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Self-adaptive Distribution System State Estimation

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Abstract. Electricity plays an increasingly important role in our society. Indeed, we are moving toward the era of "everything electric". The needs evolving, it is mandatory to rethink the way electricity is produced and distributed. This then introduces the concept of an autonomous and intelligent power system called the Smart Grid.

One characteristic of the Smart Grid is its ability to control itself. To do this, papers in literature suggest that the state of the controlled network should be estimated.

This paper proposes an agent-based architecture to enable the transition to the Smart Grid, a design and an implementation of agent behaviors aiming at solving the State Estimation problem. Based on the Adaptive Multi-Agent System theory, the developed system allows from local interactions between agents to estimate in a reasonable time and computational complexity the state of a distribution system.

1 Introduction

Nowadays, electrical networks in the world are made of a set of nodes connected with unidirectional links. This approach is used to facilitate the transport of electricity. The electricity is generated at one point by the producer, and is provided to consumers through the lines. Thus, the only control point is located at the source and if a fault occurs on a network, it is easier to locate and to isolate it. Although it has been used for decades, this approach is expected to evolve with the concept of Smart Grid [1,3,6,20].

From the papers [3,6,20], the concept of Smart Grid can be defined as follow: *the Smart Grid is an autonomous electrical network able to adapt itself to client's needs in a secured, ecological and economical way. It enables bidirectional exchanges of electricity and information through lines.*

Roche [18] presents some motivations to move from classical electrical networks toward the Smart Grid: the increase of energy demand, the global warming, the increase of distributed and renewable generation and the depletion of resources currently used for energy generation.

The demand in energy is growing fast. The worldwide energy demand is expected to rise by over 150% from 2010 to 2050 under the Energy Technology Perspectives 2010 (ETP 2010) Baseline Scenario and over 115% between 2007

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and 2050 under the Blue Map Scenario [10]. Moreover, since the 1960's, the temperatures of air and water are more and more away from normal conditions. This is called the global warming. Given this situation, some governments have decided to promote new technologies and the usage of renewable energy. Besides the global warming, we are going to run out of currently used resources. For the previously mentioned reasons, the number of distributed and renewable generators is going to increase quickly resulting in as many additional control points which will obviously result in the increase of complexity to ensure voltage range and more generally a good quality of service. It is therefore necessary to find a solution to control this new network type.

One solution to control an electrical network is to firstly determine its state. This is referred to as System State Estimation. Indeed, knowing the state of an electrical network allows for example to detect faults in a network and also to prevent or to remove them. Although efficient methods are known to solve the State Estimation problem on transmission networks (such as in the paper of Monticelli [15]), the Distribution System State Estimation is not trivial. This is mainly due to the radial structure of such systems and the low amount of sensors.

To handle the previously expressed problems, works have been realized in order to reduce the computation complexity. In works such as [5,8,14,23,24], problems are distributed between multiple agents and then aggregated to a "Control Agent" (or an "Aggregator Agent") able to interact with these smaller entities. We notably can find, in the paper of Ghazvini et al. [9], a division of an electrical network into multiple zones considered to be enough small to minimize the complexity of computations made on it while maintaining their efficiencies. This method reduces the complexity however the cutting into zones is not trivial and the synchronization of these estimations brings other problems.

This paper presents an innovative approach based on Multi-Agent System to allow the transition to the Smart Grid and notably the State Estimation by exploiting the Newton-Raphson numerical method (see [17]) locally to each bus.

In the first part of this paper, the State Estimation problem and its potential role in the Smart Grid is detailed. Secondly, the Adaptive Multi-Agent System approach is described as an alternative to traditional methods. And finally, the design and evaluation of the developed system is presented.

2 Problem Description

An electrical system is composed of various entities. Buses are nodes of the network to which can be connected lines, producers, consumers, ... These buses can be equipped with voltage magnitude sensors or power sensors. All these sensors give informations (voltage magnitude, injected power, ...) about the state of a network. However, networks can't be fully equipped because this is too much expensive and sensors are not 100% accurate. So the problem is to estimate the voltage of each bus in the network without having sensors at each bus. Moreover, the amount of power consumed at consumer sites is generally not known which increases the difficulty of the problem.

The State Estimation problem can be defined as follow: *finding the most likely state of the system based on quantities that are measured and the model of this system and filtering the errors of the sensors thanks to their redundancy.* Solving the State Estimation problem is the process of estimating the voltage of each bus of a network. To do so, the topology of the network as well as the values returned by sensors and an estimation of power injection at load buses are known.

It exists three types of measurements. ***Real measurements*** are the one provided by physical sensors, ***Pseudo-Measurements*** are rough estimations of the power injected at consumer sites and ***Virtual Measurements*** are the power injected at zero-injection buses (buses to which no generator nor load are connected).

Let z be the set of measurements (real measurements, pseudo-measurements and virtual measurements) at a given time t. These measurements can be expressed as the sum of the real observed value and an error due to the imprecision of sensors:

$$z = h(x) + e \tag{1}$$

With:

- x: the state vector of the network,
- h: the model of the network,
- e: the error vector of measurements.

In a State Estimation problem, the function h is known as well as the set of measurements z.

For this multi-agent study, we consider consumers and producers connected to the bus as an abstract and unique entity which is an integral part of the bus. Consequently, the reader must have in mind that the sum of productions and consumptions on a bus is referred to as "bus injection".

The State Estimation problem can be solved by using the statistic method of maximum likelihood estimation. By assuming the interdependence of measurements and their Gaussian distribution, determining the state of a network can be expressed as solving an optimization problem where the objective function is formulated as a sum of Weighted Least Squares in which the weighted squares are the differences between the model values and the measures weighted by the precision of the corresponding measurement type.

The corresponding objective function to minimize is:

$$\sum_{s \in \text{Sensors}} \left(\frac{z_s - h_s(x)}{\sigma_s} \right)^2 \tag{2}$$

With z_s the measure, $h_s(x)$ the value calculated with the model and σ_s the variance of the distribution of the sensor s.

A lot of works have been done on transmission system state estimation. However, classic optimization approaches applied to distribution systems have a high computational complexity [11]. Also, few studies have been made to propose

a multi-agent approach to solve the state estimation problem by applying a decomposition of the problem in smaller problems easier to solve, followed by an aggregation of these solutions [13,16,22].

The most part of these studies have formulated the problem as a Weighted Least Square Minimization problem and solved it globally with global numeric methods. It consists in minimizing the weighted square of errors between the model and measured values.

Examples of the application of such method to distribution networks can be found in the literature [4,12,19]. The main drawback of this kind of approach is that it requires to work with the whole set of equations with large matrices resulting in a resolution with a non-negligible complexity. In addition to state estimation, some works have been done to improve the estimation made for pseudo-measurements.

Most of these approaches are based on the Newton-Raphson numerical method [17]. The Newton-Raphson method is a mathematical method to find an approximation of the roots of a function. The resolution is iterative and requires that the starting point is close to the solution.

In this study, we propose to evaluate the relevance of using an Adaptive Multi-Agent System based on a local application of the Newton-Raphson method for solving the State Estimation problem in distribution networks.

3 Adaptive Multi-agent Systems

To solve this problem, the Adaptive Multi-Agent Systems approach seems to be particularly suitable and provides, thanks to its design process, an openness allowing to add future features which is a mandatory for a system aiming at controlling the Smart Grid. Moreover, the dynamic and distributed aspects of these new networks confirm the relevance of such an approach.

An Adaptive Multi-Agent System is a Multi-Agent System in which the emergence process is used to provide a global answer adapted to the problem from local cooperative interactions between agents [21].

3.1 Cooperation

The cooperation in an Adaptive Multi-Agent System is the process of mutual support between agents of this system. It is a question of finding the right equilibrium between acting to reach its own goal and helping other agents to reach their own without having a global knowledge of the system. In order to identify the agent which is struggling the most, agents have the ability to assess their criticalities.

3.2 Criticality

The criticality of an agent represents the state of dissatisfaction of it regarding its local goal [7]. The criticality of an agent is a value assessing the difficulty an agent has to reach its goal at a given situation. This value evolves and is expected to be minimal for all agents when the problem is solved.

4 An Adaptive Multi-agent System for the Distribution of Intelligence in Power Systems

In this section, we present the developed multi-agent system aiming at solving the State Estimation problem. This system was designed in accordance with the Adaptive Multi-Agent System theory and following the ADELFE (Atelier de Développement de Logiciels à Fonctionnalité Émergente) methodology (see [2]). The developed system aims at estimating the state of an electrical system. To achieve this, agents act locally to estimate the state of the bus they are associated to. The State Estimation problem also consists in benefiting of sensors redundancy to filter errors. The agents also have to cooperate to distribute the errors among the voltage sensors. From the collective resolution, it emerges the State Estimation of the global system.

This part presents the agentification of the entities composing an electrical network, the interactions between these entities and the cooperative behaviors of these agents.

4.1 Cooperative Agents

In order to allow a certain flexibility in the future evolutions of the developed system, we have made the decision to agentify the buses as well as voltage sensors as they are major actors in the State Estimation and are expected to evolve during the solving process. Agents are autonomous in their decision-making and act locally. Moreover, this fine granularity allows to reduce the impact a change can have in the controlling system.

In our system, we have defined two types of agents: Bus Agents and Voltage Magnitude Sensor Agents. For each bus, it's possible to have two associated agents: a Bus Agent and a Voltage Magnitude Sensor Agent. However, a Voltage Magnitude Sensor Agent is present on the bus only if a voltage magnitude sensor is attached to that bus.

- The goal of a bus agent is to determine a consistent voltage magnitude and phase angle (according to the network) of the bus it is associated to.
- The goal of a Voltage Magnitude Sensor Agent is to determine the voltage magnitude at the bus it is associated to thanks to the values returned by the voltage sensor and the bus agent associated to the bus.

The Fig. 1 represents an example of a piece of power system as well as all the used types of agent and their interactions.

4.2 Interactions Between the Entities

To give the ability to the agents to cooperate and reach their goal, they need to be able to interact with other agents.

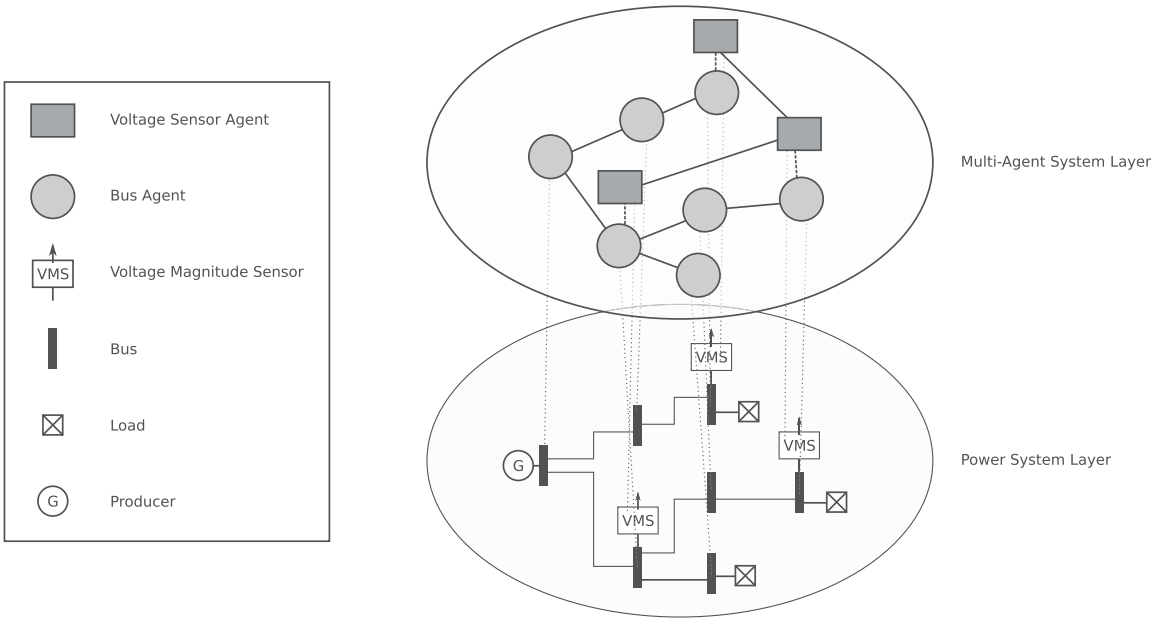

Fig. 1. Multi-agent system coupled with a piece of power system

The different interaction types are the following:

Interactions Between the Bus Agents. The goal of Bus Agents is to determine the voltage magnitude and phase angle at the bus they are associated to. To do that, they need to be aware of, at each step for each agent in its neighborhood, the current estimation of voltage (magnitude and phase angle). The only interaction between the Bus Agents is about the current value of their respective voltage estimations.

Interactions Between the Voltage Magnitude Sensor Agents and the Bus Agents. The Bus Agents need to know the value estimated by the Voltage Magnitude Sensor Agent associated to the bus if any. Moreover, the Voltage Magnitude Sensor Agents need to know the difference between their estimated voltage magnitude and the one estimated by the Bus Agent associated to the same bus.

Interactions Between the Voltage Magnitude Sensor Agents. The Voltage Magnitude Sensor Agents try to distribute the sensors errors among them. Therefore, they need to communicate in order to cooperate.

4.3 Cooperative Behavior of Bus Agents

The behavior of a Bus Agent depends on the presence of a Voltage Magnitude Sensor Agent on the bus.

– In the presence of a Voltage Magnitude Sensor Agent, the bus agent can get the current estimated voltage magnitude of the Voltage Magnitude Sensor Agent and uses it as its voltage magnitude estimation. Then, the bus agent applies the Newton-Raphson method to estimate the phase angle value.

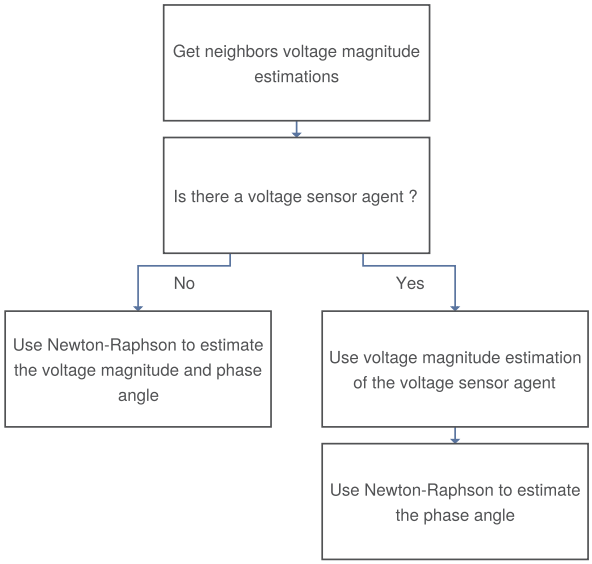

Fig. 2. Behavior of a Bus Agent for the State Estimation problem solving

– In the absence of a Voltage Magnitude Sensor Agent, the bus agent applies the Newton-Raphson method to estimate both the voltage magnitude and the phase angle.

The Fig. 2 presents the behavior of a Bus Agent. This algorithm is mainly based on the function *NewtonRaphson.Compute*. This function takes in parameters the current estimated voltage (magnitude and phase) of the agent as well as the current estimated voltage of its neighbors. From this information, the function computes an iteration of the Newton-Raphson method and returns a new voltage value.

In the decision phase, the bus agent calculates the voltage (complex number) with the Newton-Raphson method. In the case in which it is not associated to a Voltage Magnitude Sensor Agent, the bus agent uses the voltage value obtained with the Newton-Raphson method. In the other case, the bus agent uses the voltage magnitude estimated by the associated Voltage Magnitude Sensor Agent and the voltage phase angle calculated with the Newton-Raphson method.

4.4 Cooperative Behavior of Voltage Magnitude Sensor Agents

Roughly, Bus Agents are expected to find the voltage which locally satisfies the Kirchhoff's Current Law (the sum of currents flowing into a bus must be equal to the sum of currents flowing out of that bus). Voltage Magnitude Sensor Agents are here to correct the value provided by voltage magnitude sensor by cooperating with others Voltage Magnitude Sensor Agents to help Bus Agents to reach their goal (which is satisfying the Kirchhoff's Current Law on their bus).

The goal of a Voltage Magnitude Sensor Agent is to determine the real voltage magnitude thanks to the value given by the voltage sensor it is associated to and the voltage magnitude estimation made by the bus agent associated to its

bus. To do it, a Voltage Magnitude Sensor Agent knows at least one other Voltage Magnitude Sensor Agent. It allows each Voltage Magnitude Sensor Agent to cooperate with the others. Moreover, contrarily to Bus Agents, Voltage Magnitude Sensor Agents can exchange messages.

Supposing the errors of voltage sensors are equitably distributed, each Voltage Magnitude Sensor Agent negotiates with its neighbors to determine its correct value.

In order to understand the cooperative behavior of a Voltage Magnitude Sensor Agent, it is necessary to define some terms that will be used in the following parts:

- *The **Estimated Voltage Magnitude Value** is the supposed value of the voltage magnitude at the associated bus by the Voltage Magnitude Sensor Agent.*
- *The **Offset of a Voltage Magnitude Sensor Agent** is the signed difference between its Estimated Voltage Magnitude Value and the value returned by the voltage magnitude sensor.*

In order to minimize the objective function (see the formula (2)), Voltage Magnitude Sensor Agents start with the voltage magnitude given by the physical sensor. This obviously corresponds to the smallest squared value. It then changes its value to match with the constraints imposed by the Kirchhoff's Current Law. If a Voltage Magnitude Sensor Agent has to increment its estimated value to solve a constraint, it must be sure that another agent will decrease its own by the same factor and vice-versa. Thus, it allows agents to change their estimated value as long as it doesn't increase the Weighted Squares sum without calculating it. As the agents are cooperative, they will try to help each other by compensating the offset a Voltage Magnitude Sensor Agent needs to do as long as this latter is more critical.

The Fig. 3 details the three phases of a cycle of a Voltage Magnitude Sensor Agent.

Criticality of a Voltage Magnitude Sensor Agent. The criticality of a Voltage Magnitude Sensor Agent is the difference between its Estimated Voltage Magnitude Value and the voltage magnitude calculated by the associated bus agent with the Newton-Raphson method. In other words, a Voltage Magnitude Sensor Agent is satisfied when the value it has found is equal to the one found by the associated bus agent.

$$|estimatedVoltageMagnitude(self) - estimatedVoltageMagnitude(busAgent)| \tag{3}$$

Perception. The perception phase consists in acquiring all the informations the agent needs to take a cooperative decision. During the perception phase, a Voltage Magnitude Sensor Agent perceives:

- the criticality of each of its neighbors,

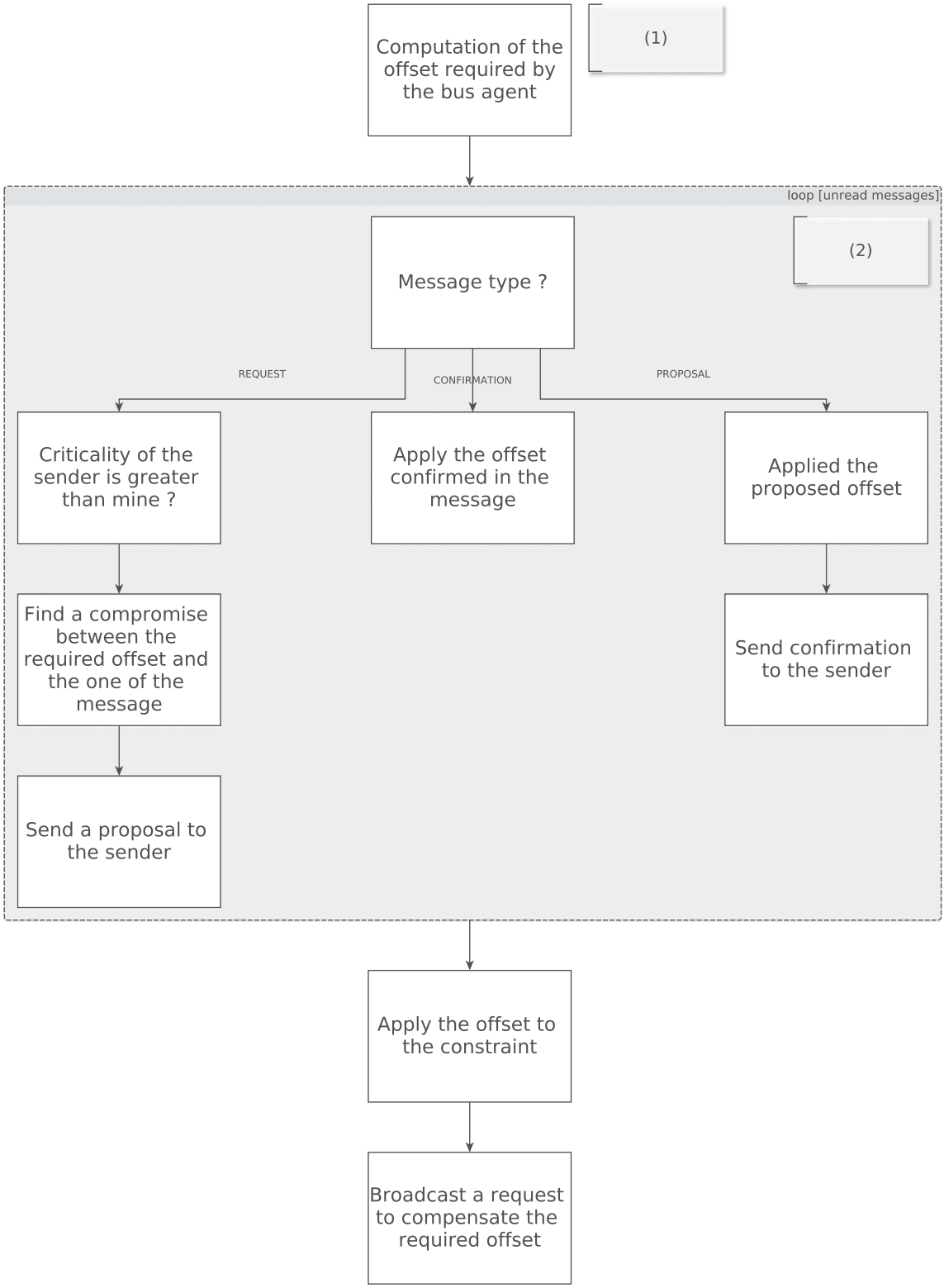

Fig. 3. Behavior of a voltage magnitude sensor agent for the State Estimation problem solving

- the messages previously sent by its neighbors,
- the last voltage magnitude sensed by the voltage sensor it is associated to,
- the voltage magnitude calculated by the bus agent of the bus it belongs to.

Decision. The first part (1) of the decision process is to compare the value estimated by the bus agent with the Newton-Raphson method and compare it to the value currently estimated by the Voltage Magnitude Sensor Agent. This gives the required offset. Then, the agent has to consider messages received from its neighbors (2). As mentioned previously, only Voltage Magnitude Sensor Agents can exchange messages. It exists three kinds of message: an offset request (REQUEST), a proposal (PROPOSAL) and an offset confirmation (CONFIRM).

Offset Request. This type of message is intended to ask a neighbor to modify its Estimated Voltage Magnitude Value in order to compensate the modification the sender wants to do on its own Estimated Voltage Magnitude Value.

Proposal. Once an agent receives an offset request, it can answer with a Proposal message to propose a modification of its own offset.

Offset Request Confirmation. The agent which has sent the first message (Offset Request) may have received a proposal. If it still fits its needs, the agent can confirm this operation.

In the case in which an agent receives an Offset Request, it has to decide if it must help the sender. To do that, it observes the criticality of the sender. If this latter is greater than its own, it answers with a proposal to inform it that it can compensate the requested offset.

In the case in which an agent receives a proposal, it has to confirm the offset it wants to be compensated.

Finally, in the case in which an agent receives an Offset Confirmation, it has to fulfill its engagement because it is cooperative and change its value.

The following table summarizes these rules:

Condition	Action
Received an offset request and the emitter is more critical	Send a proposal
Received a proposal	Send a confirmation for absorbing the offset
Received a confirmation	Absorb the offset

This cooperative behavior is intended to guarantee that if an agent moves its estimated voltage magnitude from the one of its sensor, another agent will do the same in the other direction. This behavior allows to distribute the voltage magnitude sensors errors among the sensors.

Action. In the case where its Estimated Voltage Magnitude Value is different than the voltage magnitude calculated by the bus agent, it means that the Voltage Magnitude Sensor Agent is not yet satisfied. Therefore, the agent has to

broadcast an Offset Request to its neighborhood. Finally, the agent updates its criticality value with the formula 3.

This cooperative behavior is aimed at distributing the sensors errors among these latter. The following part presents the results of evaluations made on this system.

5 Evaluation

Multiple evaluations have been made with the proposed system. In each case, at least 1,000 resolutions have been made. This part presents the results of these evaluations: Performance over the amount of voltage sensors, filtering quality, computation time and self-adaptation.

In order to determine the quality of a solution to the State Estimation problem, it is, first and foremost, necessary to define a criteria of quality. A solution to the State Estimation problem is considered as acceptable if the maximal relative voltage magnitude estimation error is lower than 1%.

The relative voltage magnitude estimation error of a bus is expressed as a percent of error and is calculated with the following formula:

$$\frac{\text{Real Value} - \text{Estimated Value}}{\text{Real Value}} \cdot 100 \tag{4}$$

5.1 Performance over the Amount of Voltage Sensors

The Fig. 4 presents performance results on the application of the developed system to solve the State Estimation problem on a 111-bus distribution system. On this network, we have defined 6 configurations of voltage sensors. The first configuration contains only one voltage sensor. The second one contains two voltage sensors and so on.

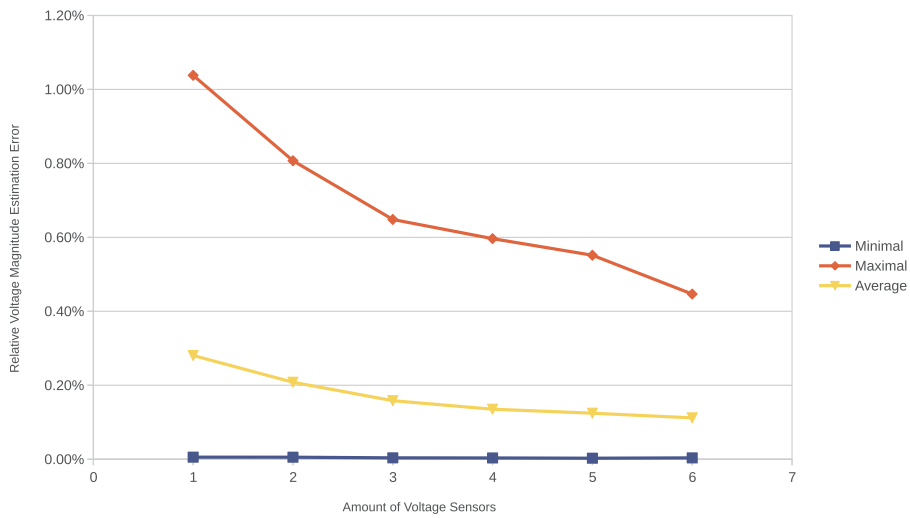

Fig. 4. Performance evaluation on a 111-bus distribution system

For each configuration, 1,000 resolutions have been made. For each of these resolutions, a random noise has been added to the voltage magnitude sensors values to simulate the imprecision of sensors.

On these 1,000 resolutions, we have measured the maximal voltage magnitude estimation errors. Finally, for each configuration, we have calculated the minimal, maximal and average of these maximal values.

We can observe on the Fig. 4 that with only two sensors, the system is able to estimate the state of the network with a maximal relative voltage magnitude estimation error lower than 1%. Moreover, this highlights the fact that redundancy of sensors improves the accuracy of the State Estimation. The errors of sensors being 1%, the results show that the system is able to improve the accuracy of the estimation thanks to the redundancy of sensors.

5.2 Filtering Quality

For a given voltage magnitude sensor and its associated bus, we have observed over 10,000 resolutions the values returned by the voltage sensor and the values found by the system. This allows to determine whether or not the system is able to provide better voltage magnitude estimation than the one provided by sensors. The Fig. 5 presents the distribution of obtained value. It can be observed that the Gaussian of the estimation is twice thinner than the one of the sensor. The parameters of the Gaussian are presented in the Table 1. This results show that the voltage magnitude estimations of the system are twice less wrong than the values returned by the sensors.

σ is the standard deviation of the voltage sensor present at this bus. τ is the standard deviation of the results obtained thanks to the system.

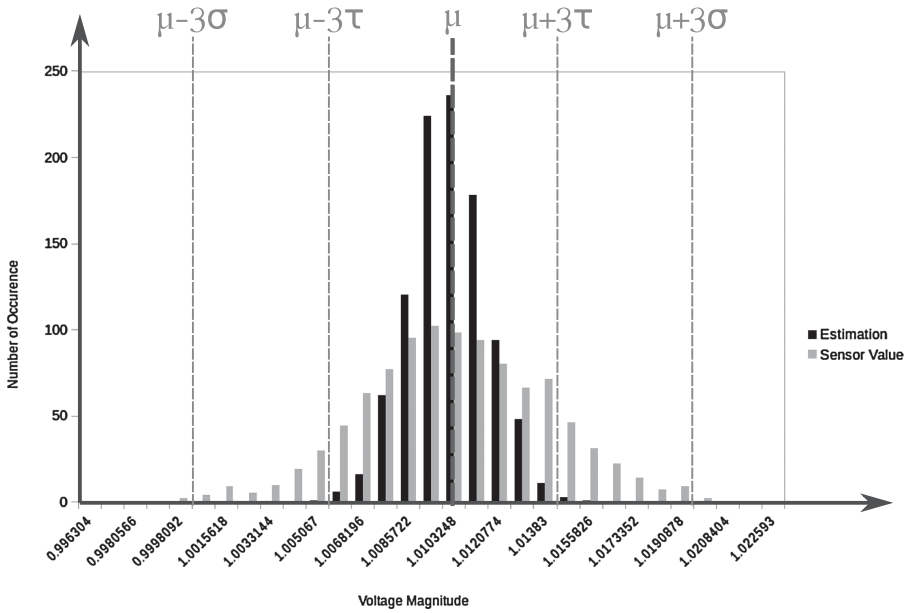

Fig. 5. Gaussian distribution of a voltage sensor and the State Estimation for a bus

Table 1. Standard deviations and mean value of the bus observed

Real value (μ)	1.014676
Estimation standard deviation (τ)	0.0014324118
Estimation mean value	1.014665402
Sensor standard deviation (σ)	0.0033071471
Sensor mean value	1.014882942

5.3 Computation Time

For a given 111-bus network and a given configuration, good performances have been observed. Generally, the system requires less than one second to provide an accurate result. However, in some cases, the system needs up to 244 ms to provide an accurate solution. This may be due to the imprecision of measurements and special situations in which agents can be.

The following values have been measured:

	Minimum	Maximum	Average
Time (in seconds)	0.104	0.244	0.13191
Number of cycles	303	714	381.591

5.4 Self-adaptation

Finally, an experimentation have been realized to determine the robustness of the developed system. In this experiment, we are looking forward to determine if the

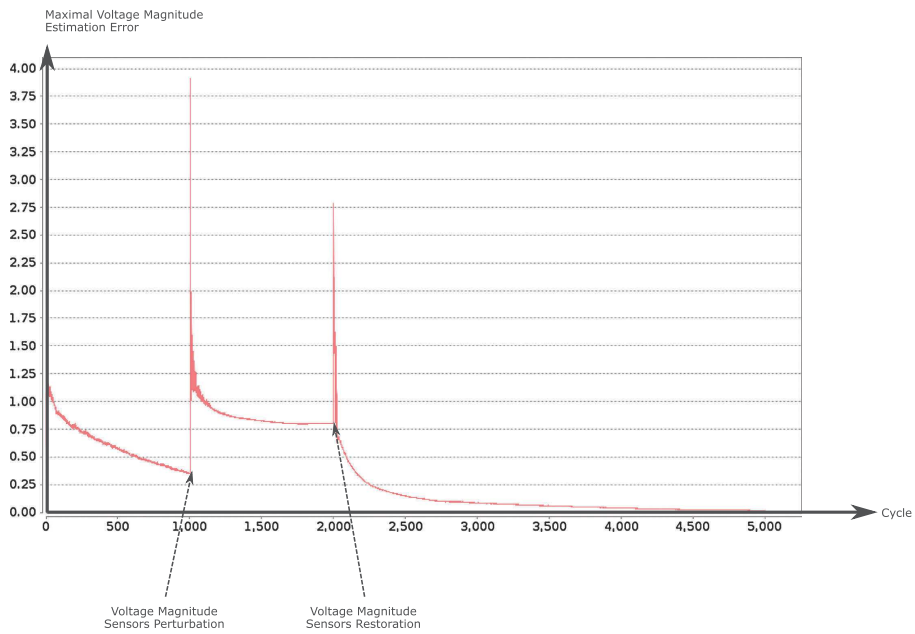

Fig. 6. Impact of the addition of a perturbation during the resolution process

system is able to resist to perturbations. We have launched a State Estimation solving on the 111-bus network. Then, at the cycle 1,000, we have introduced a supplementary random noise to each voltage sensor values to observe the reaction of the system. These noises have then been removed at the cycle 2,000.

As expected, the Fig. 6 shows that the system is able to adapt itself to perturbations and that it tries to find the most likely solution despite the noise added to sensors values.

6 Conclusion and Perspectives

In this paper, we have highlighted the fact that moving from current electrical network to the concept of Smart Grid requires a reconsideration of the way electrical network problem are treated. After a brief introduction, the State Estimation problem is presented as a Weighted Least Square optimization problem. Then, the Adaptive Multi-Agent System theory is presented. After that, an innovative approach, based on it, is proposed to solve the State Estimation problem. The cooperative behaviors of the two types of agents of this system allows them to locally estimate the state of the bus they are associated to and to filter the sensor errors. The results of the evaluations made on the system show the relevance of using an Adaptive Multi-Agent System for the Smart Grid in terms of performance and self-adaptation. Research will be continued to improve the error filtering. Also, an interesting perspective could be to evaluate the adaptation capability over configuration changes. Moreover, in real situations, communication can be suddenly interrupted. It is therefore necessary to handle this case. Finally, connecting the multi-agent system to a good quality network simulator would allow to evaluate the robustness of the system against perturbations (load evolutions, fault on lines, . . .).

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