Agent based coordination for Smart Grid and Microgrid

Prof. Nikos Hatziargyriou,
nh@power.ece.ntua.gr
National Technical University of Athens, Greece

DREAM Winter School, Grenoble, 14th December 2015
The SmartGrids TP Vision
Near Future characteristics

• Customers are part of the “network-loop”, both producer and consumer = “prosumer”
  – Real-time price information (smart meters)
  – Automated systems + convenience (DR/DSM)
  – Adequate investment and reward incentives
• Integration of millions small scale generators
• Bulk power and small scale sustainability coexistence
• Demand and supply balance solutions
• Efficient operated (and reliable) network
• Mature markets and regulation
DER Technical, economic and environmental benefits

- Energy efficiency
- Minimisation of the overall energy consumption
- Improved environmental impact
- Improvement of energy system reliability and resilience
- Network benefits
- Cost efficient electricity infrastructure replacement strategies
- Cost benefit assessment
EU SUPERGRID & SMARTGRIDS

- Integrates offshore renewable generation (offshore wind - marine - tidal energy)
  - Enables the exploitation of counter-cyclicality among primary RES
- Enables system to benefit from diversity in demand & supply across Europe
- Allows sharing of short & long-term reserves across European system (local level volatility reduces across dispersed areas).
Integrates offshore renewable generation (offshore wind - marine - tidal energy)

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Interconnection of small, modular generation to low and medium voltage distribution systems can be organized in Microgrids. Microgrids can be connected to the main power network or operated islanded, in a coordinated, controlled way.
Identification of Microgrid benefits is a multi-objective and multi-party coordination task.
Who will develop a Microgrid? Who will own or operate it?

• Investments in a Microgrid can be done in multiple phases by different interest groups: DSO, energy supplier, end consumer, IPP (individual power producer), etc.

• The operation of the Microgrid will be mainly determined by the ownership and roles of the various stakeholders. Three general models:
  – DSO owns and operates the distribution grid and also fulfils the retailer function of selling electricity to end consumers. (DSO Monopoly)
  – ESCO are the actors that maximize the value of the aggregated DG participation in local liberalized energy markets (Liberalized Market)
  – Consumer(s) own and operate DG to minimize electricity bills or maximize revenues (Prosumer Consortium)
Technical Challenges

• Use of different generation technologies (prime movers)
• Presence of power electronic interfaces
• Small size (challenging management)
• Relatively large imbalances between load and generation to be managed (significant load participation required, need for new technologies, review of the boundaries of microgrids)
• Specific network characteristics (strong interaction between active and reactive power, control and market implications)
• Protection and Safety / static switch
• Communication requirements
Market Challenges

• coordinated, but decentralised energy trading and management
• market mechanisms to ensure efficient, fair and secure supply and demand balancing
• development of islanded and interconnected price-based energy and ancillary services arrangements for congestion management
• secure and open access to the network and efficient allocation of network costs
• alternative ownership structures, energy service providers
• new roles and responsibilities of supply company, distribution company, and consumer/customer
Control & Coordination: Is it necessary?

- The coordinated operation of several DGs and Loads (Consumers) increases the efficiency and provide opportunities for better network management.
- Consumers, DG owners and the network may have financial and operational benefits.
- These benefits derive from applying DSM policies, Congestion Management, Black Start, lower losses etc.
The Market Structure

Microgrids interact to the energy market via an energy provider.

ENERGY MARKET

ESCo

Microgrid
Technical Challenges for Microgrids

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Market and Regulatory Challenges

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Microgrids – Hierarchical Control

MicroGrid Central Controller (MGCC) promotes technical and economical operation, interface with loads and micro sources and DMS; provides set points or supervises LC and MC; MC and LC Controllers: interfaces to control interruptible loads and micro sources.
Centralized & Decentralized Control

- The main distinction is where decisions are taken.
- The Centralized Approach implies that a Central Processing Unit collects all the measurement and decides next actions.
- The Decentralized Approach implies that advanced controllers are installed in each node forming a distributed control system.
- Choice of approach depends on DG ownership, scale, ‘plug and play’, etc.
The Centralized Approach

ESCo

Decision Support Tools
- Load/RES Forecasting
- State Estimation
- Unit Commitment
- Economic Dispatch
- Security Monitoring

Measurements & Setpoints

Commands

MICROGRID
The Decentralized Approach

ESCo

Decision Support Tools
• Load/RES Forecast
• State Estimation
• Security Monitoring

Measurements

Price Schedules and Policies

NEGOTIATION

IC

IC

IC

IC

MICROGRID
Implementing the Decentralized Control Concept

- One approach of implementation adopts the intelligent agent approach
- Next, some basic concepts of the agent theory will be presented as well some practical examples.
The Agent

Physical entity that acts in the environment or a virtual one

Partial representation of the environment

Agents communicate – cooperate with each other

Agents have a certain level of autonomy

The agents have a behaviour and tends to satisfy objectives using its resources, skills and services

Reactive
- partial representation of the environment
- autonomy
- possesses skills

Cognitive
- Memory
- Environment Perception
- High level communication
Physical entity that acts in the environment or a virtual one

Physical Entity: Any Hardware that acts into the electrical network!

Virtual Entity: Any (software) entity that interacts with other agents and is part of the system!
Partial representation of the environment

Environment Knowledge: Important for any control system!

- It is very hard to have knowledge of the whole electrical network.
- This is one of the fundamental problems in any power system control application.
- The agent theory suggests that only part of the knowledge may be available in an agent!

The Agent knows electrical values in the connected bus: Voltage, Current, P, Q, frequency…
Agent Communication

A significant characteristic of agents. The Agent Communication Language allows the interaction and the knowledge sharing.

One significant part of the agent communication is the auction algorithm.

According to the fundamental principles of economic theory, fair bidding leads to optimal solutions.

The auction algorithm is an important tool for agent applications.
• The intelligent agent concept requires a strong language capable to describe knowledge
• This language has a structure and a vocabulary called ontology
• The language allows the establishment of complex dialogues
Behaviour, objectives, resources, skills and services

**Behavior**
- Competitive
- Collaboration

**Objectives**
- Maximize profit
- Minimize cost

**Resources**
- Available Fuel
- Energy Stored in a Battery

**Skills**
- Load Curtailment
- Black Start

**Services**
- Yellow pages
- Data Storage
Reactive vs Cognitive

**Reactive**
- The agent react to certain signals
- The collaboration of several reactive agents may form a intelligent society
- Typical example: the ant colony
- For an electrical network a protection device is a reactive agent.
- Several protection devices may create a self healing network

**Cognitive**
- The agent has increased intelligence and advance communication capabilities.
- The collaboration is supported by the intelligence and the communication capabilities
- Typical example: the human society
Jade is a Java based platform for agent implementation.

It is compatible with FIPA requirements.

FIPA is the Foundation for Intelligent Physical Agents.

Jade provides a set of libraries that allow the implementation of the agents.
Model of the agent platform

Agent Platform

AGENT

AGENT MANAGEMENT SYSTEM

DIRECTORY FACILITATOR

MESSAGE TRANSPORT SYSTEM

Provides Yellow Pages Services
# Implementation of the dialogues

<table>
<thead>
<tr>
<th>Basic Message Structure</th>
<th>Denotes the identity of the sender of the message, that is, the name of the agent of the communicative act.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sender</td>
<td>Denotes the identity of the intended recipients of the message.</td>
</tr>
<tr>
<td>Receiver</td>
<td>Defines a communication action: Accept, Refuse, Proposal, etc.</td>
</tr>
<tr>
<td>Type of Message</td>
<td>Introduces an expression which is used to identify the ongoing conversation.</td>
</tr>
<tr>
<td>Conversation ID</td>
<td>This is the vocabulary used by the agents.</td>
</tr>
<tr>
<td>Ontology</td>
<td>Denotes the content of the message; equivalently denotes the object of the action.</td>
</tr>
</tbody>
</table>
The implementation of the system requires a network of computers capable to host Java Applications and communicate over TCP/IP (internet protocols)
MORE MICROGRIDS
“Advanced Architectures and Control Concepts for more Microgrids”, Contract: SES6-PL019864

http://www.microgrids.eu

Budget: 8M€

Prof. Nikos Hatziargyriou, DEI Invited Seminar, Durham, 15 May, 2013
Microgrids Pilots

Østkraft

Continuon

labein tecnalia

edp distribuição

AGRIA PIG FARM

MVV Energie

KAPE CRES
Supply of 12 buildings (EC projects MORE and PV-Mode)
Next generation Sunny Island inverters, to deal with islanded mode control
Intelligent Load Controllers

The test site is a small settlement of 12 houses

**Generation:**
5 PV units connected via standard grid-tied inverters.
A 9 kVA diesel genset (for back-up).

**Storage:** Battery (60 Volt, 52 kWh) through 3 bi-directional inverters operating in parallel.

**Flexible Loads:** 1-2 kW irrigation pumps in each house
The Kythnos System House
Goal of the Kythnos Experiment

- The goal of the experiment is to test the agent based control system in a real test site in order to increase energy efficiency.
- The main objective is to test the technical challenges of the MAS implementation.
- The technical implementation is based on intelligent load controllers and the Jade Platform.
- The algorithm regarding the increase of the energy efficiency is quite simple and focuses in the limitation of the pump operation.
### Goals of the Experiment

<table>
<thead>
<tr>
<th><strong>Software</strong></th>
<th><strong>Hardware</strong></th>
</tr>
</thead>
</table>
| • Java/Jade implementation  
• CIM based ontology | • Embedded Controller  
• Measurements  
• Communication  
• Control via PLC |

<table>
<thead>
<tr>
<th><strong>Technical</strong></th>
<th><strong>Electrical</strong></th>
</tr>
</thead>
</table>
| • Implement Distributed Control  
• Test in real Environment | • Increase energy efficiency  
• Manage Non Critical Loads |
The MAS System

The MAS tries to increase the energy efficiency. The steps are the following:

1. The system decides the available energy that can be used by the pumps.
2. The houses decide how to share this energy.
The general idea

The main load in each is the water pump. The goal of the system is to optimise the usage of the pumps by limiting the operation of the diesel.
The Process of the experiment

Step 1: The agents identify the status of the environment

Step 2: The agents negotiate on how the share the available energy
Intelligent Load Controllers

In each house an ILC is installed:

- Windows CE 5.0
- Intel® Xscale™ PXA255
- 64MB of RAM
- 32MB FLASH Memory
- Java VM
- Jade LEAP
Auction Algorithm

• One significant part of the agent communication and decision process is the auction algorithms.
• The auction algorithm is a tool that allows the agents to decide which one of them will acquire a certain object or a good.
In the English Auction the auctioneer seeks to find the market price of a good by initially proposing a price below that of the supposed market value and then gradually raising the price.

Each time the price is announced, the auctioneer waits to see if any buyers will signal their willingness to pay the proposed price. As soon as one buyer indicates that it will accept the price, the auctioneer issues a new call for bids with an incremented price.

The auction continues until no buyers are prepared to pay the proposed price, at which point the auction ends. If the last price that was accepted by a buyer exceeds the auctioneer's (privately known) reservation price, the good is sold to that buyer for the agreed price. If the last accepted price is less than the reservation price, the good is not sold.
Example: Policies to estimate the available energy

- SOC of the Battery: This is an indication of the available energy of the system. The amount of energy above a certain level can be used (example >90%)

- The system frequency. If the system frequency is above 50Hz this is an indication that the batteries are full and part of the PV production is rejected
The shedding procedures start later.

In this case the frequency is almost 52Hz. This is an indication that the batteries are full and the PV inverters via the droop curves limit their production.
The main goal of this installation is to test a real MAS.

One critical part of any implementation MAS implementation is the ontology.

In Kythnos test site a CIM (IEC 61970) based ontology was tested.
Highlights

**Control**
- Implementation of Distributed Control
- The houses decide their actions

**Software**
- Java Based Application
- FIPA Compliant Architecture
- CIM Based ontology

**Hardware**
- Embedded Controller
- Communication & Control Capabilities
Conclusions

• The Kythnos was the first test site where the MAS system was implemented.

• A Controller with an Embedded processor has been used to host the agents.

• New techniques have been tested such as: negotiation algorithms, wireless communication, CIM based ontology etc..

• The architecture is too complex for small systems but offers great scalability.
It works !!!
Virtual Power Plants

- Internet model
Virtual Power Plant Implementation using MAS in EU-DEEP

• The goal of the experiment is to create a Virtual Power Plant using the agent technology

• This is a scheduling problem: the agent should decide a set of actions in the next period (example 24h).

• The system was tested in a real distributed test site in Athens
The Concept

The goal is to combine several units in order to act as a single unit.

CHP
PV 1
PV 2
Battery

24h
Goals of the Experiment

Software
- Java/Jade implementation
- CIM based ontology

Hardware
- Embedded Controller
- Control of CHP, batteries
- Long distance communication

Technical
- Advanced Scheduling Algorithms
- Advanced System Architecture

Electrical
- Virtual Power Plant
- Energy Market
The theoretical problem

• The agents should learn how to create a schedule of actions
• The first challenge is that the environment is stochastic: for example you cannot predict the production of a PV
• The second challenge is that the system should reduce the amount of data exchange: knowing the decisions of all agents means a very large amount of information.
Markov Decision Process

Definition \(<S,A,T,R>\)

- **S** is a finite set of states.
- **A** is a finite set of actions.
- **R** : \(S \times R \rightarrow R\) is the immediate reward.
- **T** : \(S \times R \rightarrow \prod(S)\) description of each action’s effect in a state

A Markov Decision Process is a discrete time stochastic control process. At each time step, the process is in some state \(s\), and the decision maker may choose any action \(\alpha\) that is available in state \(s\). The process responds at the next time step by randomly moving into a new state \(s'\), and giving the decision maker a corresponding reward \(R_\alpha(s, s')\). Reward Table: States X Actions

The probability that the process moves into its new state \(s'\) is influenced by the chosen action, it is given by the state transition function \(P_\alpha(s, s')\).
Q-Learning

Q-learning is a specific kind of reinforcement learning that assigns values to action-state pairs.

Q-Table has states (rows) and actions (columns)

The transition rule of Q learning is a very simple formula:

\[ Q(s, \alpha) = R(s, \alpha) + \gamma \times \text{Max}[Q(s', \alpha') \text{ for all actions}] \]

A value assigned to a specific element of matrix Q is equal to the sum of the corresponding value in matrix R and the learning parameter \( \gamma \), multiplied by the maximum value of Q for all possible actions in the next state.
Q-Learning

• Instead of explicit specification of the transition probabilities, these are accessed through a simulator that is typically restarted many times from a uniformly random initial state.

• Update the values in the Q table according to:

\[ Q(s, a) = (1 - \varepsilon)Q(s, a) + \varepsilon(r + \gamma \max_a Q(s', a')) \]

where \( \varepsilon \) is the learning factor and \( \gamma \) is the discount factor.
Our Approach

- Each agent runs its own RL algorithm without knowing the exact actions of all the other agents.
- The knowledge of the actions of the other agents is replaced by a variable called “transition variable”.

<table>
<thead>
<tr>
<th>The structure of Q table considering the actions of all players</th>
<th>Q(s,α1,α2,α3,…αn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The structure of Q table with the transition variable</td>
<td>Q(s,α1,tr)</td>
</tr>
</tbody>
</table>
The transition Variable

Example Battery Management (3 Batteries)

Three states $s\{\text{Produce, Store, Do nothing}\}$

<table>
<thead>
<tr>
<th>$t=1$</th>
<th>$t=2$</th>
<th>$t=3$</th>
<th>....</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bat 1 Produces</td>
<td>Bat 1 Produces</td>
<td>Bat 1 Produces</td>
<td>***</td>
</tr>
<tr>
<td>Bat 2 Produces</td>
<td>Bat 2 Produces</td>
<td>Bat 2 Produces</td>
<td></td>
</tr>
<tr>
<td>Bat 3 Produces</td>
<td>Bat 3 Produces</td>
<td>Bat 3 Produces</td>
<td></td>
</tr>
<tr>
<td>Bat 1 Produces</td>
<td>Bat 1 Produces</td>
<td>Bat 1 Produces</td>
<td>***</td>
</tr>
<tr>
<td>Bat 2 Stores</td>
<td>Bat 2 Stores</td>
<td>Bat 2 Stores</td>
<td></td>
</tr>
<tr>
<td>Bat 3 Produces</td>
<td>Bat 3 Produces</td>
<td>Bat 3 Produces</td>
<td></td>
</tr>
<tr>
<td>Bat 1 Produces</td>
<td>Bat 1 Produces</td>
<td>Bat 1 Produces</td>
<td>**</td>
</tr>
<tr>
<td>Bat 2 Stores</td>
<td>Bat 2 Stores</td>
<td>Bat 2 Stores</td>
<td></td>
</tr>
<tr>
<td>Bat 3 Stores</td>
<td>Bat 3 Stores</td>
<td>Bat 3 Stores</td>
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<td>*</td>
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<td>*</td>
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<td>*</td>
<td></td>
</tr>
</tbody>
</table>

The size of the table is $27 \times \text{Horizon} \ (3^{3})$
The transition Variable

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<table>
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<tr>
<th>t=1</th>
<th>t=2</th>
<th>t=3</th>
<th>…</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bat 1 Produces Other Batteries Produce</td>
<td>Bat 1 Produces Other Batteries Produce</td>
<td>Bat 1 Produces Other Batteries Produce</td>
<td>***</td>
</tr>
<tr>
<td>Bat 1 Produces Other Batteries Store</td>
<td>Bat 1 Produces Other Batteries Store</td>
<td>Bat 1 Produces Other Batteries Store</td>
<td>***</td>
</tr>
<tr>
<td>Bat 1 Produces Other Batteries Do nothing</td>
<td>Bat 1 Produces Other Batteries Do nothing</td>
<td>Bat 1 Produces Other Batteries Do nothing</td>
<td>**</td>
</tr>
<tr>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
</tbody>
</table>

The size of the table is 9 X Horizon (3↑2)
In this example the agents decide when to buy or sell energy

Environment state $s$:

- Sell to the grid
- Buy from the grid
- No actions

**Actions**

<table>
<thead>
<tr>
<th>Type</th>
<th>Action $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load</td>
<td>On</td>
</tr>
<tr>
<td></td>
<td>Off</td>
</tr>
<tr>
<td>Storage</td>
<td>Storage</td>
</tr>
<tr>
<td></td>
<td>Stop</td>
</tr>
<tr>
<td></td>
<td>Production</td>
</tr>
<tr>
<td>Production</td>
<td>Stop</td>
</tr>
<tr>
<td></td>
<td>Production</td>
</tr>
</tbody>
</table>

*Immediate reward* $r = \text{Income} - \text{Cost} - \text{Penalty}$
Formulation of the Q Table

- Storage: $Q (\text{Horizon}^{24}, \text{SOC}^3, \text{Environment}^3, \text{Transition}^3, \text{Action}^3) = 1944$ elements.

- Production: $Q (\text{Horizon}^{24}, \text{Fuel}^3, \text{Environment}^3, \text{Transition}^3, \text{Action}^2) = 1296$ elements.

- Load: $Q (\text{Horizon}^{24}, \text{Environment}^3, \text{Energy Demand}^3, \text{Transition}^3, \text{Action}^2) = 1296$ elements.
Results of the algorithm

This is part of the Q table of the battery. It provides information about the best action according to the system state.
Reinforcement Learning Algorithm

The scheduling problem is equivalent with the problem of finding the “Shortest Path” of the system. Its one has a weight representing the cost of this transition.
Multi Agent Reinforcement Learning

1. State $s$
2. Action $a$
3. Immediate Reward $r$

$Q(s, a) = (1 - k)Q(s, a) + k(r + \gamma \max_a Q(s', a'))$

Training: The system creates the Q Matrix which has the information of what the best action is.

Operation: The agent takes decisions according to the Q Matrix.
Optimum Strategy
Decision < 0: Buy energy,
Decision > 0: Sell energy

Cheap prices: Buy Energy
Expensive prices: Sell Energy
Reinforcement Learning (Q-learning) is used for the optimal market participation of the agents taking into account the environment uncertainties.

One Agent (battery)  

All Agents
Scalability

• The system as presented here cannot cope with large number of agents.
• A new architecture must be used in order to allow large number of agents to participate in the system.
• The main idea is to organize small groups of agents and these groups form a larger system.
In the final system there are only 3 agents.
Conclusions

• The usage of MAS for the creation of a VPP plant has been tested
• This technology is promising for small DG and Microgrids
• Can integrate large number of units
• The critical part of VPP is the scheduling problem.
• Local information should be added especially for certain type of units (CHP)
Applications of Purely Decentralized Methods

- Power grid state estimation by distributed calculation of electric quantities
- Distributed optimization of grid operation (congestion management, losses reduction, voltage deviations) gaining access only to locally available information
- The wide deployment of smart meters with enhanced capabilities (bidirectional communication, information storage and processing) creates the infrastructure for such applications
Further Reading…


http://www.smartrue.gr