Electric vehicles fleet for frequency regulation using a multi-agent system

Jean-Baptiste Blanc-Rouchossé, Anne Blavette, Guy Camilleri, Marie-Pierre Gleizes

Electric vehicles fleet for frequency regulation using a multi-agent system

Jean-Baptiste Blanc-Rouchossé[1], Anne Blavette[2], Guy Camilleri[1], and Marie-Pierre Gleizes[1]

[1] IRIT, Université de Toulouse, 118 Route de Narbonne, 31062 Toulouse
{Jean-Baptiste.Blanc-Rouchosse,camilleri, Gleizes}@irit.fr
[2] Univ. Rennes, SATIE, CNRS, Rennes, France
anne.blavette@ens-rennes.fr

Abstract. The production of PhotoVoltaic (PV) energy depends on the solar irradiance level. The PV power plant fluctuations may have a significant impact on the frequency regulation in sufficiently small power systems, such as islands. The objective of this paper is to present a method using cooperative multi-agent systems to reduce the frequency fluctuations due to the unpredicted fluctuations of the PV production using electric vehicles as electricity storage units in an isolated power system.

Keywords: Smart grids · PV power plants · Electric vehicles · Multi-agent systems · Frequency regulation

1 Introduction

The portion increase of renewable energies in the energy mix may cause stability issues. Actually, the stability of the electric network depends on the balance between the generated power and the consumed power. In fact, the electric power is a flux: the incoming power in the network (generated power) and the outgoing power (consumed power) must be equal to insure the flux conservation. The kinetic energy stored in synchronous generators of producers connected to the network compensate the consumption/production discrepancy. This compensation entails a change in the kinetic energy, thus a variation of the generators speed and of the grid frequency. They increase if the production is higher than the consumption and decrease if the production is lower than the consumption. Hence, the stability is insured by speed regulation of these generators around its target speed. So the stability relies mainly, on a second-to-second basis, on the inertia of the synchronous generators connected to the network (primary frequency response). Therefore, the global power unbalance has to be minimised to reduce the kinetic energy variation, and the frequency deviation. Ideally, to do that, the consumption has to be forecast. Then, the production of power plants has to be planned a day-ahead in order to balance the forecasted consumption. However, some renewable power plants (PV and wind powered for example) cannot be considered as other power plants since their production is poorly dispatchable. To control them, a part of the energy they could produce can be shedded. But this energy is then lost. So their production must be forecast: the manager of the PV power plant has to provide a day-ahead production commitment. The use of a storage equipment can be a solution to this issue. In fact, a virtual power plant can be defined by associating this storage equipment to a renewable power plant. In this way, when the production is lower than the forecast, the storage equipment can be discharged to to counterbalance the discrepancy between production and consumption.

In this work, we propose a multi-agent system for regulating the frequency of an isolated electric grid including PV power plant and electric vehicles. The frequency is supposed to be unstable due to the presence of an unexpected gap between the actual production of a PhotoVoltaic (PV) power plant and the forecast production of this power plant. The frequency is regulated by defining the action of each vehicle taking into account criteria on the vehicle. The multi-agent architecture developed is mainly composed of vehicle agents corresponding to physical vehicles which are the considered storage means; and charging station agents which are associated to physical charging stations. Each EV agent does not communicate with other EV agents, but only with the charging station agents. This choice in addition to the cooperative attitude of agents enable to reduce the complexity of the solution, and therefore its efficiency.

This paper is organised as follows: firstly, some approaches are presented. Secondly, the models used in the simulation are introduced followed by the proposed multi-agent system architecture. Finally, some results obtained with this system are analysed.

2 Related works

When there is an overproduction compared to the commitment, the storage equipment is recharged. In this way, this virtual plant should be able to respect its commitment [1–3]. However, this solution may require an important storage equipment capacity. Using EV batteries could be a solution to avoid to invest in batteries reserved to this application. Lund et al. ([4]) showed the interest of coupling EV batteries with high integration of wind power. These studies have been realised considering multiple management strategies of the fleet. However, the low energy capacity of EV batteries imposes to have an important number of vehicles. Each vehicle behaviour needs to be defined in order to solve the stability issue, so the frequency regulation. This problem is then complex due to the large amount of entities (variables) which are present.

To manage this complex issue, artificial intelligence approaches have been proposed (see [5]), including fully-distributed approaches based on multi-agent systems. These approaches are characterised by a high-level of flexibility, scalability and robustness while requiring a reduced computing time which makes them well-suited for solving large problems. Two major aspects should be considered to improve the performance of a multi-agent system: its architecture and the actions that the agents can undertake. Concerning the architecture, it has been shown in [6] that for a given problem, the architecture type achieving the best performances could vary as a function of the parameters of the problem, such as the electrical network conditions for instance.

However, to the best of the authors knowledge, the multi-agent approach for the frequency regulation seems to be absent from the literature. Yet, this approach has been considered widely in the context of smart grids. Many of these studies consider the power regulation issue [7, 8]. Paniah et al. ([7]) propose a solution consisting in associating an agent to each actor: EV, power plants, etc. and some additional agents are used to realise a particular function: combine power plants, produce production schedules, etc. The different agents communicate by exchanging schedules and negotiate between each other until they find a solution respecting all the constraints. These provisional schedules are adjusted during operation to adapt the system to the production hazards. Hernandez et al. ([8]) include in the multi-agent system a forecast of energy demand. This forecast is necessary to manage the energy in the virtual power plant considering the upcoming needs.

More generally, several studies have already been carried out on the management of a vehicle fleet to respond to smart grid issues: respect of a power profile [1, 3, 2], frequency stability [9, 10], etc. Different methods have been used to manage this fleet in spite of the complexity. In the case of the frequency regulation ([9]), a first solution is to treat the issue locally. A term proportional to the frequency deviation is added to the charging reference power of the vehicle [9]. When there is an overproduction, therefore a frequency increase, the vehicle increases its consumption and decreases it when there is an underproduction. However, this method does not take into account criteria on the vehicle such as constraint on its state of energy (ratio between the stored energy and the capacity). Another possibility is to recharge vehicles by default. Then, in the case of a fall of production, vehicles are disconnected from the grid or are discharged to the grid if their state of energy is greater than a predefined threshold [10]. Other methods use an aggregator to solve a global issue such as the minimisation of the cost due to different factors such as operating cost of generators and vehicle-to-grid services [11]. These two solutions take into account the criterion on the state of energy of vehicles. But the ageing issue of the batteries has not been discussed.

3 Model of the grid

For this study, the gap between production and consumption is supposed to come from the PV power plant and from the consumption of the fleet. In fact, synchronous generators speed is not supposed to be regulated to counteract second-to-second fluctuations generated by the PV power plant. This forces the EV fleet to be the sole responsible for frequency regulation on a second-to-second basis. However, it is considered that the EV fleet energy needs are provided by both the synchronous generator and the PV power plant on a day-to-day basis. In this way, the gap between produced power (P_{prod}) and consumed power (P_{cons}) is fully offset by the kinetic energy variation of the synchronous machines: $\Delta P = P_{prod} - P_{cons} = \eta \frac{dE_k}{dt}$, with η the energy efficiency of generators, $E_k = Kf^2$ the kinetic energy of all the synchronous generators, K (set to 3.10^5 $kW.s^3$) the image of their inertia and f the grid frequency.

In this study, the power gap is composed of two terms: $\Delta P = \Delta P_{PV} - P_{fleet}$, with ΔP_{PV} the production gap of the PV power plant. In fact, the power of the radiant flux perceived by the PV panels, the irradiance, is supposed to be perfectly forecast at a 30 second time step, which is the minimum limit reached by the best available techniques. The actual average irradiance over 30 seconds is therefore equal to the forecast. However, the instant irradiance (Irr) is not equal to this forecast ($Irr_{forecast}$): it leads to a production gap ΔP_{PV} supposed proportional to the irradiance gap ($\Delta P_{PV} = \eta_{PV} \cdot S \cdot (Irr_{forecast} - Irr)$, $\eta_{PV} = 0.1$ the energy efficiency of the PV power plant, $S = 10^6 m^2$ its surface). This is a simple model but it should not influence the presented method. As regards P_{fleet}, it is the total power consumed by the fleet of vehicles connected to the grid. EVs are supposed to be connected when they are not travelling. All the vehicles make two trips a day: the journey to work between 8am and 10am and the return trip between 5pm and 7pm [12]. In this paper, the trips distance are considered equal to 35 km$\pm$10%. The departure time of each vehicle is supposed to be known.

The first constraint of the problem is to maintain the frequency in the allowed interval [49.5 Hz; 50.5 Hz]. To do so, each EV state needs to be defined: recharging, discharging or idling. However, constraints on the EV need to be taken into account. Firstly, the vehicle has to be sufficiently charged at departure time. In other words, the battery State of Energy (SoE),i.e. the ratio between the energy stored in the battery ($E_{bat}(t)$) and its capacity (E_{bat}^{cap}), $SoE(t) = \frac{E_{bat}(t)}{E_{bat}^{cap}}$, has to be greater than a threshold SoE_{min}: $SoE(t_{departure}) \geq SoE_{min}$. The state of energy has been simulated by the equation $SoE(t + \Delta t) = SoE(t) + \Delta SoE(t)$, with $\Delta SoE(t)$ defined in Equation 1, and with α the recharge and discharge power loss rate. The power $P_{ev}(t)$ is the power absorbed from the network, with $P_{ev}(t) > 0$ if the vehicle is recharging and $P_{ev}(t) < 0$ if it is discharging.

$$\Delta SoE(t) = \frac{\Delta t \cdot (1 - sign(P_{ev}(t)) \cdot \alpha) \cdot P_{ev}(t)}{E_{bat}^{cap}} \qquad (1)$$

A second objective on the vehicles is to limit the ageing of the battery due to these additional solicitations. Most of lithium-ion batteries ageing models are based on the concept of half-cycle i.e. the phase during which the battery performs a recharge or a discharge. The Depth of Discharge (DoD) of the half-cycle is the difference between the final SoE and the initial SoE [1]. For exemple, if a battery has its SoE at 0.6 (charged at 60%), and is discharged until its SoE gets to 0.4 (charged at 40%), then the DoD of this half-cycle is -0.2. To identify the cycles, the instantaneous depth of discharge ($DoD(t)$) has been used. It corresponds to the depth of discharge of the current half-cycle if it ended at that instant (Equation 2).

$$DoD(t+\Delta t) = DoD(t) + \Delta SoE(t) \text{ if } DoD(t) \cdot P_{ev}(t) \geq 0, \text{ else } DoD(t+\Delta t) = 0 \quad (2)$$

In the study, decisions are taken at a very short time (one second). Hence, micro-cycles of recharge and discharge of few seconds can appear. To avoid to excessively speed up the batteries ageing, an objective on the depths of discharge has been taken into account: it consists in maintaining the battery in half-cycles of recharge or discharge of about 30 seconds minimum.

4 Implemented system based on multi-agent systems

In order to achieve the best performances for regulating dynamically energy networks, we adopted an Adaptive Multi-Agent System approach (AMAS). This approach aims to propose solutions applicable to complex systems. It is based on the concept of emergence, concept that makes it possible to explain phenomena difficult to decompose: these phenomena are both a consequence of the parts that make up the system and of their interactions [13]. Thus, the aim of an AMAS is to have the required functionality which emerges from the behaviour of agents: autonomous and active entities in an environment, having a goal and cooperating with each other. To design the AMAS, the ADELFE toolkit has been used [14].

4.1 Environment and agents identification

The environment of the multi-agent system in this application is the electric grid, the producers and the consumers: the PV power plant and the fleet of EV respectively.

Each agent corresponds to a domain entity. Among the possible entities, there are vehicles, charging stations, buses, power lines and producers. The objective is to have, just as in [15], an agent to control each constraint: about the frequency, the batteries state of energy and the cycles depth of discharge. For the batteries state of energy constraint, it is natural to match an agent with each vehicle. For the frequency constraint, an agent has been associated to the charging stations. Indeed, the charging stations has access to the frequency. Moreover, vehicles are connected to the charging stations: they should be able to communicate in order to cooperate. Moreover, the number of interactions between agents is limited, because a vehicle agent cannot communicate with the other vehicle agents.

Charging stations. The agents associated with a charging station aim at keeping the frequency of the network in the allowed interval by sending cooperation requests to connected vehicles: increase or decrease of the consumption.

Electric vehicles. The objective of this agent is to ensure that the constraints regarding its vehicle are satisfied. These agents act by defining the action to applied to the battery: recharge, discharge or idle, according to the vehicle state, the departure time and the cooperation request received from the charging station agent.

4.2 Agents behaviour

In an AMAS, agents are autonomous and have cooperative attitude : an agent acts in order to help another agent if the latter encounters difficulties in achieving its goal [16]. To this end, it needs to have quantitative criteria of comparison: the criticality. A normalised criticality between 0 and 1 is associated to each objective or constraint of the agents. A 1 criticality value means that the agent is far away from its objective. If it reaches its goal, criticality is equal to zero.

Criticality on the minimum state of energy. This criticality, defined by Equation 3, depends on SoE_{min}, the minimum state of energy required by the driver and t_r, the remaining time before departure. t_{min} is the minimum time required to reach the requested SoE. Thus, if $t_{min} = t_r$, the vehicle has to be recharged until departure: the criticality is maximum. In return, if $t_{min} << t_r$, the vehicle can postpone its recharge if necessary. It can afford to cooperate, even by discharging itself: the criticality has to be low.

$$Cr_{SoE} = \frac{t_{min}}{t_r} \text{ if } 0 \leq t_{min} \leq t_r, \text{ with } t_{min} = \frac{(SoE_{min} - SoE(t)) \cdot E_{bat}^{i,cap}}{P_{ev,max}} \quad (3)$$

Criticality on the depth of discharge. In Equation 4, DoD_{ref} is the depth of discharge for which the criticality is null. This value has been set to have a null criticality for a 30-second cycle for a 30 kWh battery with a nominal 20 kW power rating. The choice of 30 seconds has been made in such a way that the battery does not suffer from cycles more dynamic (i.e. frequent and deep) than when the vehicle is used for transport purposes only, with respect to the FTP75 [3] profile.

$$Cr_{DoD} = \left(1 - \frac{|DoD(t)|}{DoD_{ref}}\right) \text{ if } DoD(t) \neq 0, \; Cr_{DoD} = 0 \text{ otherwise} \quad (4)$$

Criticality on frequency. In Equation 5, f is the grid frequency, f_0 the nominal frequency (50 Hz) and Δf the allowed frequency deviation (0.5 Hz). This criticality is low when the frequency is close to 50 Hz and increases until reaching its maximum at the limit of the allowed interval.

$$Cr_f = \frac{|f - f_0|}{\Delta f} \text{ if } |f - f_0| \leq \Delta f \quad (5)$$

Charging station behaviour. The charging station agent receives the grid frequency. It deduces the value of the criticality defined previously (Cr_f). From this frequency, the agent is able to know if there has been an unbalance between production and consumption. Then, it sends a cooperation request to connected vehicles. It also defines two criticality thresholds ($Th(discharge)$ and $Th(postpone)$) that helps the vehicles to make a decision.

[3] EPA Federal Test Procedure. This is a series of tests defined by the US Environmental Protection Agency (EPA) modeling the speed of a vehicle under urban conditions.

Electric vehicle behaviour. The agent receives the data associated to the vehicle. It calculates its criticalities (Cr_{SoE} and Cr_{DoD}). It also receives the message from the charging station agent containing the cooperation request and the thresholds.

This agent has three possible actions: recharge the vehicle, discharge it or be idle. According to the received request, they may have several possibilities.

If it receives an *ABSORB* request, it must absorb power to cooperate. This action is in favour of the goal on the minimum state of energy. If the objective on the depth of discharge is not considered, it is not prejudicial to cooperate.

When it receives a *PRODUCE* request, it must discharge to cooperate, which is an action that may prevent its individual goal fulfillment. Yet, it can also cooperate by delaying its recharge. It does not deliver power but does not consume it either. If its criticality is lower than both thresholds, it is not critical. It can cooperate by discharging the battery. However, if its criticality is greater that one threshold, it postpones the recharge to limit its consumption. Finally, if its criticality is greater than both thresholds, it is too critical to cooperate, so it recharges the battery.

If the objective on the depth of discharge is considered, the corresponding criticality has to be taken into account. Indeed, if the vehicle has to change the sign of the charging power to cooperate, the condition to make the decision to cooperate or not has to be done taking the maximum of criticalities on the state of energy and on the depth of discharge ($Cr_{max} = \max(Cr_{SoE}, Cr_{DoD})$) or the criticality on the depth of discharge. The behaviour of vehicles is summarised in Table 1.

Table 1. Behaviour of vehicles

Current cycle	$DoD < 0$ (discharge)		$DoD > 0$ (recharge)	
Request	Conditions	Decisions	Conditions	Decisions
PRODUCE	$Cr_{SoE} < Th(discharge)$	DISCHARGE	$Cr_{max} < Th(discharge)$	DISCHARGE
	$Th(postpone) > Cr_{SoE}$ $Cr_{SoE} > Th(discharge)$	IDLE	$Th(postpone) > Cr_{SoE}$	IDLE
	$Th(postpone) < Cr_{SoE}$ $Cr_{SoE} > 0.6$	RECHARGE	$Th(postpone) < Cr_{SoE}$ $Cr_{SoE} > 0.6$	RECHARGE
ABSORB	$Cr_{DoD} < Th(postpone)$	RECHARGE	Always true	RECHARGE
	$Cr_{DoD} > Th(postpone)$	IDLE		

4.3 Synchronisation

The synchronisation of the agents has been one of the difficulties encountered in this approach. Indeed, the simulation is executed sequentially. Therefore, from a frequency simulation point of view, all vehicles make their decisions with the same view of the situation, therefore simultaneously. Depending on the number of vehicles connected, the effects of vehicles cooperation may be greater than the power deviation that need to be compensated. For example, if there is an under-production, some vehicles will make the decision to inject power into the network in order to reduce the energy unbalance between consumption and production. Then, the total power injected into the network by the fleet may be greater than the power gap to be compensated: there is an overproduction. Therefore, oscillations can appear.

Desynchronisation by simulation step decrease. A first solution to desynchronise the vehicles is to decrease the frequency simulation step. In the current system, a one-second simulation step is performed. A life cycle is then carried out for each agent, first the charging station agents and then the vehicle agents. However, for the proposed desynchronised approach, the simulation step of frequency is inferior to one second. At each step, only a fraction of the vehicle fleet makes a decision. Thus, for each step, the number of vehicles acting will be much lower: the risks of having a too strong compensation are therefore lower. Meanwhile, the vehicles still act at every second. This solution seems consistent with the assumption of an implementation on a real system since the agents would be implemented on desynchronized calculators. However, the charging station agents have a period execution time lower than the second. This assumes that the calculator running the algorithm executes its cycle in this new period, and that the system allowing the measurement of the frequency is fast enough.

Desynchronisation by vehicle agents behaviour. A second possible solution is to desynchronise the vehicles through their behaviour. In fact, for this solution, the decision to cooperate by discharging, if the conditions are satisfied, is replaced by a probability to cooperate. Thus, it avoids to have too many vehicles that begin cooperating at the same time and thus reduces the risk of overcompensation. This probability is proportional to the difference between the discharge threshold defined by the charging station agent and the criticality of the agent: the higher the network criticality is, or the lower the vehicle criticality is, the greater the probability of cooperation is.

5 Results and analysis

This last section presents the obtained results. These results are based on irradiance data from Oahu, on the 17th February 2011, from the National Renewable Energy Laboratory [17], between 4:30 pm and 6:30 pm are presented. The system is confronted to fairly large production gaps while at the same time managing the second departure of vehicles between 5:00 pm and 6:20 pm. The state of energy of the batteries at the beginning of the simulation are random between 0.3 and 1. For each simulation, the constraints on the state of energy of the vehicles at the departure time have been verified. The number of agents in each test corresponds to the number of vehicles in the situation added to the number of charging stations (2 in these simulations). The first simulations have been realised without considering the criterion on the depth of discharge of batteries.

5.1 Frequency regulation

Influence of the number of vehicles on the frequency regulation. This first test consists in observing the frequency obtained for different sizes of fleet.

Figure 1 shows the frequency obtained over a 5 minute range considering a fleet of 100 and 300 vehicles. It also presents the case where no vehicle is present: the frequency is therefore not regulated. We suppose here that the synchronous generators do not play any role in second-to-second frequency regulation, as our goal is to assess the quality of this regulation when an increasing number of electric vehicles take it in charge.

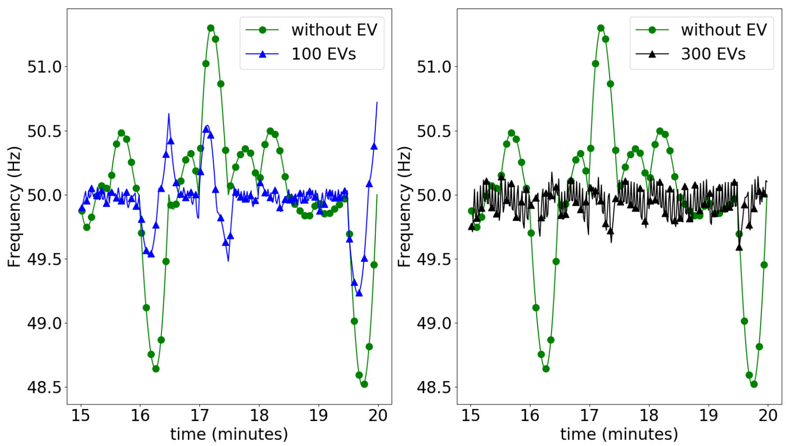

Fig. 1. Influence of the size of the fleet

These simulations show that by increasing the size of the fleet, the system reduces the fluctuations (peaks and throughs) due to the production gaps of the PV power plant more efficiently. During the simulation with 300 vehicles, the peaks are negligible. However, when the power gap is low (the frequency is stable), oscillations on the frequency appear. The amplitude of these oscillations increases with the number of connected vehicles. This phenomenon is due to the synchronisation of the vehicles present in the fleet (section 4.3).

This first test shows that two properties of the system will be in conflict: the ability of the system to keep the frequency close to 50 Hz despite large production gaps and its ability to limit oscillations of the frequency.

Desynchronisation. To reduce the frequency oscillations, vehicles have to be desynchonised. Two methods have been proposed section 4.3, either by reducing the simulation step or by adding a probabilistic behaviour to the vehicles.

Three cases have been simulated considering 300 EVs: reducing the simulation step (1st case), adding a probabilistic behaviour to the vehicles (2nd case) and a third one combining the two methods (3rd case). The average frequency deviation and the maximum frequency deviation are presented in Table 2.

Table 2. Results

	Synchronised vehicles			Desynchronised vehicles (300 EVs)		
	100 EVs	200 EVs	300 EVs	1st case	2nd case	3rd case
$\overline{\lvert \Delta f \rvert}$ (Hz)	0.035	0.052	0.078	0.038	0.073	0.018
$max(\lvert \Delta f \rvert)$ (Hz)	0.77	0.43	0.41	0.30	0.54	0.19

The method involving the reduction of the simulation step is more effective: the frequency oscillations are reduced. Adapting the behaviour of agents associated with EV to have a stochastic behaviour has a more reduced effect. However, when these two methods are combined, the oscillations amplitude and the maximum deviation are significantly reduced.

5.2 Limitation of micro-cycles

For this simulation, the EV agents take into account the depth of discharge by making their decisions in a way to reduce micro-cycles of charge and discharge. Table 3 shows that the majority of the cycles experienced during the previous simulations (between 94 % and 100 %) have an amplitude lower than 0.09 %, which corresponds to recharges or discharges of 5 seconds at nominal power.

Taking into account the criterion on depth of discharge and desynchronising by the two methods previously presented, only 3 % of cycles have their depth of discharge under 0.09 % (5 second recharge or discharge at nominal power) and 50 % greater than a 30 second-long recharge or discharge.

Table 3. Distribution of depth of discharge of cycles

Cycles duration time (d_{cycle})	$0 < d_{cycle} \leq 5\ s$	$5\ s < d_{cycle} \leq 30\ s$	$30\ s < d_{cycle}$
Synchronised vehicles	$> 99\%$	$< 1\%$	0
Diminution of the step simulation	$> 99\%$	$< 1\%$	$< 0.1\%$
Combined methods	94%	5.7%	$< 0.1\%$
criterion on DoD taken into account	3%	47%	50%

Nevertheless, the maximum frequency deviation obtained in this simulation is 0.30 Hz and the average frequency deviation is 0.034 Hz. Thus, the frequency regulation has been lightly deteriorated compared to the previous simulations.

Furthermore, the average execution time of a cycle of the AMAS in this simulation case is 64.5 µs on a core i7-7820 HQ, 2.90 GHz of CPU, 32 Go of RAM, running on Windows 10.

Finally, the frequency obtained is poorly dependent on the initial state defined by the initial state of energy and the departure time of each vehicle. In the test case taking into account the depth of discharge, the maximum standard deviation on the frequency obtained for 40 simulations is 0.1556 Hz, and the average standard deviation is 0.0186 Hz.

6 Conclusion

An adaptive multi-agent system (AMAS) has been proposed to achieve the frequency regulation using electric vehicles to counterbalance the production gaps of a PV power plant between its forecast average production over 30 seconds and its actual production. Agents have been defined to manage at least one of the objective or constraint of the issue: frequency regulation for the charging station agents and the constraints on the batteries for the vehicle agents: minimum state of energy and cycles depth of discharge.

Agents associated with charging stations must enforce the constraint on frequency sending requests to connected vehicles for them to produce or absorb power. Each agent associated with a vehicle is then able to decide if it accepts or declines the request, according to its criticalities, and the information transmitted by the charging station agent: the cooperation request and the criticality thresholds.

The implemented system has been able to reduce the impact of the production gaps, and thus to ensure the frequency constraint, while satisfying as well the constraints on the batteries state of energy. However, the obtained frequency by this regulation oscillates significantly. These oscillations have been reduced by desynchronising the vehicles in two ways: by modifying the simulation in the way that the vehicles act at different times and by making the behaviour of the vehicles stochastic. The architecture used implies that EV agents do not communicate with each other: they only communicate with charging station agents. Moreover, the life cycle of each agent is only executed once per decision.

Other constraints of the electric grid may be taken into account in the system. For example, taking into account local network phenomena, such as voltage and line congestion, is currently investigated. In fact, this constraint would be interesting since the power circulating in each line is a local information since it can be measured only on the considered line, contrary to the frequency which is a global information in the electric grid.

Acknowledgments. The authors wish to acknoweldge Riadh Zorgati, Senior Research Engineer at EDF R&D, France, for his technical help and Alexandre Perles, from IRIT, for the AMAK framework used to support our experiments.

References

[1] Haessig, P., Multon, B., Ben Ahmed, H, Lascaud, S., Bondon, P. (2015). Energy storage sizing for wind power: impact of the autocorrelation of dayahead forecast errors. Wind Energy, 18(1), pp. 43-57.

[2] Codani, P., Perez, Y., Petit, M. (2015). Electric Vehicles as a Mobile Storage Device. Wiley. Handbook of Clean Energy Systems, 5, 2015, Energy Storage.
[3] Le Goff Latimier, R., Multon, B., Ben Ahmed, H., Baraer, F., Acquitter, M. (2015). Stochastic optimization of an Electric Vehicle Fleet Charging with Uncertain Photovoltaic Production. International Conference on Renewable Energy Research and Applications, ICRERA 2015, pp. 721-726.
[4] Lund, H., Kempton, W. (2008). Integration of renewable energy into the transport and electricity sectors through V2G. Energy Policy, 36(9), pp. 3578-3587.
[5] Rigas, E. S., Member, S., Ramchurn, S. D., Bassiliades, N. (2015). Managing Electric Vehicles in the Smart Grid Using Artificial Intelligence : A Survey. IEEE Transactions on Intelligent Transportation Systems, 16(4), pp. 1619-1635.
[6] Crawley, C., Cameron, B., Selva, D. (2015). System Architecture: Strategy and Product Development for Complex Systems (1st ed.). Prentice Hall Press, Upper Saddle River, NJ, USA.
[7] Paniah, M. C., Mercier, D., Gil-Quijano, J. (2013). Multi-agents system for the management of renewable energy sources and mass storage.
[8] Hernandez, L., Baladron, C., Aguiar, J. M., Carro, B., Sanchez-Esguevillas, A., Lloret, J., Chinarro, D., Gomez-Sanz, J., Cook, D. (2013). A multi-agent system architecture for smart grid management and forecasting of energy demand in virtual power plants. Communications Magazine, IEEE, 51(1), pp. 106-113.
[9] Lopes, J. A. P., Almeida, P. M. R., Soares, F. J. (2009). Using vehicle-to-grid to maximize the integration of intermittent renewable energy resources in islanded electric grids. International Conference on Clean Electrical Power, ICCEP 2009, pp. 290-295.
[10] Mu, Y., Wu, J., Ekanayake, J., Jenkins, N., Jia, H. (2013). Primary frequency response from electric vehicles in the Great Britain power system. IEEE Transactions on Smart Grid, 4(2), pp. 1142-1150.
[11] Gao, S., Chau, K. T., Liu, C., Wu, D., Chan, C. C. (2014). Integrated energy management of plug-in electric vehicles in power grid with renewables. IEEE Transactions on Vehicular Technology, 63(7), pp. 3019-3027.
[12] Depoorter, S., Assimon, P. M.: Les véhicules électriques en perspective, analyse coûts-avantages et demande potentielle, 2011.
[13] Serugendo, G. D. M., Gleizes, M. P., Karageorgos, A. (Eds.). (2011). Self-organising software: From natural to artificial adaptation. Springer Science & Business Media.
[14] Bernon, C., Gleizes, M. P., Peyruqueou, S., Picard, G. (2002). ADELFE: a methodology for adaptive multi-agent systems engineering. International Workshop on Engineering Societies in the Agents World, vol 2577.
[15] Jorquera, T.: An Adaptive Multi-Agent System for Self-Organizing Continuous Optimization. Doctoral thesis, Université Paul Sabatier, 2013.
[16] Georgé, J. P., Gleizes, M. P., Camps, V. (2011) Cooperation. In: Di Marzo Serugendo G., Gleizes MP., Karageorgos A. (eds) Self-organising Software: From Natural to Artificial Adaptation. Natural Computing Series, Springer-Verlag.
[17] Sengupta, M.; Andreas, A. (2010). Oahu Solar Measurement Grid (1-Year Archive): 1-Second Solar Irradiance; Oahu, Hawaii (Data); NREL Report No. DA-5500-56506. http://dx.doi.org/10.5439/1052451.