliability of others Smart Grid applications such as distribution automation and we will extend the analysis to others backup standards.

Acknowledgement

Part of this work is supported by the project SOGREEN (Smart pOwer GRid for Energy Efficient small cell Networks), which is funded by the French national research agency, under the grant agreement coded: N ANR-14-CE28-0025-02 and by Région Bretagne, France.

References

[1] R. E. Brown, “Impact of smart grid on distribution system design,” in *Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*, pp. 1–4, July 2008.

[2] F. Cleveland, “Use of wireless data communications in power system operations,” in *Power Systems Conference and Exposition, 2006. PSCE ’06. 2006 IEEE PES*, pp. 631–640, Oct 2006.

[3] J. Gao, Y. Xiao, J. Liu, W. Liang, and C. P. Chen, “A survey of communication/networking in smart grids,” *Future Gener. Comput. Syst.*, vol. 28, pp. 391–404, Feb. 2012.

[4] G. Karagiannis, G. T. Pham, A. D. Nguyen, G. J. Heijenk, B. R. Haverkort, and F. Campfens, “Performance of lte for smart grid communications.,” in *MMB/DFT* (K. Fischbach and U. R. Krieger, eds.), vol. 8376 of *Lecture Notes in Computer Science*, pp. 225–239, Springer, 2014.

[5] J. Brown and J. Y. Khan, “Key performance aspects of an LTE FDD based smart grid communications network,” *Computer Communications*, vol. 36, no. 5, pp. 551–561, 2013.

[6] G. C. Madueo, . Stefanovi, and P. Popovski, “Reengineering gsm/gprs towards a dedicated network for massive smart metering,” in *Smart Grid Communications (SmartGridComm), 2014 IEEE International Conference on*, pp. 338–343, Nov 2014.

[7] J. Mitola, *Cognitive Radio — An Integrated Agent Architecture for Software Defined Radio*. DTech thesis, Royal Institute of Technology (KTH), Kista, Sweden, May 2000.

[8] S. Haykin, “Cognitive Radio : Brain-Empowered Wireless Communications,” *IEEE Journal on Selected Areas in Communications*, vol. 23, pp. 201–220, february 2005.

[9] M. T. Zhou, M. Oodo, V. D. Hoang, L. Lu, X. Zhang, and H. Harada, “Greater reliability in disrupted metropolitan area networks: use cases, standards, and practices,” *IEEE Communications Magazine*, vol. 53, pp. 198–207, August 2015.

[10] X. Mamo, S. Mallet, T. Coste, and S. Grenard, “Distribution automation: The cornerstone for smart grid development strategy,” in *Power Energy Society General Meeting, 2009. PES ’09. IEEE*, pp. 1–6, July 2009.

[11] U.S. Department of Energy, “Communications Requirements of Smart Grid Technologies,” 2010.

[12] W. Jouini, D. Ernst, C. Moy, and J. Palicot, “Upper confidence bound based decision making strategies and dynamic spectrum access,” in *Communications (ICC), 2010 IEEE International Conference on*, pp. 1–5, May 2010.

[13] K. S. J. Pister and L. Doherty, “Tsmp: Time synchronized mesh protocol,” in *In Proceedings of the IASTED International Symposium on Distributed Sensor Networks (DSN08)*, 2008.

[14] M. Lopez-Benitez, F. Casadevall, A. Umbert, J. Perez-Romero, R. Hachemani, J. Palicot, and C. Moy, “Spectral occupation measurements and blind standard recognition sensor for cognitive radio networks,” in *2009 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, pp. 1–9, June 2009.

[15] N. Sornin and M. Luis and T. Eirich and T. Kramp and O. Hersent, “LoRaWAN Specification,” tech. rep., LoRa Alliance, Inc., January 2015.

[16] P. Auer, N. Cesa-Bianchi, and P. Fischer, “Finite-time analysis of the multiarmed bandit problem,” *Machine Learning*, vol. 47, no. 2, pp. 235–256.