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Decentralized Computing in Smart Grids by Self-Organizing Sensor Networks

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Problem Formulation

$$f_1(x) = \sum |V_i - V_n|^2 \quad f_2(x) = \max |V_i - V_n| \quad f_3(x) = \sum (P_{loss_i} - P_{loss_j})$$

$$\min_{x \in R^n} f(x) \quad f_4(x) = C_{gen} Q_{gen} + C_{cap} Q_{cap} + C_{slack} Q_{slack}$$

$$\begin{cases} g(x) \leq 0 \\ h(x) = 0 \\ m \leq x \leq M \end{cases} \rightarrow \begin{cases} P_i = V_i \sum_{j \in i} V_j [G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)] & i = 1, 2, \dots, N \\ Q_j = V_j \sum_{k \in j} V_k [G_{jk} \sin(\theta_j - \theta_k) + B_{jk} \cos(\theta_j - \theta_k)] & j = 1, 2, \dots, N_c \end{cases}$$

$$x = [Q_{dg,1}, \dots, Q_{dg,N_g}, \dots, Q_{cap,1}, \dots, Q_{cap,N_c}, V_{DFTS,1}, \dots, V_{DFTS,N_f}, m]$$

Centralized Solution Paradigm

- Nonlinear programming approaches for OPF have been widely proposed in the literature.
- These techniques propose the adoption of centralized control strategies that identify, for each network state, the optimal set points of the voltage regulators by solving the previously formalized optimization problem.
- In addressing this need they employ a mathematical model of the power network.

Main Limitations

- This hierarchical control paradigm asks for the deployment of a central fusion centre acquiring and processing all the grid measurements.
- It could be not affordable in addressing the increasing network complexity and the massive pervasion of distributed generators characterising modern smart grids.
- **Unaffordable complexity, hardware redundancy, network bandwidth and data storage resources** are the main barriers imposed by technology and costs

Modern Trends and Enabling Technologies

- Conceptualization of new control paradigms for distribution of the intelligence at urban substation level (e.g. delocalization of functions usually processed by the remote control centres)
 - Implementation of communications from urban substations to remote centres but also among substations and among systems at substation level (pervasive communication networks);
 - Use of international standards to improve interoperability
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Modern Trends and Enabling Technologies

- In this connection the integration of **bio inspired computing** and **agent based design** has been recognized as a very promising research domain.
 - This is mainly due to broad application of distributed decision making in coordinating networks of dynamic agents aimed at enhancing operational effectiveness in networked autonomous systems
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The Proposed Approach

- According to this scientific trend, we intend to make a further contribution toward the **conceptualization of decentralized non-hierarchical computing architectures based on cooperative dynamic agents.**
- Similarly to self-organizing biological populations, the network voltage control is achieved by **cooperation of the single agents that communicate with a reduced number of surrounding elements** by short range communication links

The Proposed Approach

- The systems of nearby agents are updated by proper local coupling strategies derived from the **theory of distributed consensus**.
 - This strategy allows all agents to quickly synchronize to a function of the variables sensed by all agents in the Smart Grid.
 - Thanks to this feature, each agent can assess, in a **totally decentralized way**, the most relevant variables of the **global Smart Grid**.
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The Proposed Approach

- The global variables are amalgamated with local measurements and processed by each agent according to several control algorithms.
- This allow control agents to decide if and when a reactive power flow injection in the network is most useful, based on the global network conditions.

The Proposed Architecture

The proposed architecture is based on a network of cooperative smart controllers, each regulating the voltage magnitude of a specific Smart Grid bus.

Each controller is equipped by five basic components:

- a set of sensors measuring the available set of local electrical variables (i.e. voltage magnitude, active and reactive bus power);
- a dynamical system, whose state is initialized by sensor measurements and evolves interactively with the states of nearby controllers according to a bio-inspired paradigm;
- a short range communication interface carrying the interaction among controllers by transmitting the state of the dynamical system and receiving the state transmitted by the other nodes.
- a local optimizer regulating the reactive power flows injected by the DGS into the electrical grid.

Theory of Operation

Let's consider a set of N agents $\Gamma = (v_1, \dots, v_N)$, interacting over a network whose topology is described by a graph $G(\Gamma, A)$ with adjacency matrix $A = \{a_{ij}\}$. Let $N_i = \{v_j \in \Gamma : a_{ij} \neq 0\}$ be the set of neighbours of agent v_i . (i.e. agent v_j can exchange information to agent v_i if and only if $v_j \in N_i$).

Let $x_i \in \mathfrak{X}$ represent the state of the agent v_i . We say the agents network have reached a *consensus* if and only if $x_i = x_j$ for all $i, j \in [1, N]$ and $i \neq j$.

We suppose that the agent state x_i evolves according to the following differential equation:

$$\dot{x}_i = f(x_i, u_i) \quad i \in [1, N]$$

And the network state evolves according to the *network dynamics* $\dot{x} = F(x, u)$. Where, $x = (x_1, \dots, x_N)$ and $F(x, u)$ is the columnwise concatenation of the elements $f(x_i, u_i) \quad i \in [1, N]$.

Theory of Operation

Let $\gamma: \mathfrak{R}^N \rightarrow \mathfrak{R}$ be a N variables function and $a = x(0)$ denote the initial state of the system.

The γ -consensus problem is a distributed way to calculate $\gamma(a)$ by applying inputs u_i that only depend on the states of agent v_i and its neighbours.

We say a state feedback $u_i = k_i(v_{j_1}, \dots, v_{j_{n_i}})$ is a distributed protocol if the cluster $J_i = (v_{j_1}, \dots, v_{j_{n_i}})$ of agents with indices (j_1, \dots, j_{n_i}) satisfies the property $J_i \subset \{v_i\} \cup N_i$ and $|J_i| < N$.

A distributed protocol asymptotically solves the γ -consensus problem if and only if there exists an asymptotically stable equilibrium x^* of $\dot{x} = F(x, k(x))$ satisfying $x_i^* = \gamma(x(0))$ for all $i \in [1, N]$.

In our study we are mainly interested in computing $\gamma(x) = \frac{1}{N} \sum_{i=1}^N x_i$, $\gamma(x) = \max_i x_i$, $\gamma(x) = \min_i x_i$ denoted as *average consensus*, *max-consensus*, and *min-consensus* respectively.

Theory of Operation

In solving the average consensus problem we adopted the following linear coupling protocol:

$$u_i = \sum_{j \in N_i} a_{ij} (x_j - x_i)$$

It is possible to rigorously demonstrate that this protocol allows the agents to asymptotically reach a consensus.

Besides the convergence proprieties of this consensus protocol is governed by the eigenvalues of the network topology.

Theory of Operation

As far as the max-consensus is concerned, it can be solved by adopting the following distributed protocol:

$$\begin{cases} x_i(k+1) = \max(x_i(k), u_i(k)) \\ u_i(k) = \max_{j \in N_i} x_j(k) \end{cases}$$

This protocol allows all the agents to iteratively converge to the state of the max leader (namely the agent characterized by the highest state) after a maximum of $N-1$ iterations. A similar distributed approach could be used to solve the min-consensus problem.

Theory of Operation

In particular, if the sensor nodes sense the bus voltage magnitude, the following vector of observations could be adopted to initialize the dynamical systems:

$$\Theta_i = (V_i, |V_i - V_i^*|)$$

where V_i and V_i^* are the current and nameplate voltage magnitudes at bus i , respectively.

In this case, it is easy to show that the dynamical systems synchronize to the mean grid voltage magnitude and the average voltage magnitude deviation:

$$\dot{\Theta} = \left(\frac{\sum_{i=1}^n V_i}{n}, \frac{\sum_{i=1}^n |V_i - V_i^*|}{n} \right)$$

where n is the number of buses.

Theory of Operation

Other variables of interest can be easily assessed by a proper selection of the vector of observations.

In particular if the sensor nodes sense the active and reactive bus power, the following vector of observations could be adopted to initialize the dynamical systems:

$$\Theta_i = \left(n \cdot (P_{Gi} - P_{Li}), n \cdot c_{pi}(P_{Gi}) \cdot P_{Gi}, n \cdot c_{qi}(Q_{Gi}) \cdot Q_{Gi} \right)$$

where P_{Gi} and P_{Li} are the active power generated and absorbed at bus i ; Q_{gi} is the reactive power generated at bus i ; $c_{pi}(P_{Gi})$ and $c_{qi}(Q_{Gi})$ are the costs of the active and reactive powers generated at bus i ;

In this case, the dynamical systems synchronize to the active system losses and to the total cost of active and reactive power:

$$\dot{\Theta} = \left(\sum_{i=1}^n (P_{Gi} - P_{Li}), \sum_{i=1}^n (c_{pi}(P_{Gi}) \cdot P_{Gi}), \sum_{i=1}^n (c_{qi}(Q_{Gi}) \cdot Q_{Gi}) \right)$$

Theory of Operation

- Thanks to the employment of this bio-inspired paradigm, each voltage controller knows both the **variables characterizing the monitored bus** (sensed by in-built sensors) and the **global variables describing the actual performance of the entire Smart Grid** (assessed by checking the state of the dynamical system).
- The knowledge of these variables allows each controller **to assess the evolution of the objective function** and, consequently, to search for its minimum.

Theory of Operation

In searching for the minimum of the objective function two direct search algorithms have been proposed:

- Gradient descent
- Simulated Annealing

Distributed Gradient Descent

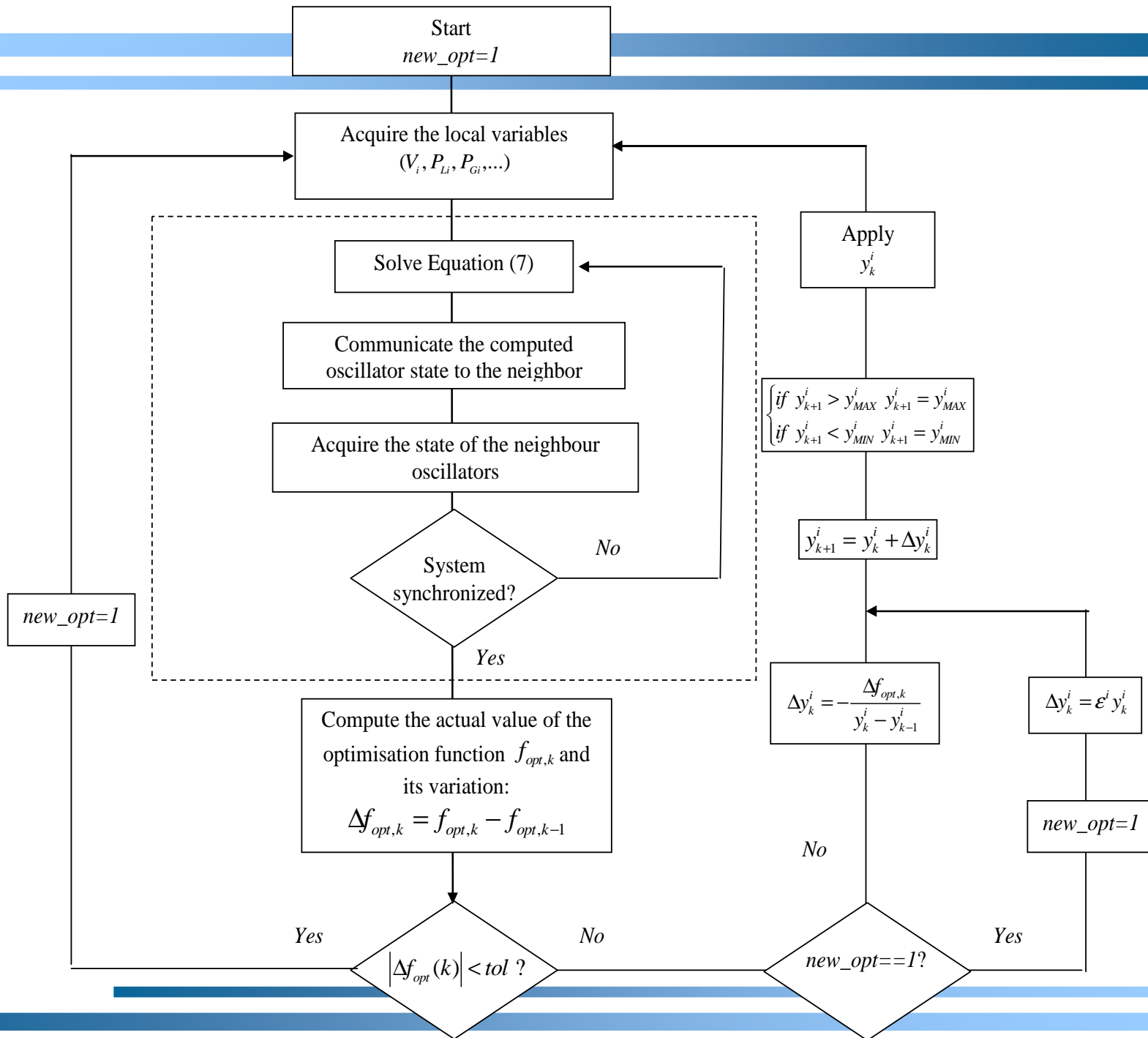
- The proposed algorithm first estimates the global variables characterizing the actual operation of the Smart Grid by adopting the described bio-inspired paradigm.
- These variables are then processed in order to estimate $f_{opt,k}$ and $\Delta f_{opt,k}$ representing, respectively, the value and variation of the objective function describing the regulating objectives at time step .

Distributed Gradient Descent

Once these variables have been assessed, the variation of the i -th continuous control variable at time step k can be identified by adopting a gradient descent algorithm:

$$\Delta y_k^i = -\mu \frac{\Delta f_{opt,k}}{y_k^i - y_{k-1}^i}$$

where μ is a parameter that controls stability and rate of convergence



Simulated Annealing

- The agents first estimate the global variables characterizing the actual operation of the power distribution system by adopting the described distributed consensus protocols.
- These variables are then amalgamated in order to compute the value of the objective function describing the regulating objectives at the time step t_k .
- Once this variable has been assessed, the new regulation asset can be identified by adopting a SA based search technique.

Simulated Annealing

- The rationale of this algorithm is to interpret the objective function as an energy function and to randomly generate a new candidate solution in the neighborhood of the current one.
- The move to the new candidate feasible solution is accepted if it is minor in the objective value to the current one.
- Nevertheless, an inferior candidate solution has a chance of acceptance with a probability, P , given by the Boltzmann distribution:

Simulated Annealing

- Nevertheless, an inferior candidate solution has a chance of acceptance with a probability, P , given by the Boltzmann distribution:

$$P = e^{\frac{-\Delta E}{kT_{t_k}}} \rightarrow \begin{aligned} \Delta E &= J_{k+1}(x_{k+1}, \Gamma) - J_k(x_k, \Gamma) \\ T_{t_k+1} &= \alpha T_{t_k} \end{aligned}$$

- The move to the inferior solution is accepted only if $P > r$, where r is a distributed random number drawn in the range $[0, 1]$.

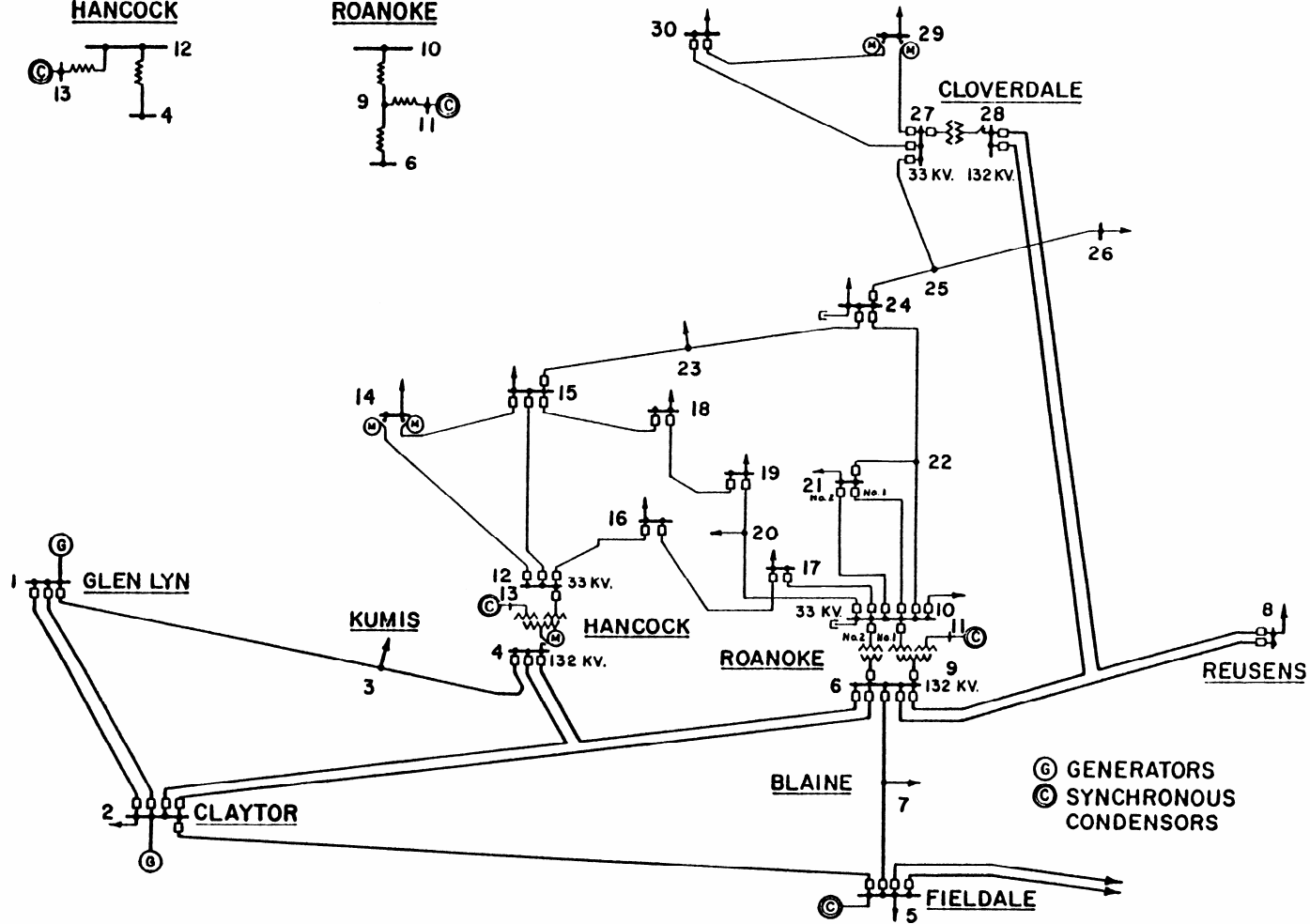
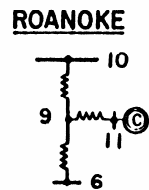
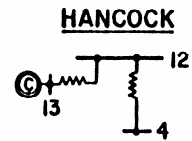
Simulated Annealing

- This iterative process terminates when a fixed stopping criterion is reached (i.e. the absolute value of the objective function variation is less than a fixed tolerance).
- In this case no optimization is required and the optimizer agents compute only the actual value of the objective function.
- When an objective function variation is sensed by the optimizer agents network (i.e. due to grid state variation) then a new optimal asset should be identified.
- In this case the temperature is fixed to its initial value and the iterative search algorithm is reactivated

Simulation Studies

The IEEE 30 bus Test System

THREE WINDING TRANSFORMER EQUIVALENTS



The IEEE 30 bus Test System

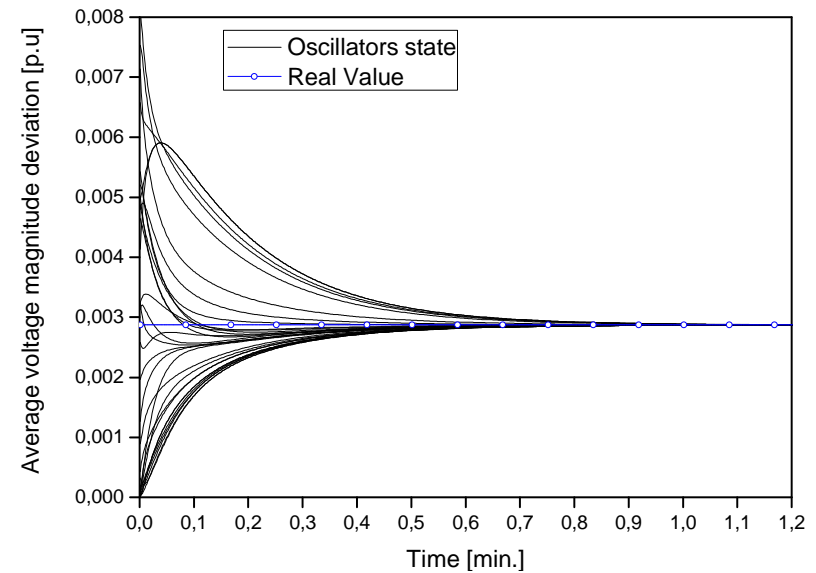
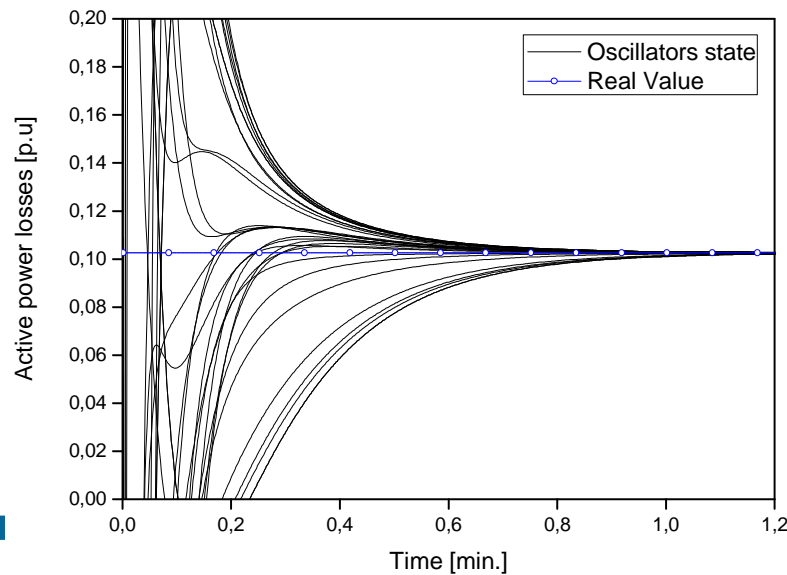
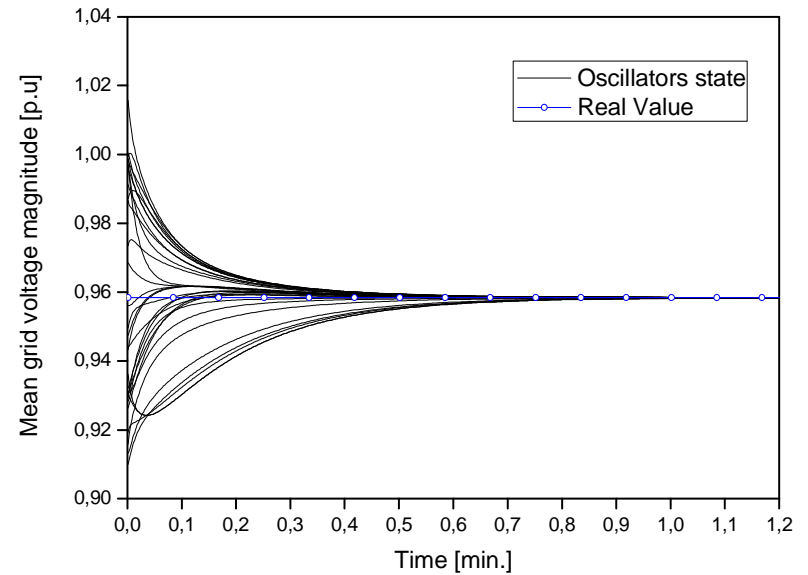
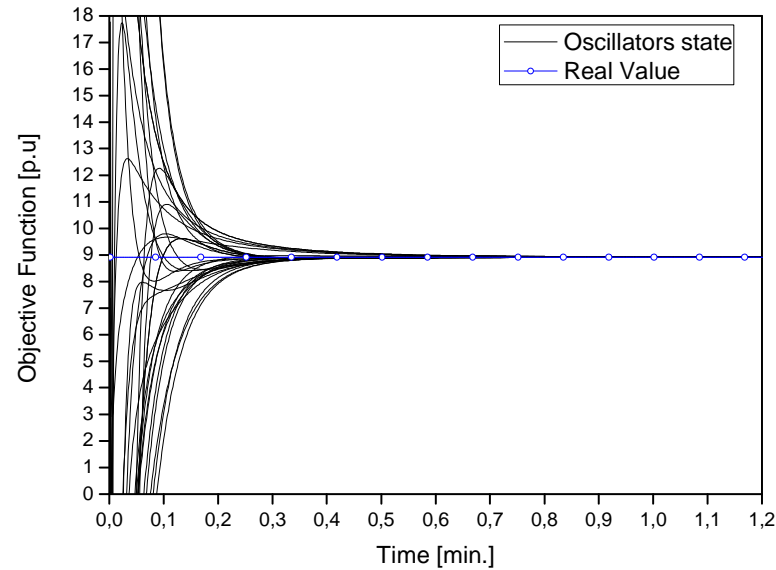
- A network of **30 optimizer agents** characterized by the same adjacency matrix of the power network have been deployed on each bus.
- Six dispatchable generators have been considered in our studies

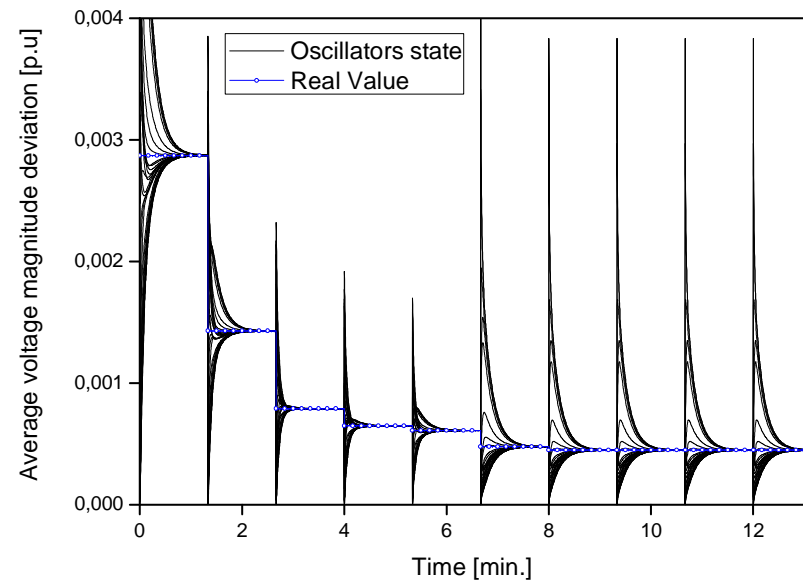
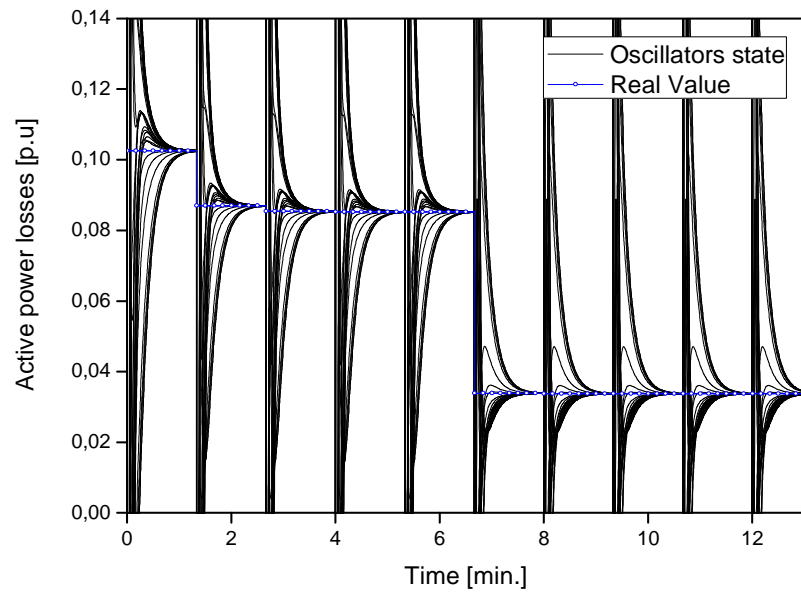
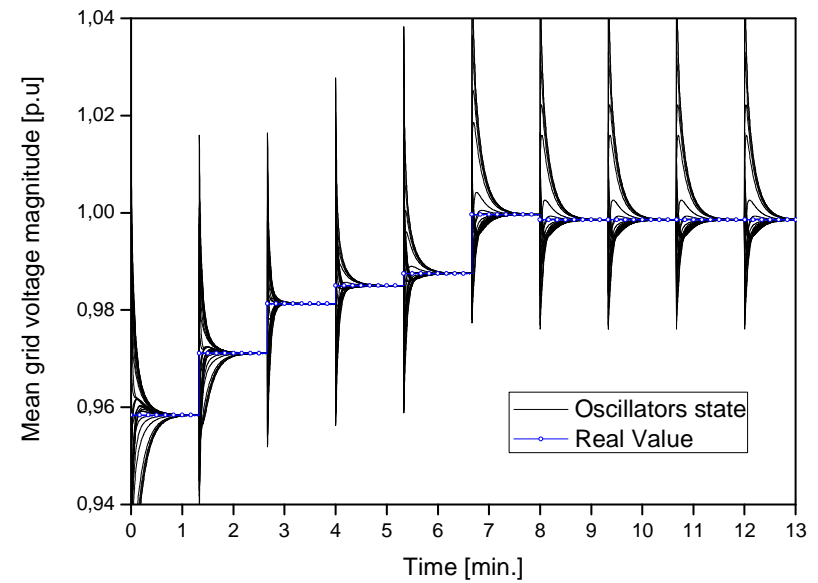
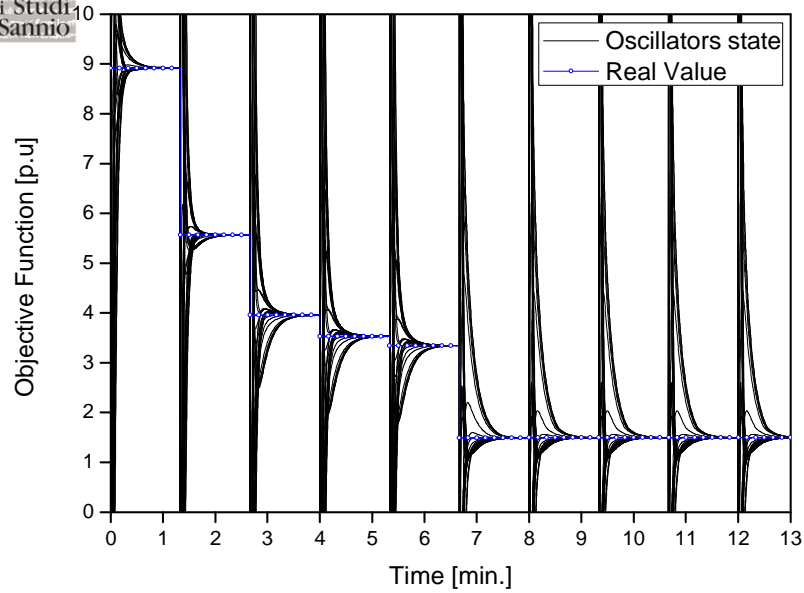
$$x = \left[Q_{DG,1}, Q_{DG,2}, Q_{DG,3}, Q_{DG,4}, Q_{DG,5}, Q_{DG,6} \right]$$

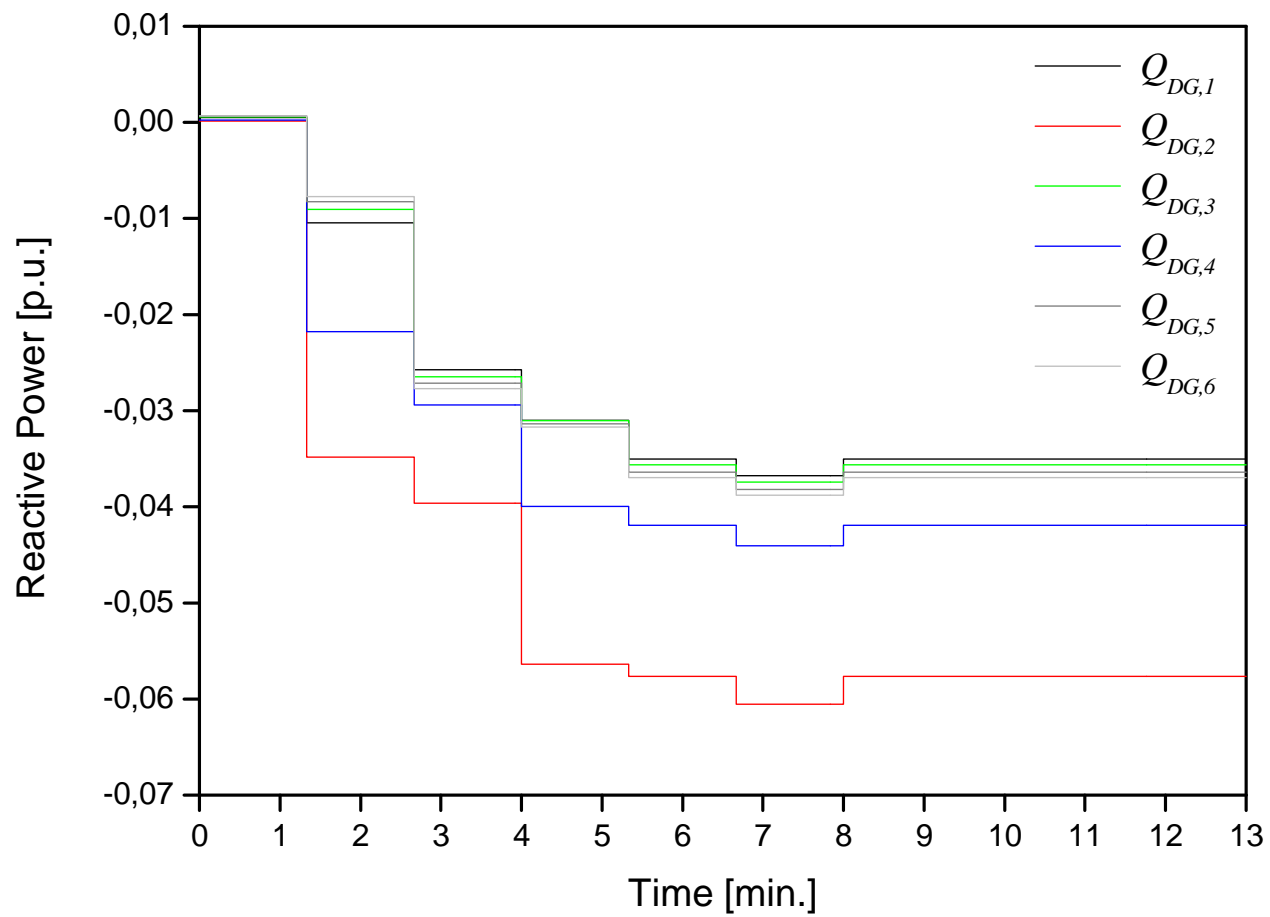
$$f(x, \Gamma) = \frac{\frac{1}{N} \sum_{i=1}^N |V_i - V^*|}{\bar{F}_1} + \frac{\frac{1}{N} \sum_{i=1}^N (V_i - V^*)^2}{\bar{F}_2} + \frac{\sum_{i=1}^N P_i}{\bar{F}_3}$$

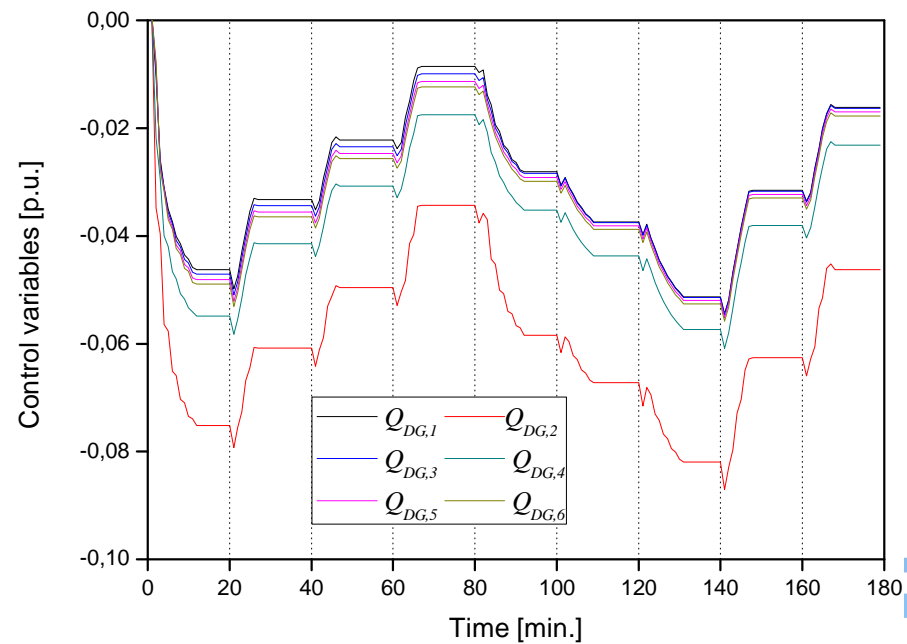
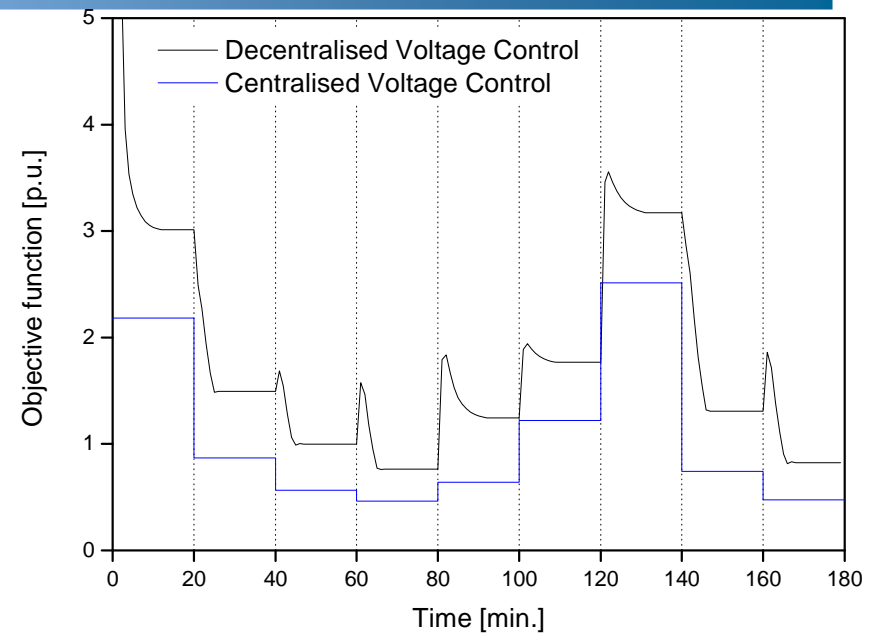
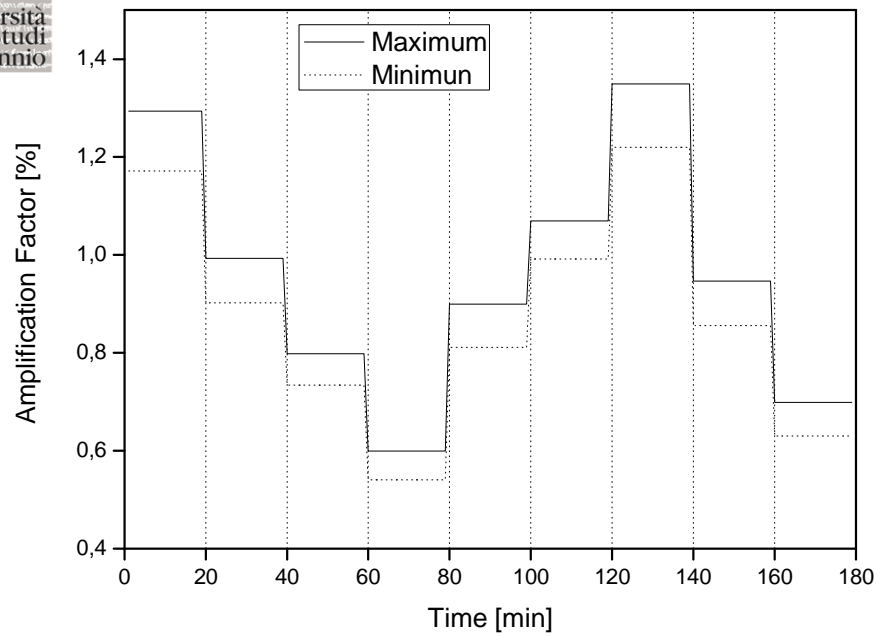
Obtained Results

Distributed Gradient Descent



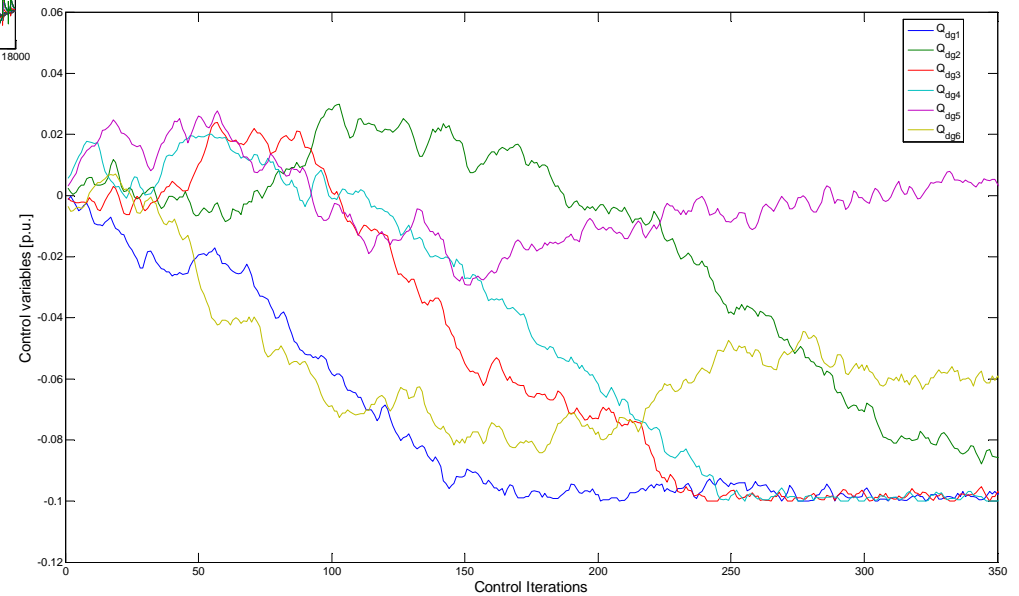
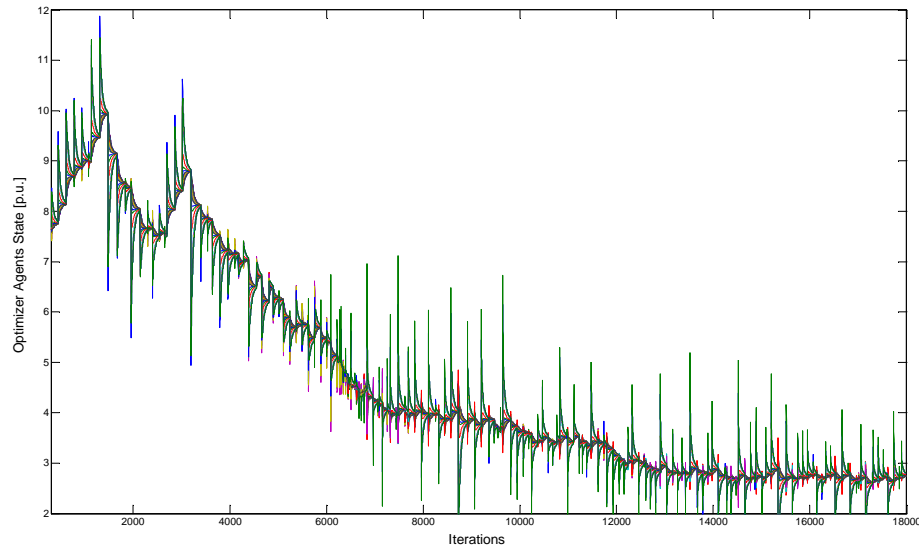






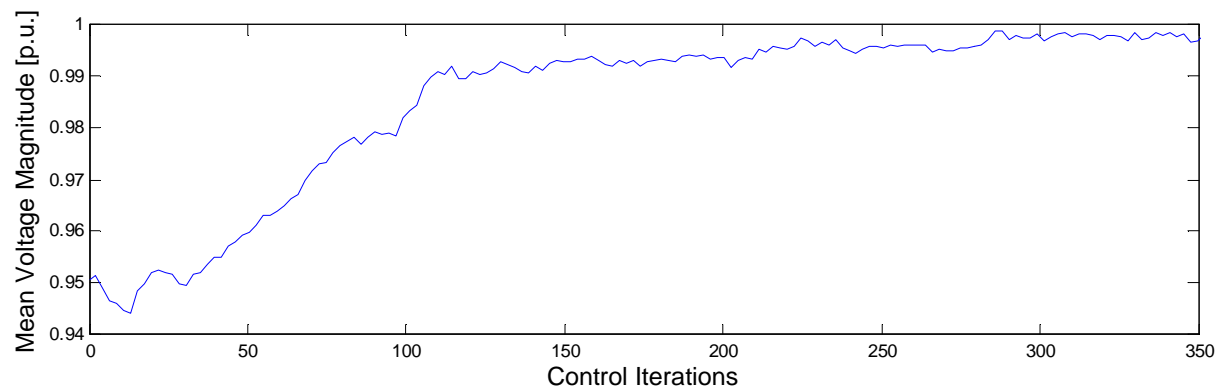
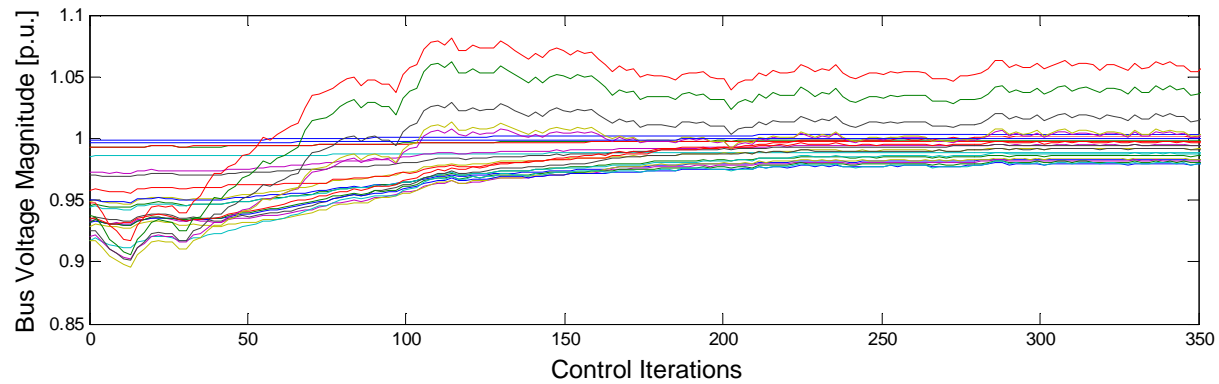
Obtained Results

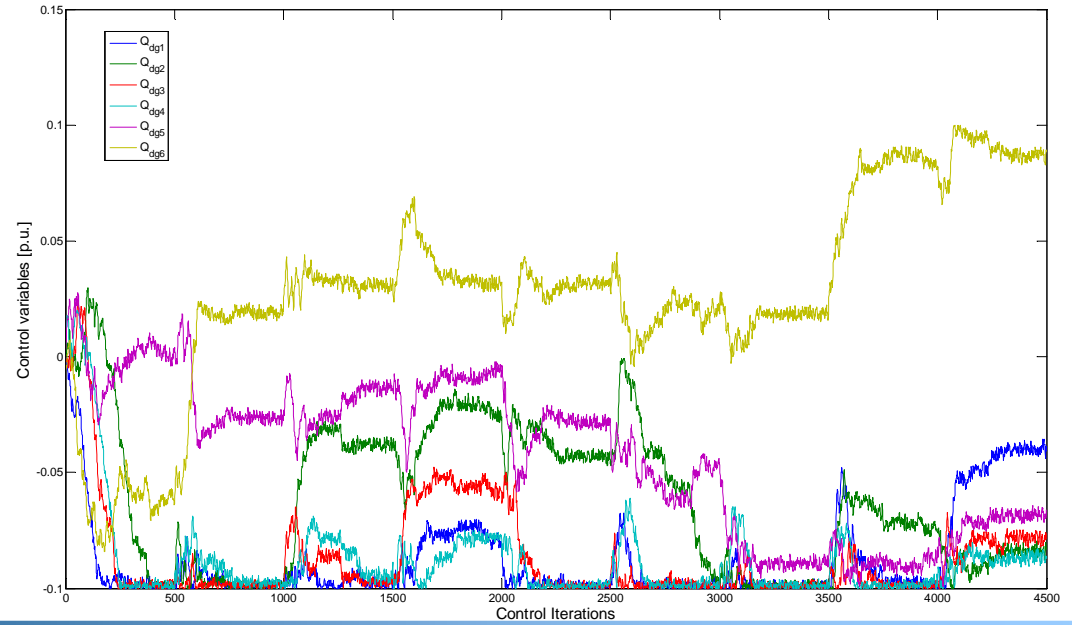
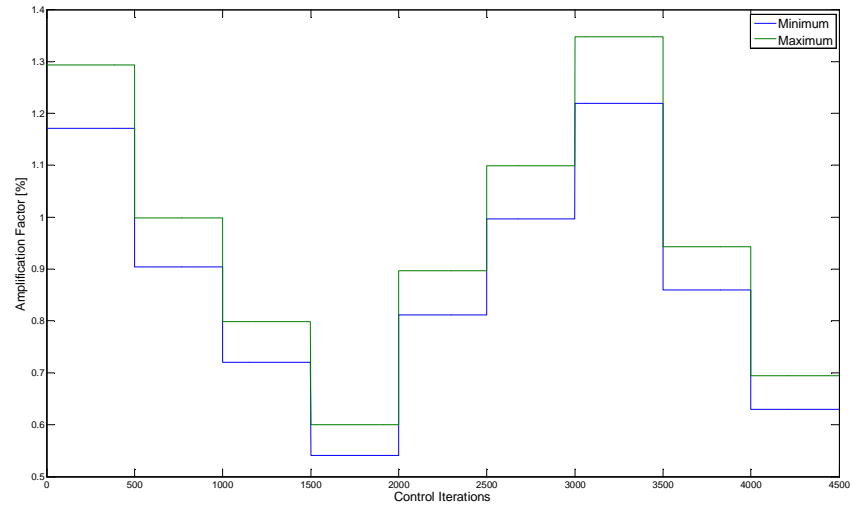
Distributed Simulated Annealing

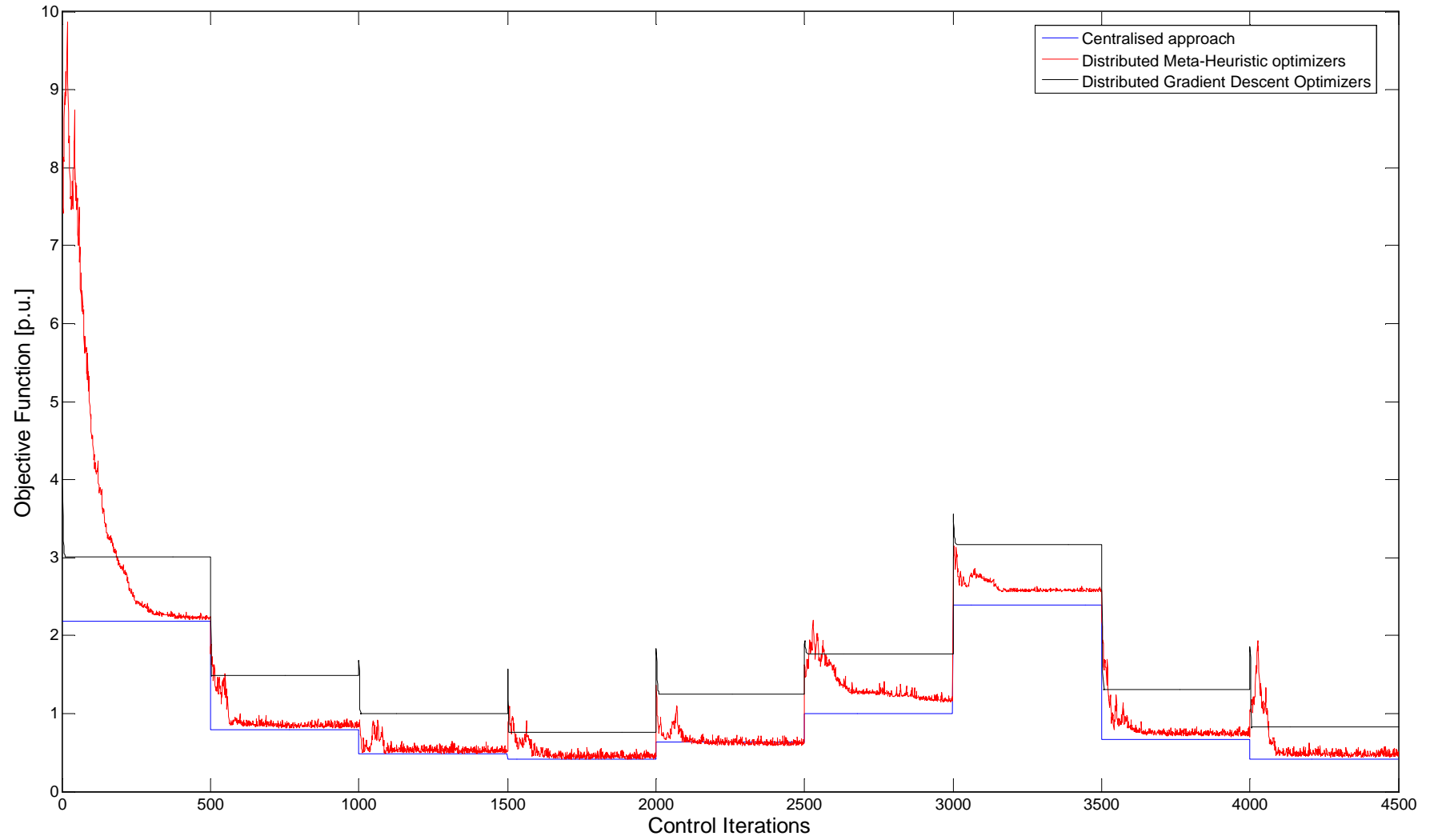


Obtained Results

Distributed Simulated Annealing







Result Discussion

- The obtained results show that the solution computed by the meta-heuristic optimizer agents **is very close to the centralized solution** computed by the rigorous optimization algorithm.
- As expected the interior point based optimization method exhibits better performances in terms of convergence. On the other hand it requires a **detailed model of the power system** and a **data fusion center** acquiring and processing all the power systems measurements.
- On the contrary the proposed approach addresses the voltage regulation problem by employing a **fully decentralized / non-hierarchical paradigm**.
- In fact the actual values of the objective function have been assessed without the need for a data fusion center, while the regulation strategies have been identified by optimizer agents processing global and local variables.

Result Discussion

- As far as the results comparison with the distributed gradient descent technique is concerned, it is possible to note that the SA method exhibit better performances in terms of minimization performances.
- This is mainly due to the effectiveness of the SA based minimization technique which allows the optimizer agents to escape from **local minima**.
- In this connection we strongly believe that a synergic integration of these two techniques could allow us to improve the overall performance of the distributed regulating framework.

A Different Perspective

Solving the Voltage Regulation Problem
by Distributed and Cooperative Fuzzy
Agents

Prolegomeni

- Fuzzy logic has been recognized as an effective tool in designing prompt, effective and robust **centralized** voltage control strategies.
- Our idea is to support the evolution of fuzzy based regulation architectures from traditional client/server to highly scalable, self-organizing and distributed paradigms.
- In addressing this need we propose the employment of cooperative and distributed fuzzy agents

Prolegomeni

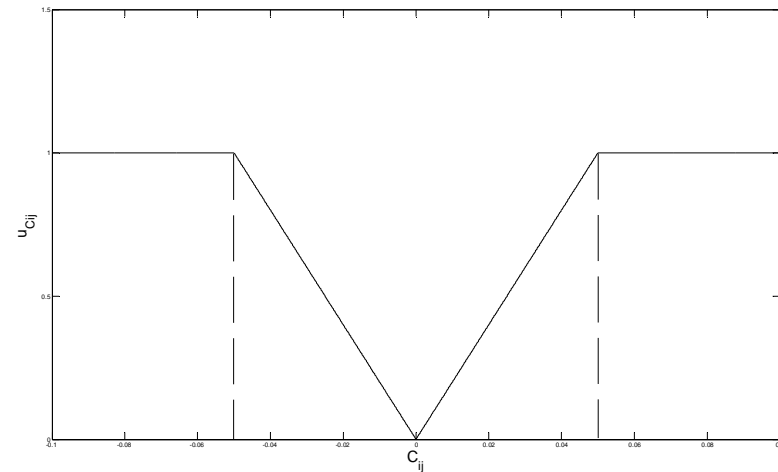
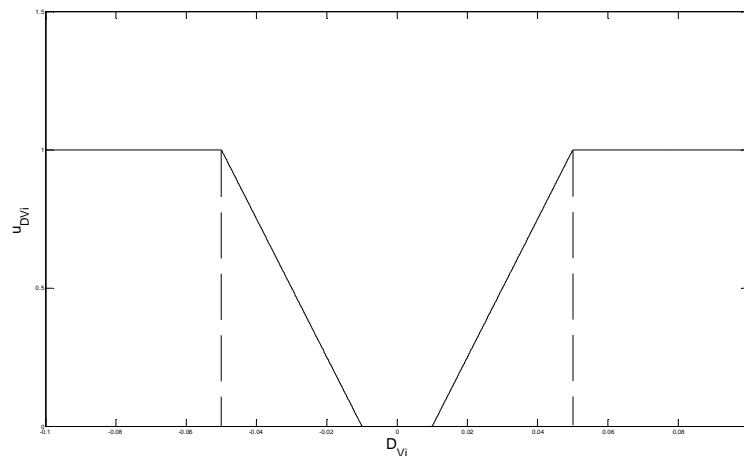
- The insight is to distribute the fuzzy operators needed to address the voltage regulation problem by a totally decentralized/non hierarchical paradigm.
- This is obtained by applying the theory of consensus decision making for coordinating a networks of dynamic agents

A Centralized fuzzy based solution paradigm

- The most common fuzzy based solution algorithm currently adopted in addressing the voltage control problem is structured in two computation phase.
- In the first stage the fuzzy sets theory is employed to **identify a feasible solution set** while, in the second stage, a proper selection criteria aimed at identifying **the optimal control solution** is applied.

A Centralized fuzzy based solution paradigm

The insight is to introduce two fuzzy variables aimed at describing **the voltage violation level** for each violation bus and the **controlling ability** for each voltage control device.



A Centralized fuzzy based solution paradigm

These two fuzzy variables are processed by using the max–min operation in order to identify a **feasible solution set** for voltage quality enhancement:

$$R_{opt,j} = \max \min_i \left(u_{\Delta V_i}, u_{C_{ij}} \right)$$
$$\begin{cases} i = 1, 2, \dots, N_L \\ j = N_L + 1, N_L + 2, \dots, N - 1 \end{cases}$$

- $R_{opt,j}$ represents the membership value of controlling ability for voltage controlling device installed at bus j on the controlled
- bus i .

A Centralized fuzzy based solution paradigm

Starting from these candidate control solutions, in the next phase proper selection criteria aimed at identifying the optimal control solution should be applied:

$$R_{j^*} = \max_j R_{opt, j}$$

$$R_{j^*} = \min(P_L^{(1)}, P_L^{(2)}, \dots, P_L^{(N-N_L)})$$

A Centralized fuzzy based solution paradigm

- Once the optimal control solution has been identified, its impact on the power system is assessed by a power flow analysis and, **if all the buses voltage magnitude satisfies the network constraints**, the control algorithm terminates.
- Otherwise a new control iteration aimed at removing the voltage anomalies should be processed.

A distributed fuzzy based solution approach

- We propose an alternative control paradigm based on the “think locally act globally” principle.
- The insight is to employ the theory of consensus decision making for coordinating a networks of dynamic agents
- Thanks to this feature the fuzzy based operations needed to address the voltage control problem could be easily computed by the agents according to a totally decentralized/non hierarchical paradigm.

A distributed fuzzy based solution approach

To this aim the following issues should be fixed:

- the mean, minimum and maximum load buses voltage magnitude should be computed by the agents in order to activate the voltage control adjustment procedure;
- all agents should know the controlling margin of each voltage controlling device in order to compute and fuzzify the corresponding control ability
- The agents should implement the desired selection criteria by computing R_j .

First Phase

In addressing the first issue all agents should acquire the local bus voltage magnitude.

This measurement is adopted as the initial value of the agent state vector:

$$\bar{x}_i(0) = [V_i, V_i, V_i] \quad i \in [1, N]$$

The first component of this vector evolves according to the linear coupling protocol, while the second and third component evolve according to the maximum and minimum coupling protocol respectively.

First Phase

Consequently when the consensus are reached, the state of all agents converges to the following values:

$$\bar{x}^* = \left[\frac{1}{N} \sum_{i=1}^N V_i, \max_i V_i, \min_i V_i \right]$$

Second Phase

In addressing the second issue, the state of each control agent should be broadcasted along the network. To this aim the agent state vector should be initialized by:

$$\begin{cases} \bar{x}_i(0) = [0, \dots, 0, \dots, 0] & i \in [1, N_L] \\ \bar{x}_i(0) = [0, \dots, M_i, \dots, 0] & i \in [N_L + 1, N] \end{cases}$$

and an average consensus problem should be solved according to the linear coupling protocol

Second Phase

In this case, when the consensus is reached the state of all control agents converges to the following values:

$$\bar{x}^* = \left[NM_{N_L+1}, NM_{N_L+2}, \dots, NM_N \right]$$

Third Phase

Finally, as far as the issue 3 is concerned, the state of each agent should be initialized by the following values depending by the selection criteria adopted:

$$\bar{x}_i(0) = R_{opt,i} \quad i \in [1, N_L]$$

$$\bar{x}_i(0) = P_L^{(i)} \quad i \in [1, N_L]$$

and an average consensus problem should be solved according to the linear coupling protocol

Final Phase

The optimal control strategy is finally selected by the agents by solving a maximum or minimum consensus problem respectively.

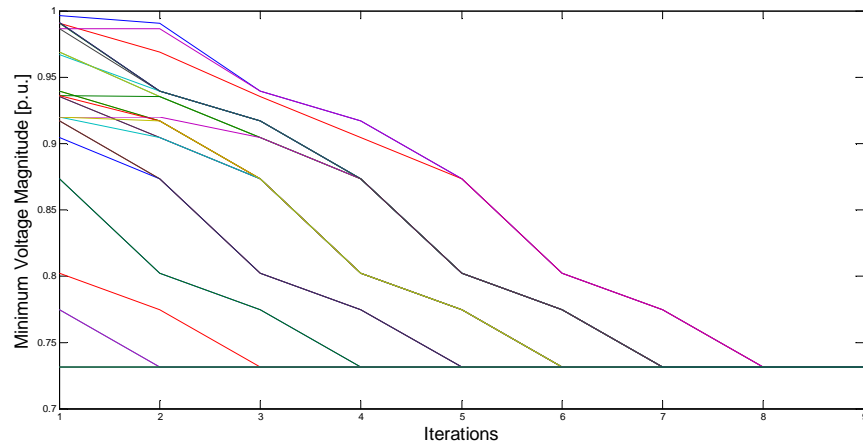
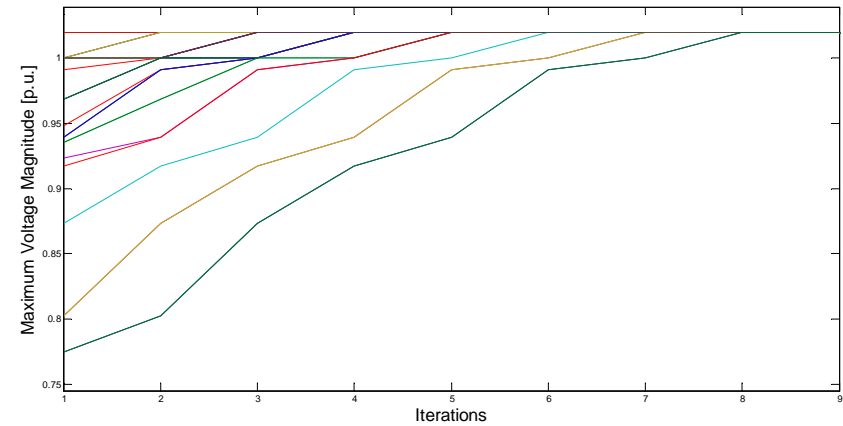
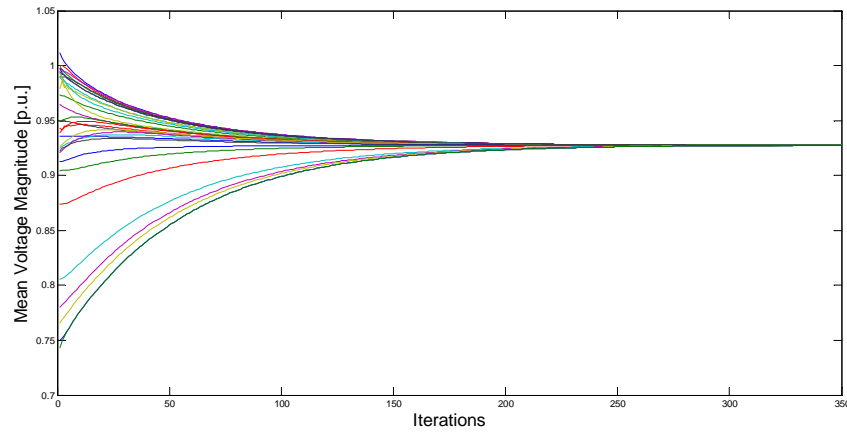
Simulation Results

Available voltage controllers

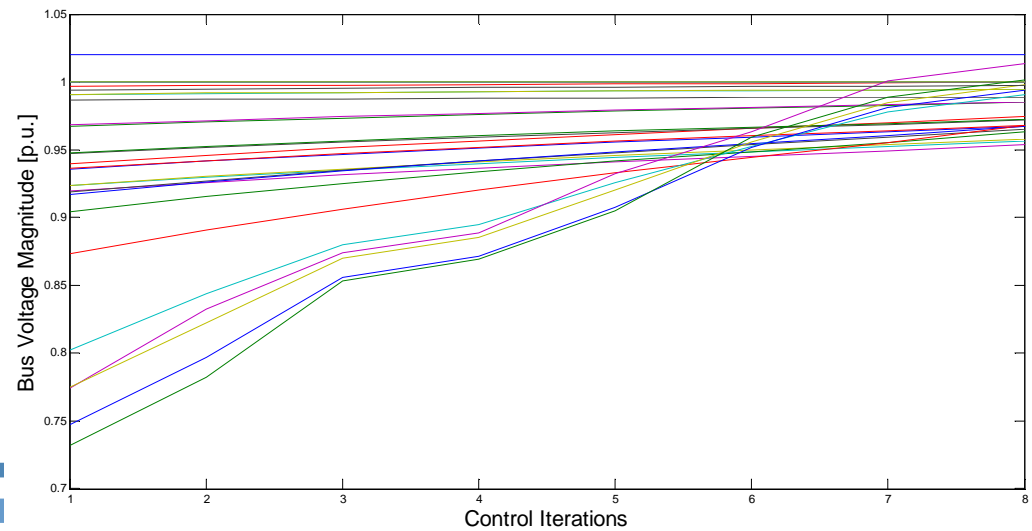
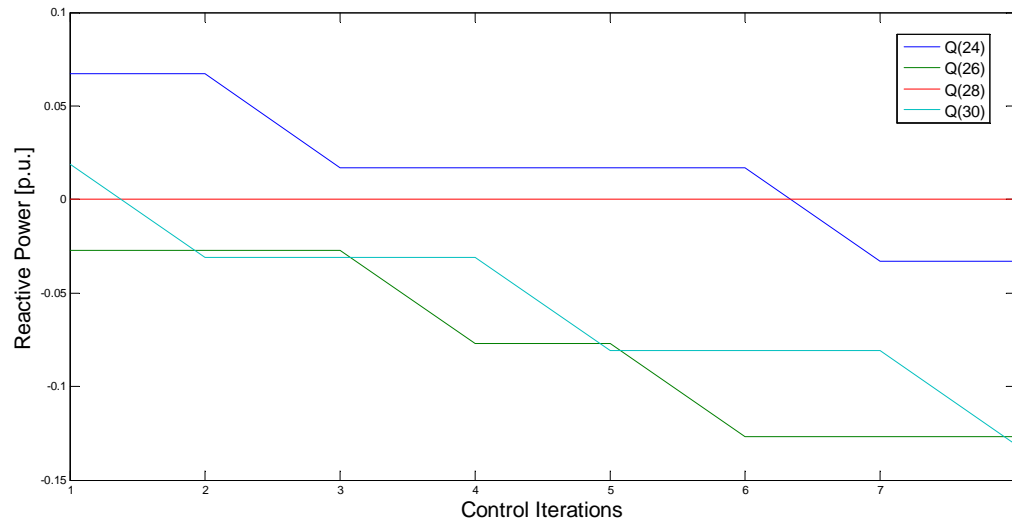
Bus	Controlled Variable	Upper Bound [p.u.]	Lower Bound [p.u.]
1	Bus voltage magnitude	0.95	1.05
2	Bus voltage magnitude	0.95	1.05
5	Bus voltage magnitude	0.95	1.05
8	Bus voltage magnitude	0.95	1.05
11	Bus voltage magnitude	0.95	1.05
13	Bus voltage magnitude	0.95	1.05
24	Reactive Power	-0.2	0.2
26	Reactive Power	-0.2	0.2
28	Reactive Power	-0.2	0.2
30	Reactive Power	-0.2	0.2

A sensor network composed by 30 cooperative agents distributed along the power system (one for each bus) has been deployed.

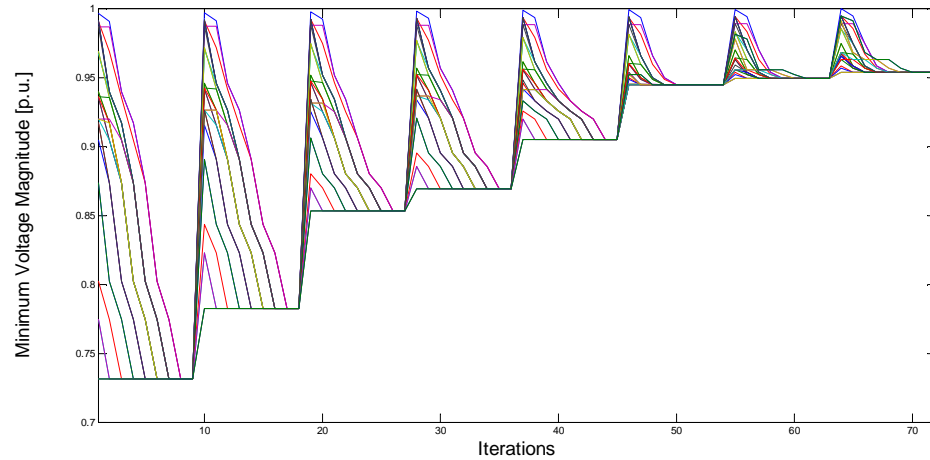
Evolution of the Agent states in the task of computing global grid variables



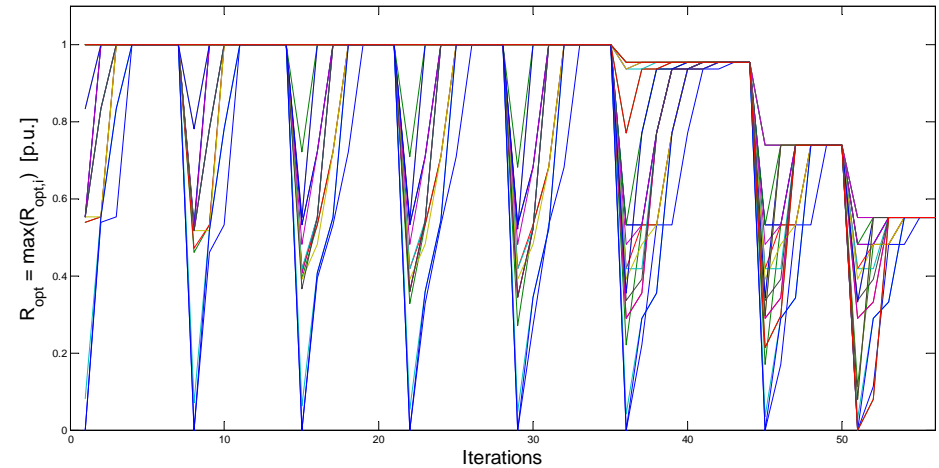
Effects of the Voltage Control Strategy



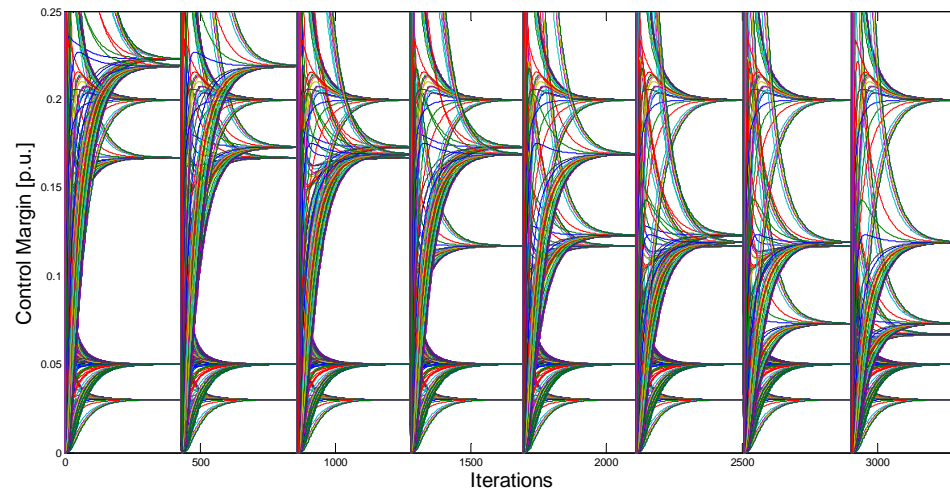
Effects of the Voltage Control Strategy



Evolution of the Agent states in the task of estimating the minimum voltage magnitude



Evolution of the Agent states in the task of selecting the optimal control action



Evolution of the Agent states in the task of estimating the control margin

Conclusions

- Modern trends in Smart Grids are oriented toward the deployment of control architectures that move away from the older centralized paradigm to a system distributed in the field with an increasing pervasion of smart agents where central controllers play a smaller role.
- In supporting this complex task we proposed the concept of a distributed and self-organizing voltage control architecture based on cooperative dynamic agents.

Conclusions

- The distributed agent employ traditional sensors to acquire local bus variables and distributed consensus protocols to assess the main variables that characterize the global Smart Grid operation.
- These variables are then amalgamated in order to identify proper control actions aimed at improving the bus voltage magnitude profile.
- The results obtained on a test power system show as this control paradigm allows the dynamic agents to detect local voltage anomalies since they know both the performances of the monitored buses and the global performances of the entire grid.

Conclusions

- The convergence of this process corresponds well with the time constraints characterizing the voltage regulation process in Smart Grids.
- This is obtained without the need of a central fusion center acquiring and processing all the node acquisitions.
- This makes the overall monitoring architecture highly scalable, self-organizing and distributed.