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Principle and Evaluation of a Self-Adaptive Multi-Agent System for State Estimation of Electrical Distribution Network

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Abstract— In our daily life, electricity becomes more and more important. Mainly for environmental concerns, governments tend to encourage integration of generators which rely on renewable energy sources. Therefore, it is necessary to move from present electrical networks to smarter ones. These issues have contributed to the development of the concept of Smart Grid. One might well ask the question: how to add a layer of intelligence on electrical networks as we know them?

The work presented in this paper is mainly focused on the State Estimation as a way to observe the evolution of low voltage or medium voltage disturbances in order to mitigate them using innovative regulation functions. The Atena platform presented in this study has shown the feasibility and some advantages of using an adaptive multi-agent system for the estimation of the network state within a reasonable time, with encouraging accuracy for voltage regulation, with a linear complexity and with the capacity to adapt itself to changes that can occur in the network. Each agent has only a local perception of the grid and interacts with its immediate neighbors according to the network topology, without any information on the global state.

Multi-Agent System; State Estimation; Distribution Network; Smart Grid; Cooperation

I. INTRODUCTION

Before the 1990's, the state estimation of electrical networks has never been a major concern. Indeed, the way these networks have been designed and dimensioned suits perfectly with the use which has been made of it. However, the ever-growing needs in electricity as well as the environmental concerns have led providers to find smarter ways to produce, distribute and consume energy. Researches around the concept of "Smart Grids" have therefore boomed [1].

In this study, we propose to evaluate the Adaptive Multi-Agent System theory as a candidate for distributing intelligence in electrical networks. In the first place, we will explain why the State Estimation of Distribution Systems is an important and complex problem and review related works which have tried to solve this problem. Secondly, we will present the theory of Adaptive Multi-Agent Systems. Then, through the application of this theory, we will describe the proposed system

called Atena (Adaptive Transport of Energy in Networked Areas) aiming at solving this problem. Next, an evaluation of the system will be presented. And finally, we will conclude and discuss perspectives.

II. STATE ESTIMATION IN DISTRIBUTION SYSTEM

A distribution system is the part of an electrical network which distributes electricity from transmission systems to consumers. These systems are made of nodes, also called buses, which are linked with other nodes through lines which may have various admittances. In order to have a power flow in these systems, there must be at least one producer (generator) and at least one consumer (load) each one connected to a bus. For each node to which a producer or a consumer is connected, there is a power sensor (or at least a load-pattern). In addition, some other voltage sensors can be associated with other buses. These sensors provide noisy data about the state of the network.

A. Problem Description

The state estimation problem can be expressed as **finding a voltage magnitude and a voltage phase for each node in order to be consistent with the network characteristics (topology, lines admittance ...) and to enable a filtering of data provided by various sensors**. More generally, the objective of state estimation is to determine the most likely state of the system based on quantities that are measured which are assumed to have a Gaussian (normal) distribution. One way to accomplish this state estimation is by using the statistic method of maximum likelihood estimation. By assuming the independence of measurements and their Gaussian distribution, determining the state of a network is equivalent to solving an optimization problem where the objective function can be expressed as a sum of Weighted Least Squares.

In case we do not have power sensors associated with a consumer (or a producer), we use load-patterns (or pseudo measurements) generated from load forecasts or historical data. However, the producers are always instrumented with power and voltage magnitude sensors.

It is therefore a question of finding the voltage of nodes that satisfy the model of the network while minimizing the distance between found values and sensed ones.

The problem can be then divided in two parts:

1) Kirchhoff's Current Law

The first constraint is derived from the Kirchhoff's current law which must be fulfilled. The power is defined according to the consumption, production and lines power transit at the considered node. By convention, the currents are assumed to flow from the bus to the terminal of each component connected on it.

Fig. 1 represents the current flows between four buses. For bus 2, the Kirchhoff's Current Law is verified if $I_{24} + I_{21} = 0$. For bus 3, the current of the producer (or consumer) has to be taken into account.

The model retained for each underground or overhead line is provided by Fig. 2. Thus, the current at each bus of a line is entirely determined by (1). The complex values of these currents (I_1, I_2) depend both on the line node matrix and the voltage complex value at each bus. Let:

- 1 and 2 be two buses connected through a line,
- Y be the admittance matrix of the line,
- V_j be the voltage (complex value) of the node j ,
- I_j be the current flowing from the node j to the line,
- $Variable^*$ be the conjugate of the variable.

The admittance matrix of a line is defined in table I.

According to (1), the apparent power flow from bus 1 to bus 2 is determined by (2).

$$\begin{bmatrix} I_1 \\ I_2 \end{bmatrix} = \begin{bmatrix} Y_{11} & Y_{12} \\ Y_{21} & Y_{22} \end{bmatrix} \cdot \begin{bmatrix} V_1 \\ V_2 \end{bmatrix} \quad (1)$$

From this equation, we can deduce (2) to compute the power S_{12} provided by bus 2 through the line to bus 1.

$$S_{12} = V_1 \cdot (V_1^* \cdot Y_{11}^* + V_2^* \cdot Y_{12}^*) \quad (2)$$

2) Data to be filtered by state estimator

Sensors are not perfect, their native inaccuracy can have a non-negligible impact on the voltage estimates. The number of measurements has to be limited in order to reduce the costs of the proposed solution. Consequently, active and reactive power pseudo measurements have to be used at each consumption point (load models).

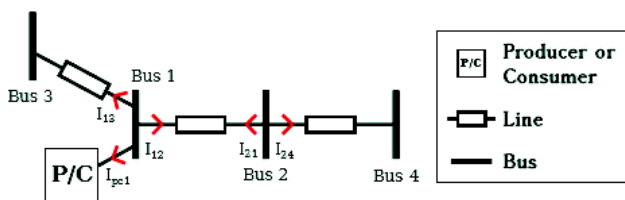


Figure 2. Current Flows

TABLE I. ADMITTANCE MATRIX

$Y_L + Y_T$	$-Y_L$
$-Y_L$	$Y_L + Y_T$

B. State of the Art

Although the concept of state estimation has appeared in 1969, notably thanks to the works of Schweppe [2], this concept has been considered only for transmission systems for 20 years. State Estimation applied to distribution system has been considered only since 1990. With the evolution of consumption, network managers are more and more expected to provide a more reliable supply of energy and reduce energy losses. This leads to the concept of Active Management and notably to the active voltage regulation which requires an important knowledge of the network. Overequip the network with sensors is not economically feasible. It is therefore necessary to find alternative ways to determine the state of a network. This introduces the concept of "Distribution State Estimation" [3]. The first ones who have published about this are Roytelman and Shahidehpour in their publication called "State estimation for electric power distribution system in quasi real-time conditions" [4].

A lot of works have been done on transmission system state estimation. However, classic optimization approaches have a high computational complexity [5]. 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 [6], [7], [8].

The most part of these studies have formulated the problem as a Weighted Least Square Minimization problem and solved it with global numeric methods. This approach consists in minimizing the weighted square of errors between the model and measured values [4], [9], [3].

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.

III. THE MULTI-AGENT SYSTEM ATENA FOR STATE ESTIMATION

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 methodology [10].

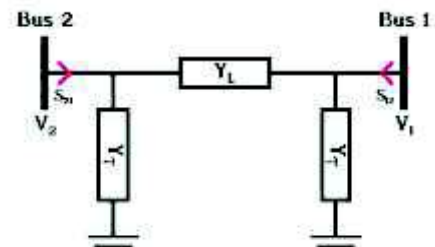


Figure 1. Example of π -line model

A. Multi-Agent System

A Multi-Agent System is a system in which a certain amount of autonomous entities, called agents, interact with one another and the environment for accomplishing a collective task.

1) Agent

A commonly admitted definition of an agent is that it is an autonomous entity that can be seen as perceiving its environment through sensors and acting on it through effectors [11]. This definition can be completed by telling that an agent can have the ability to communicate with other agents and is able to take decisions on its own [12]. An agent has only a limited view of its environment.

2) Environment

We consider two kinds of environment:

- The environment of the multi-agent system contains everything that is not part of the multi-agent system. When solving an optimization problem, the environment of the multi-agent system is the problem itself;
- The environment of an agent contains the environment of the multi-agent system and some other agents of this system. It is however important to notice that agents perceptions are limited and therefore they are only able to observe a small part of this environment.

3) Adaptive Multi-Agent System Theory

An Adaptive Multi-Agent System (AMAS) is a multi-agent system in which agents have a coherent collective activity to achieve the right task. It has been proved that: **“For any functionally adequate system, there is at least a cooperative interior medium system which fulfills an equivalent function in the same environment”**.

This then introduces the concept of cooperative agent. A cooperative agent is an agent which cooperates with the others in order to satisfy its goals and the ones of its neighbors. As the resolution of the global problem is not implemented in agents, one can talk of emergence [13], [14].

4) Self-organization and Self-Adaptation

The concept of “Emergence” seems to be suitable to conceive adaptive systems for dynamic environments. Emergence and self-organization are similar concepts as they appear to have common characteristics such as non-linearity. Self-organization is a physical and biological notion about the state of some systems able to display functions or structured forms without any outside intervention. This can be understood by the ability for a program to modify its organization without receiving commands from the user. Self-adaptation defines the ability for a system to adapt its structure according to the evolution of its environment in order to keep its normal functioning.

Accordingly to the decentralized nature of the problem and the amount of uncertainties we have on it, the concept of Adaptive Multi-Agent System seems to be a good candidate to solve the state estimation problem.

B. The AMAS Atena

1) Environment of the System

The environment of Atena is the electrical network for which it tries to estimate the state. Based on the terms proposed by Russell and Norvig [11], the environment of Atena can be characterized as being:

- **Inaccessible:** Sensors are not perfect and are limited in number. Furthermore, load patterns are used instead of real measures in order to reduce the costs of deployment;
- **Continuous:** Electrical networks are discontinuous as the retained model neglects transitory states caused by variations of various system variables. However, the various measurements provided to Atena are averaged in a sliding window of 10 minutes. Consequently, the electrical system is considered as continuous;
- **Deterministic:** The Multi-Agent System has an averaged vision of the operating point of the network. From these measurements, the Multi-Agent System estimates this operating point without acting on the electrical system. Therefore, for agents, the environment is considered as deterministic;
- **Dynamic:** As mentioned before, the state of the environment is influenced by various external factors. Thus, even if agents never modify the environment it cannot be guaranteed that this latter will remain the same between two perceptions.

2) Identification of Agents

The identification and characterization of agents for state estimation has to be as close as possible to the various entities of the physical system. Consequently, the system is made of “bus agents”. It seems obvious that this choice will facilitate the design, the understanding and the analysis of the multi-agent system. In addition to this, the system contains resources “Line”. The transit of each line can be calculated according to the current voltage state at each bus on either side of the line.

The internal state of a bus agent is characterized by four real variables: the active power produced (or consumed) C_P , the reactive power produced (or consumed) C_Q , the voltage magnitude C_V , the phase angle C_θ .

Fig. 3 represents an example of an electrical network made of four buses. As we can see, a bus agent is associated with each node.

One objective of a bus agent is to modify its internal state

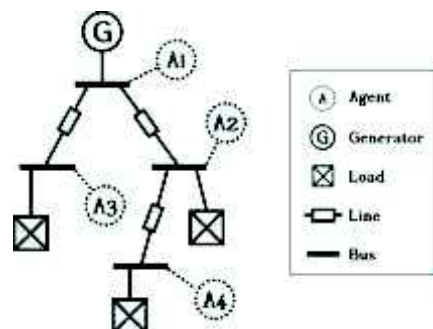


Figure 3. Example of an electrical network with associated agents

to respect the Kirchhoff's Current Law.

The sum of active and reactive power flows of a bus agent A_b associated with a bus b can be expressed in the following way:

- For active power: $C_p + Re(\sum_{n \in Neighbors_b} V_b \cdot (Y(1,1)_{b,n}^* \cdot V_b^* + Y(1,2)_{b,n}^* \cdot V_n^*))$
- For reactive power: $C_q + Im(\sum_{n \in Neighbors_b} V_b \cdot (Y(1,1)_{b,n}^* \cdot V_b^* + Y(1,2)_{b,n}^* \cdot V_n^*))$

With:

- $Neighbors_a$ the direct neighbors of the agent A_a associated with bus a ,
- $V_b^{(current)} = C_V \cdot e^{iC_\theta}$ the complex number made of the state variables C_V and C_θ of the agent A_b ,
- $Y(i,j)_{b,n}$ the mutual admittance between nodes i and j of the node matrix of the line connected between buses b and n ,
- $Y(i,i)_{b,n}$ the self-admittance of the node i of the line connected between buses b and n ,
- $Re(X)$ and $Im(X)$ the real and imaginary parts of the complex X .

These formulas directly come from (1) where bus b stands for the node 1 and bus n for the node 2.

A function F has been implemented in each agent such as $V_i^{(new)} = F(V_i^{(current)})$ where $V_i^{(new)}$ is the new voltage of the bus agent i and $V_i^{(current)}$ the old voltage. The application of this function will reduce the sum of weighted least squares which includes implicitly the Kirchhoff's Current Law.

More precisely, each agent has a local objective function O allowing it to evaluate the distance to its objective. Agents try to minimize it with the Weighted Least Squares method. The function F comes from the derivative of this function O .

Fig. 4 presents the state of two bus agents which both have an associated voltage sensor. Each bus agent has a current voltage magnitude estimation represented by a circle. Using the function F , they are able to determine if they have to decrease or increase their voltage magnitude. In this example, the agents are unable to make these moves as their respective authorized deviations are too low. In order to do these moves, the agent 1 has to increase its authorized deviation by α while the agent 2 has to increase it by $-\beta$.

As mentioned previously, the state estimation problem is also a balance problem between distances to sensor values. Given the fact that agents' perceptions are limited, they are not able to benefit directly of data redundancy. Thus, the agents need to cooperate.

In the case where the agents are limited by their authorized voltage deviation (as in Fig. 4), they have to find a compromise with other agents. In other words, if an agent A wants to increase its authorized deviation by α , it has to find an agent that will do the same in the opposite way. If the value $|V_i^{(new)}|$

is within the authorized interval or the agent does not have a voltage sensor, the agent can directly use $V_i^{(new)}$ as its new state value. In the case where the $|V_i^{(new)}|$ is outside of the authorized interval, the agent has to send a message to its neighbors to ask them to change their deviation value in the other direction than the one it needs.

3) Neighborhood

The neighborhood of an agent is composed of the set of agents that are directly connected to it. In the field of this study, we consider that two agents are directly connected if it exists a line linking the two buses they are associated with. For example, in Fig. 3, the neighbors of agent A1 are A2 and A3, the neighbors of A2 are A1 and A4, the neighbor of A3 is A1 and the neighbor of A4 is A2. 4)

4) Perception of an agent

An agent is able to perceive two categories of data. The first one is data provided by its neighbors and the second one is data provided by sensors connected to the bus it belongs to. The data that can be perceived from a neighbor is its current voltage magnitude and phase angle estimation. In the case of the presence of a voltage sensor attached to the bus, the agent can perceive the voltage magnitude returned by it and its precision in percent. In the case of the presence of a power sensor (or a pseudo-power sensor), the agent is able to perceive the returned values of active and reactive power and the precision in percent of these values. In addition to these abilities of perceptions, an agent is able to send and receive messages to its neighbors.

5) Behavior

a) Perception

During the perception phase, an agent observes its neighbors and gets the updated information about their voltage magnitude and phase angle estimations. Let us call VP_n the complex made of the data perceived from the neighbor n . The agent also gets messages sent by its neighbors since the last perception phase.

b) Decision

At first, in the decision phase, the agent evaluates the result $V^{(new)} = |V^{(new)}| \cdot e^{i\theta^{(new)}}$ of the function F applied to its current representation of its environment.

Let us consider $V = |V^{(current)}| \cdot e^{i\theta^{(current)}}$ the current voltage estimated by the agent.

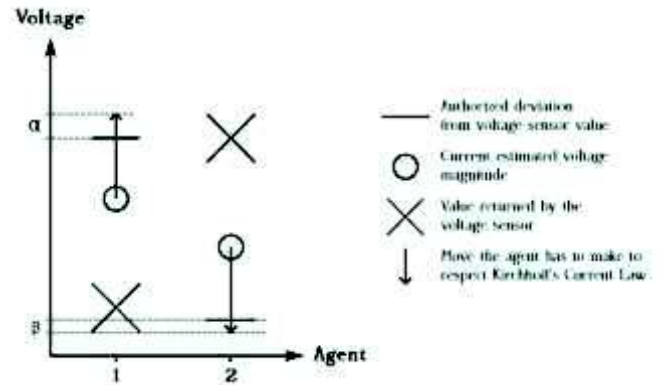


Figure 4. Example of a situation in which two agents can help each other

In the case where the agent has an associated voltage sensor, it also has an authorized voltage deviation value Dv .

$|V^{(new)}| - |V^{(current)}| > Dv$ means that the value proposed by the function F exceeds the authorized voltage deviation Dv .

The agent may have received messages from agents which have the same problem.

In this case, the agent has to check if it can modify its authorized voltage deviation to satisfy itself and the others. In the case where the agent has received messages that it does not understand or whose the contained request run contrary to its desire, the agent places them in a temporary stack Ts .

After this process, the value Dv may have been updated.

c) Action

If the value V_{new} is within the authorized voltage range, then the agent sets its state to $|V^{(new)}| \cdot e^{i\theta^{(new)}}$. On the contrary, the agent sets its state to the closest allowed value: $(|V^{(current)}| + Dv) \cdot e^{i\theta^{(new)}}$ and broadcasts a help request to its neighbors. Finally, if messages remain in the temporary message stack Ts , the agent broadcasts them to each neighbor except the one which has sent it.

Such a behavior allows agents to cooperate and count on other agents to help them. It is clearly visible that although each agent tries to pursue their own goal, they also have the capacity to help agents which cannot. Therefore, agents will help each other provided that it does not make them more unsatisfied. Talking to this capacity of interactions, we come back to the notion of “emergence”. The self-organization realized by the agents leads the system to provide a solution to a problem agents are not aware of.

Such a behavior allows agents to optimize a weighted least square locally with their neighbors and the cooperation between agents brings the system to tend to a global maximum likelihood.

IV. ATENA EVALUATION

A 64-buses network has been used as a test case. A power and voltage sensor is installed at the slack bus and a pseudo-power sensor is associated with each consumer. For each of the 64 buses, an agent is created, linked with the proper neighboring bus agents.



Figure 5. Performance evaluation on a 64-bus distribution network

The system has been evaluated on four criteria:

A. Atena Performance Over the Amount of Voltage Sensors

In this evaluation, we have determined the impact of the number of voltage sensors over the performance using the multi-agent system Atena. The performance of a system is the percentage of successful resolutions over the total number of resolutions. We consider a successful resolution, a resolution in which the relative error on voltage magnitude estimation is lower than 1%. For each configuration, the resolution has been launched 1,000 times without changing sensors locations and the operating point of the network. It is also necessary to know, that for each resolution, sensors can return different values because they are noisy.

Fig. 5 represents the performance evaluation realized on 64-buses network. We can see that with the configuration with two voltage sensors, the system has a performance really near to 100%. Based on what the state estimation is intended for, it may be not enough but we can see than with only three voltage sensors, the system is able to reach a performance of 100%. The results of this evaluation seem to indicate that this approach is valid and is suitable for distribution network.

B. Filtering Quality

Fig. 6 represents the number of occurrences of voltage magnitudes obtained for 5,000 resolutions on the 64-buses network for a given node. μ represents the real voltage magnitude for this node. 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. Table II presents the value corresponding to Fig. 6. We can see on this figure that the system effectively filters errors of the voltage sensor. The filtering of errors provided by the various sensors is a prerequisite of the state estimation. However, this study should be continued in this direction to filter even more the sensors data.

TABLE II. MEASURED VALUES

	Minimum	Maximum	Average
<i>Time (in seconds)</i>	0.002	8.506	0.707
<i>Number of cycles</i>	2	4829	380

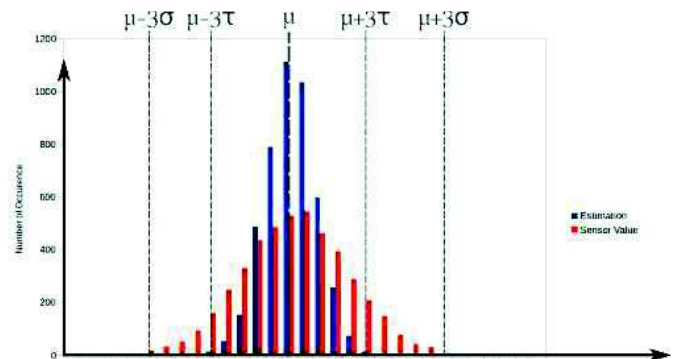


Figure 6. Gaussian distribution of a voltage sensor and the state estimation for a bus over multiple resolutions

C. Computation Time

For this evaluation, we have measured the time and amount of cycles the system has to do to reach a valid solution. These measurements have been made on the state estimation of the 64-bus network launched 1,000 times. On the set of resolutions, we have decided to remove the ones in which the system was too close to the solution.

In order to regulate the voltage, it is mandatory for the system to respond in a minimum time. Indeed, in order to take a decision for voltage regulation, the state estimation must be as precise as possible. The state of a network is in constant evolution. Consequently, the more the system takes time to estimate the state, the more the estimation will be incorrect. Despite the fact that it highly depends on the performance of the computer the system runs on, these results are encouraging.

D. Test of the AMAS Theory

The AMAS theory considers that when all agents at the micro-level are in cooperative situations, the global system at the macro-level is functionally adequate (its gives correct results): this is its emergence property. For Atena, an agent estimates to be in a cooperative local situation when the Kirchhoff's Current Law is verified. The global estimation is given by the state voltage estimation for each bus is close to its theoretical one. Fig. 7 gives these results for an Atena solving process on a given topology experiment. From evidence, the correlation between the micro and macro states assumed by AMAS theory is verified.

V. CONCLUSION AND PERSPECTIVES

We have determined that using an Adaptive Multi-Agent System is an interesting approach to make networks smarter.

This system agentifies all buses of the electrical network as well as voltage sensors. The lines linking two buses are considered as resources. The solving process is strictly local and according to the cooperation process of the AMAS theory, this leads to satisfying results (Quality of results, Performance, Computation time ...)

Through this study, we have seen that using the Adaptive Multi-Agent System theory can be an interesting and innovative approach in term of performance and robustness.

From literature, we have observed that adapting transmission networks techniques does not solve all the problems of Distribution Systems State Estimation. The work presented in [3] shows that the transmission networks

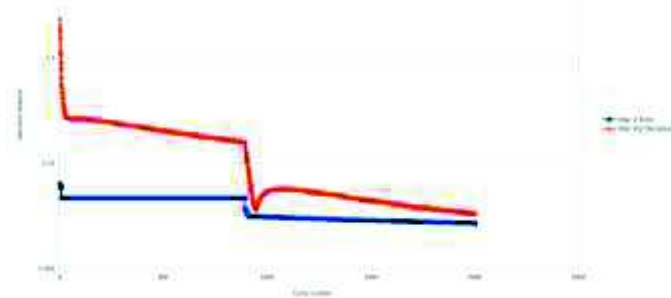


Figure 7. Correlation between voltage magnitude estimation and distance to Kirchhoff's Current Law

techniques can be used for distribution systems. However, the performances are reduced and such a system is only able to estimate accurately some variables. Given these limitations, the state estimator produced can only handle the voltage regulation problem [15].

The error filtering realized by Atena is a first step toward a robust and efficient Distribution System State Estimation, however it is far less efficient than classical approaches derived from transmission network state estimation such as the one presented in [3].

These researches will be continued targeting a highest filtering of sensor data and giving the ability to the system to regulate the voltage of the network it is connected to.

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