# Micro Smart Grids and Electromobility Charging Optimisation with a Distributed Agent Application

# (Demonstration)

Christopher-Eyk Hrabia, Marco Lützenberger, Tobias Küster, and Sahin Albayrak Technische Universität Berlin, DAI-Labor Ernst-Reuter-Platz 7 10587 Berlin, Germany firstname.lastname@dai-labor.de

### **Categories and Subject Descriptors**

I.2 [**Computing Methodologies**]: Distributed Artificial Intelligence—*Multiagent systems* 

## Keywords

multi-agent systems; distributed information systems; optimisation; simulation; smart grids

#### 1. INTRODUCTION

In recent years, several countries and organisations increased their efforts on the use of renewable energy and electromobility [1]. Reaching the goal of a more environmentfriendly energy production together with less expensive transportation by using electromobility concepts is much more complicated as expected. Energy from renewable energy sources (e.g., wind or water) have the disadvantage of being highly variable and volatile. Furthermore, the occurrence of renewable energy and energy demand is highly asynchronous, such that the most energy from renewable sources is produced around noon and midnight, while energy demand commonly peaks around the morning- and evening time. The dephased occurrence aggravates any successful integration of renewable energy sources into today's energy infrastructures.

In fact, there are stakeholders that share the opinion that future distribution systems will not be as stable as present systems, but significantly suffer from the fluctuating occurrence of heterogeneous energy sources [2].

For solving these issues, energy providers intend to use electric vehicles (EVs) as cheap and distributed 'buffers' for surpluses of energy and to replace expensive backup power plants that are used to provide regulatory energy. Yet, the first generation of field-test projects [5] proofed that neither energy grid infrastructures nor the capability of electric vehicles will feature the requirements for this application any time soon.

On the other hand, concepts of using renewable energy in a more local context like micro smart grids to save line and

Appears in: Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France. Copyright © 2014, International Foundation for Autonomous Agents and Multiagent Systems (www.ifaamas.org). All rights reserved. transformation losses while increasing the use of local renewable energy show promises. A *Micro Smart Grid* (MSG) is a local energy network with intelligent management capabilities to balance and combine energy producers, consumers, and storages, to enable an increased use of renewable energy while keeping this sub grid as self-sufficient as possible.

### 2. PROBLEM STATEMENT

We are looking at the attempt to integrate an electric car sharing fleet with an MSG infrastructure in an urban test-bed. Such integration was done within the government-funded research project *Berlin elektromobil 2.0*, or *BeMobility 2.0*.

The aim of the project was to increase the  $CO_2$  efficiency of the electric car sharing fleet and to facilitate grid autarchy, while maintaining a balanced grid. We accomplished this goal by optimising charging schedules of available vehicles and by simulating the effects of this optimisation.

The success of combining electric vehicles and MSG architectures is mainly determined by the quality of two forecasts, namely the energy demand of the MSG architecture and the availability of electric vehicles for charging- and feeding purposes. The precision of the energy demand forecast can be significantly increased by analysing historic data. The vehicle availability forecast can be improved by selecting a fleet with a maximum of usage information—such as a car sharing fleet. Car sharing vehicles are booked with a certain amount of lead time, thus, it is possible to arrange chargingand feeding processes in order to meet required objectives.

Despite the large amount of information, the optimisation problem remains complex. Continuous and time-depending variables (e.g., the charging current) have to be determined, which makes the solution space considerably large.

Due to the complexity of the problem, we implemented our solution based on Evolution Strategy [4] and used the multi-agent paradigm in order to distribute calculation process.

Our software system is deployed at the *Europäisches Energieforum* in Berlin, Germany, where it manages charging processes of electric vehicles from the *Flinkster* fleet. A simulation mode is supported as well and facilitates efficiency analyses of hypothetic car fleet/infrastructure configurations. This feature helps to determine the effects of potential settings, thus, adjustments can be done in the most suitable way.

## 3. SYSTEM ARCHITECTURE

In order to create a system which can adapt to a dynamic environment and varying performance requirements, the different modules of the application were implemented as a multi-agent architecture. Our system was developed with the Java Intelligent Agent Componentware (JIAC) [3], a Java-based multi-agent development framework and runtime environment. The system consists of several agents, which communicate with each other using the JIAC included messaging capabilities.

A Supervisory Control and Data Acquisition (SCADA) adapter is used to collect data from the grid management and control systems, as well as data from other external system components (weather- and booking services). Moreover SCADA returns optimised charging schedules back to the grid management system. The human agent interface is a bridge between the agent infrastructure and the user interface. A database agent provides required information and data gathered by the SCADA adapter and all configurations.

The simulation mode replaces the SCADA adapter with a distinguished agent: the simulation agent. Similar to SCADA, the simulation agent exchanges information with the planner agent, mimicking real-life operation. Moreover the simulation agent takes care of initialisation, execution and analysis of the simulation process. The planer agent manages the optimisation procedure and distributes the optimisation task among a number of optimisation agents. Optimisation agents independently calculate a charging schedule, which is returned to the managing planer agent. From all available proposals, the planer agent selects the best option, which is executed.

The multi-agent approach allows to distribute and deploy all agents dynamically. The increased number of initial populations helps to overcome the well known problem of stochastic optimisation to get stuck in local optima. Due to the loose coupling, additional optimisation agents can be deployed at runtime, thus, the performance can be tailored to the problem complexity (e.g., for simulation purposes).

#### 4. OPTIMISATION

For the reasons above, our solution is based on evolution strategy and the multi-agent paradigm. Yet, any softwaredevelopment begins with the formalisation of the problem domain. We developed a meta model for this purpose.

The central element of the meta model is the *MSG*, aggregating a number of *electric vehicles*, *storages*, *charge controller* and *prosumers*. Storages can be both local energy storages likewise EV batteries, and each one is associated to a charge controller, describing how that storage can be (de-)charged. Electric vehicles add vehicle-specific information on top of that, e.g., range or consumption. Prosumers combine both producers and consumers of electric energy, e.g., locally installed power plants and buildings.

The model also holds prospected information. Each prosumer has a *prognosis* of it's future energy production and consumption that is either derived from historical data or from auxiliary information such as weather forecasts for wind and global radiation. Also, the projected *energy price* can be taken into account using, e.g., data provided by the energy spot marked. Further, a list of *bookings* provides information about the availability of vehicles. The actual *charging schedule* is represented as a list of *charging events*.

We follow the work of Rechenberg [4] and use the princi-

ples of mutation, recombination and selection to iteratively improve on existing solutions and to converge to an optimal solution. In more detail, we apply a variant of evolution strategy and use one or more *populations* of charging schedules, from which a number of *parents* are randomly selected, recombined, and mutated. Resulting individuals are simulated and assessed. The best individuals are selected as input for the next generation until the quality converges.

To determine the quality of a charging schedule, several parameters of the MSG-model are tracked during the simulation, e.g., the state of charge of each individual electric vehicle and storage, the overall energy consumption, and information about the feasibility of bookings. The result of the optimisation can be adjusted by manipulating weight parameters of the fitness function.

#### 5. INTERFACES

The application provides a web-based user interface which allows to custom define simulation scenarios. After optimisation and simulation are finished, it also visualises results, including key values of the MSG like grid usage, energy production and  $CO_2$  emissions. The optimised schedule can be compared to naively optimised ones.

The integration into the full featured MSG-SCADA-system on the test-bed was implemented with *SOAP* web services and specialised database views.

#### Acknowledgements

This work was partially funded by the *Federal Ministry of Transport, Building and Urban Development* under the funding reference number 03EM0101C.

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