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Multi-Agent Systems' Asset for Smart Grid Applications

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Abstract. Multi-agent systems are a subject of continuously increasing interest in applied technical sciences. Smart grids are one evolving field of application. Numerous smart grid projects with various interpretations of multi-agent systems as new control concept arose in the last decade. Although several theoretical definitions of the term 'agent' exist, there is a lack of practical understanding that might be improved by clearly distinguishing the agent technologies from other state-of-the-art control technologies. In this paper we clarify the differences between controllers, optimizers, learning systems, and agents. Further, we review most recent smart grid projects, and contrast their interpretations with our understanding of agents and multi-agent systems. We point out that multi-agent systems applied in the smart grid can add value when they are understood as fully distributed networks of control entities embedded in dynamic grid environments; able to operate in a cooperative manner and to automatically (re-)configure themselves.

Keywords: computer science, information systems, multi-agent systems, smart grid, power systems, agent-based control systems

1. Introduction

Agent-based systems have been implemented in the field of technical engineering, having been adopted as new concepts for control systems during the last few decades [25], [28]. Derived from the computer sciences [9], [14], [35] the broad usage of agent technology in the technical domain has resulted in an ambiguous use and interpretation of the notions 'agent' and 'multi-agent systems'; this is especially apparent in current smart grid research projects. The common understanding of the term smart grid in research projects encompasses the development of new power control strategies and communication systems to face the challenges (e.g.

fluctuating power generation, higher dynamics in grid frequency and grid voltage) which arise from the expansion of renewable energies (e.g. photovoltaic systems, wind turbines, and combined heat and power systems) and new electrical loads (e.g. heat pumps and electrical vehicles) [8], [38]. Numerous smart grid projects labeled with the term 'agent' sprouted up in the last few years, exhibiting various interpretation of when and how to apply the term 'agent' [19], [24]. It seems that engineers use the term 'agent' without a common understanding of what it actually embodies.

In the present paper, we aim at providing a clear definition of multi-agent systems in the realm of smart grid distributed control applications[1]. We do so by first identifying the characteristics that a control system should posses to be appropriately labeled as an agent system by emphasizing the differences between agents, optimizers, closed-loop controls, and learning systems. Second, we systematically analyze the interpretations and implementations of multi-agent systems in recent smart grid projects. We then contrast our understanding of agents and multi-agent systems with the existing multi-agent based smart grid projects and discuss which systems can be really understood as such. Finally, we describe the extent to which agent technologies may be of further value in improving smart grid applications, and give directions for future research and practice in the realm of agent-based systems.

2. Smart Grid – Definition and Applications

In accordance with the goals defined by the European Union, central Europe is striving for an energy supply powered by renewable energies [7]. With a rising share of distributed fluctuating renewable energy resources, it will become more and more challenging to ensure a secure and reliable energy supply in the future. This is due to:

Firstly, weather dependent fluctuation of the power supply of renewable energies (e.g. wind turbines or photovoltaic systems) makes the indispensable balancing of power generation and consumption more challenging.

Secondly, the generated renewable electricity is fed mainly into distribution and low-voltage grids. In the past, energy was only consumed in these grids while it was produced by large fossil power plants connected to the transmission and sub-transmission grids (see Fig. 1). Thus, the recent primary grid infrastructure (e.g. local transformers, circuit breakers, lines) is designed and parameterized for these unidirectional flows. In combination with the rising electricity generation in distribution grids, problems (e.g. over-voltage and over-currents) are to be assumed.

[1] [24] identifies four different power engineering domains where recent multi-agent systems are applied. These are: Protection, Modeling & Simulation, Distributed Control, and Monitoring & Diagnostics

Thirdly, the rising amount of distributed energy generation affects the grid frequency today already. Since the frequency is a grid-wide value, it is also necessary to ensure that the controllers of distributed energy resources are parameterized properly to ensure a stable grid. European standardization committees are currently addressing the 50.2 Hz problem, which occurs with a common switching threshold of 50.2 Hz in current inverters. This parameterization involves the danger of a major disturbance in the main grid when suddenly several gigawatt of generation disconnect in case of an underload (frequency above 50.2 Hz) and cause thereby an overload [17].

Fourthly, new applications and business models such as consumption of self-produced energy, electric vehicles, or the bundling of distributed generation to virtual power plants, will change the current static time-invariant behavior of grids to a more dynamic one.

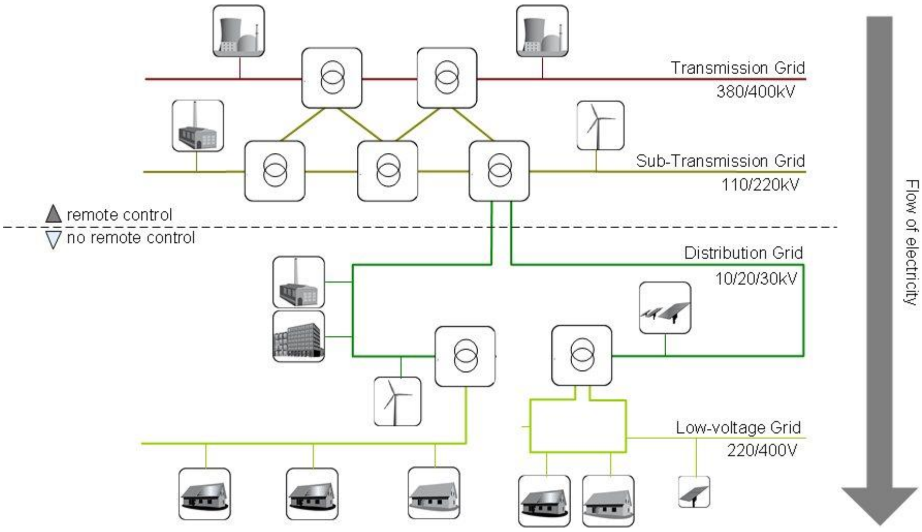

Fig. 1. Structure of today's (centralized) electricity supply system

One approach to handle these new challenges is the extension of recent grids to "Smart Grids". Various interpretations of what the term "Smart Grid" subsumes exist. For example, the European Technology Platform for Smart Grids defines a smart grid as, "an electricity network that can intelligently integrate the actions of all users connected to it - generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies" [8]. Slightly variegated, and with an emphasis on the communication systems, the International Electrotechnical Commission (IEC) understands a smart grid as integration of "electrical and information technologies in between any point of generation and any point of consumption" [38]. Thus, the core idea of smart grid is the development of new control strategies and systems – using information and communication technologies – which are necessary, particularly nowadays, due to the injection of renewable and fluctuating energy (e.g. by wind turbines and photovoltaic systems). The complexity of smart grids' applications arises from their interdisciplinary character, requiring the joint work of various research disciplines: electrical engineering, control theory, information technology, jurisprudence, economics and psychology. In this paper we focus mainly on control issues while briefly describing necessary interdisciplinary background.

Numerous different smart grid control systems have been developed to find cost-efficient solutions and to approach the above-mentioned problems. One of the most popular concepts to encourage users or systems to consume power when it is produced by the fluctuating energy resources is known as Demand Side Management (DMS). Mainly based on dynamic pricing, DMS encounters users or devices to redistribute electric demand over a certain period of time [36]. Another example for a smart grid control concept is the pooling of distributed generation and loads that are collectively controlled by a central control entity. These systems are known as virtual power plants [31], [41]. Furthermore, various projects can be found which take the control of so-called 'micro-grids' into consideration. Here, micro-grids are understood as small, local distribution grids containing electric generation and loads, which can be totally separated from, or (re-)connected to, the main distribution grid [30]. Among these examples numerous other smart grid control concepts have been developed. [12] gives a broad overview about recent smart grid projects in Europe.

3. State-of-the-Art versus Agent Technology

In this section we discuss and define an agent from an engineer's perspective. Agents are first defined in an independent application way and then discussed in the context of smart grid applications in section 5. While [9], [14], and [44] discuss the difference between agent technology and various IT domains (e.g. artificial intelligence, web-services and expert systems and grid computing) we analyzed the differences between well established engineering control technologies and agent technology. This section begins with computer science's definition of agents. Based on that, we differentiate in detail between an optimizer, a closed-loop controller, learning systems, and an agent.

While numerous definitions of agents have been discussed in the past, we here post the definition of Jennings and Wooldridge [44], [45]. We consider their approach a good balance between an overly-restrictive and a too-loose definition. A survey of 'agent' definitions can be found in [11]. Jennings and Wooldridge understand an autonomous intelligent agent to be a software artifact which exhibits the following capabilities:

"**Reactivity** Intelligent agents are able to perceive their environment, and respond in a timely fashion to changes that occur in it in order to satisfy their design objectives.

Proactiveness Intelligent agents are able to exhibit goal-directed behavior by taking the initiative in order to satisfy their design objectives.

Social ability Intelligent agents are capable of interacting with other agents (and possibly humans) in order to satisfy their design objectives."

It seems that these attributes are to some extent also manifested in engineers' state-of-the-art control technologies. To a certain degree this assumption is valid. For the sake of clarity, we work out how an agent can be distinguished from other control technologies, and why that makes sense.

In the rest of the paper we use the term 'agent' instead of 'intelligent agent'. We do so because we believe that labeling a software artifact as 'agent' only offers added value if agents at least constitute a certain degree of intelligence, thus exhibiting the above listed attributes. Hence, the adjective 'intelligent' is dispensable.

3.1. Why Is an Agent More Than Just an Optimizer?

The classic mathematical definition describes optimization as the task of finding a $f \in F$ for which

$$c(f) \leq c(x) \text{ for all } x \in F \tag{1}$$

while

$$c : F \rightarrow \mathbb{R}$$

Thereby f is the global optimum from the domain of feasible alternatives (feasible points) F and c the objective function [27]. Thus, an optimizer is a software tool which finds the optimal solution f. The optimizer's objective function is formulated once for a specific system with specific constraints. Systems can be of any kind, such as an economic system or a technical system. An example of a technical smart grid system is the cost-optimal operation of a grid-connected Combined Heat and Power Plant (CHP) [13]. Optimizers are not aware of, or in touch with, their system in terms of sensing system behavior or maintaining it like a controller does. This is of paramount importance for reaction, however. Thus, the optimizer example given above calculates the optimal set points for the CHP's operation once, and delivers these set points to a controller which is then responsible for reacting to system changes. Although we consider optimizers as non-reactive entities, it could be said that optimizers are to some extent goal-oriented and therefore proactively. Even if they try to find the best solution out of many, they are not acting proactive in terms of taking the initiative. Normally, optimizers do not automatically adapt their objective function when the system's behavior changes. Thus, the program will fail to reach its goal (i.e. finding a valid optimum). But proactive self-configuration, as we shall see in section 5, is essential for smart grid control systems.

Furthermore, optimizers are neither programmed to converse with a human, nor with other computer programs, hence they exhibit no social behavior.

3.2. Why Is an Agent More Than Just a Digital Closed-Loop Control?

Regarding the core definition of closed-loop controllers, it seems they are fairly similar to an agent. Indeed, closed-loop controllers exhibit a reactive behavior through their feedback loop. Figure 2. depicts the basic structure of a closed-loop control. The control variable y is measured and compared with the defined set point value w. Error e is fed to the controller, which then calculates actuating variable u as reaction to the control path's changes. Although conventional closed-loop controllers react to small changes in their control path (environment), they are not able to handle changes beyond the assumed system behavior of the path or an unpredicted situation. This is because closed-loop controller parameters (e.g. the integral part of a PID-controller) are tailored for the specific control path. When designing conventional controllers, it is assumed that control path behavior is time-invariant, completely known, and mathematically describable. However, conventional closed-loop controller robustness fails when the control path exhibits a time-variant dynamic.

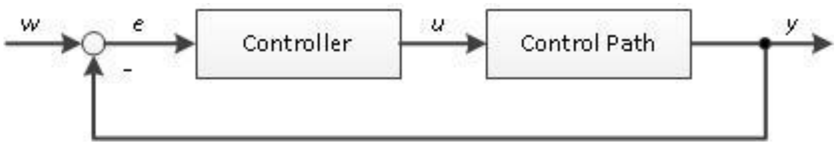

Fig. 2. Basic structure of a conventional closed-loop control

Adaptive controllers appear to approximate an agent's proactive behavior. Adaptive controllers can adjust their control parameters during run time by measuring the current actuating and control variables. Adaptive controllers do this directly or indirectly, and they decide how to adjust their parameters from these measurements [20]. Figure 3 shows the Model Reference Adaptive Control (MRAC) as an example for illustrating the main principle of adaptive controllers. In contrast to the conventional controller, the MRAC exhibits a reference model of the control path. As an indirect adaptive control system, it calculates the difference e_2 between the reference model's behavior and the control path. Based on e_2 and u, the adjustment mechanism calculates new control parameters [40].

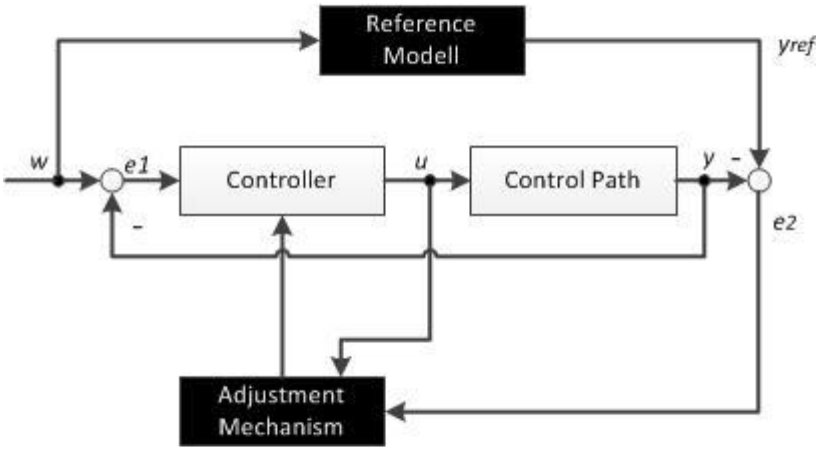

Fig. 3. Basic structure of a Model Reference Adaptive Control (MRAC)

Thus, adaptive controllers recognize environmental changes and react proactively in the sense that they adapt their initial parameters. Nevertheless, the controller is a "functional system" rather than a goal-oriented system aware of alternative ways to reach its goal. This can be illustrated with a simple logistic system:

Imagine a transport unit responsible for transporting a product from one work station to another, which has two alternative tracks available. Equipped with an adaptive control, the transport unit might be able to deliver the product in time, even when there are small obstacles on the track. But the adaptive control is not capable of choosing an alternative path through the production hall, should the track be blocked by other transport units. That is because the adaptive control is not aware of itself, what it actually performs, or the environment in which it operates. It processes the task of ensuring a stable steady state purely. In regard to the example, the controller does not know that it is operating in a production hall which features different corridors to arrive at a destination workstation. For similar reasons, the Model Predictive Control (MPC) can not be understood as proactive. MPCs predict the control path's behavior by using a reference model, but they are not capable of adapting their model to time-variant environments, nor do they have knowledge of themselves and the surrounding environment.

Thus, neither adaptive controllers nor model-predictive controllers can be deemed proactive in the manner agents are proactive. Furthermore, normally controllers are not designed to get in social contact with other controllers, technical systems, or humans. Doubtless, controllers can receive set points and communicate (actual) values of their actuating or controlled value, but they can not interact with other devices in the sense of cooperation or negotiation. This is of prime importance when several distributed controllers influence the same control path, such as in an electricity distribution grid.

3.3. Why Is an Agent More Than Solely a Learning System?

Learning systems are computer programs that use machine learning techniques. Learning as such, is described as a task which "[…] denotes changes in the system that are adaptive in the sense that they enable the system to do the same task or tasks […] more efficiently and more effectively the next time" [37]. Learning systems exhibit neither reactiveness nor proactiviness. This is because, in contrast to controllers or agents, they are not designed to control a system. First and foremost they are software artifacts which facilitate other computer programs or control systems adjustment in response to environmental changes, or the discovery of new patterns in measured data. To do so, they maintain an interaction with their environment, but only in the sense of; a) measuring data (passive unsupervised learning) or; b) experience with the environment while measuring the resulting effects (active unsupervised learning). Furthermore, learning systems have no real social ability. If social ability is exhibited, they are part of distributed problem solving systems which are commonly implemented as multi-agent system.

3.4. Functionalities of Agents

We pointed out that none of the analyzed technologies incorporate all attributes of an agent as described by Jennings and Wooldridge [16]: Reactiveness, proactiveness, and social ability. However, the functionalities of the above described technologies are joined together within an agent. Thus, an agent should not be conceived as synonym for the above mentioned state-of-the-art control technologies. Instead, the term 'agent' expresses a specific software artifact that joins together functionalities of optimizers, controllers, and learning systems.

In contrast to the agent definition of [35], we do not view "anything that […] [is] perceiving its environment through sensors and acting upon environment through actuators" as an agent. As said before, we base our understanding of agents on the definition of Wooldridge and Jennings. Thus, we claim that a software artifact labeled as a (holistic) agent must exhibit, in addition to optimization and controlling the following functionalities; i) some kind of reasoning; and ii) a communication system which allows a high-level agent-to-agent interaction flexible enough to achieve social speech acts as humans do. Therefore, we understand multi-agent based control systems as systems consisting of distributed agents capable of coordination, cooperation and negotiation to gain a stable common control path (environment) while reaching their individual goals. Figure 4 depicts the five functionalities that a holistic agent should exhibit and which impart the attributes of autonomous agents as defined by Wooldridge and Jennings: reactiveness, proactiveness, and social ability. Since the extent of the functionality "Learning" can vary from one application to the other and is in some application even undesirable we marked "Learning" in Figure 4 with a dashed frame as an optional functionality for agents. The five functionalities are described in detail in turn.

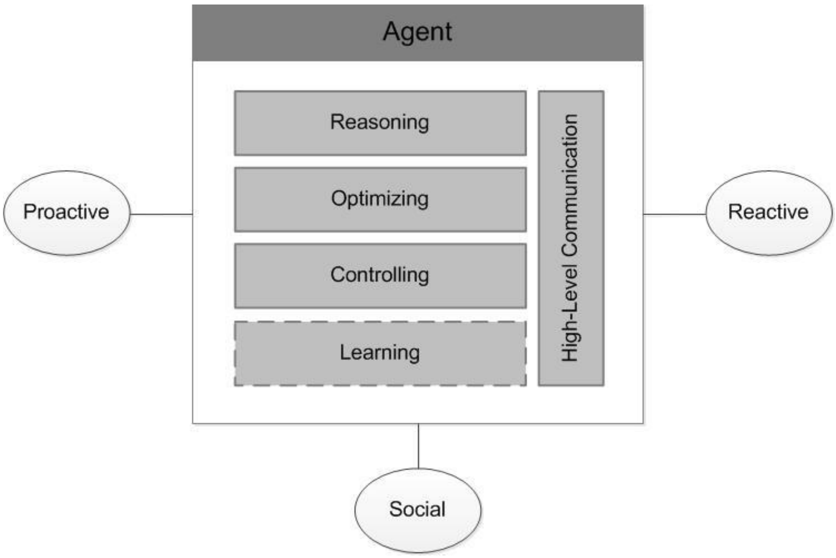

Fig. 4. Functionalities of an agent: reasoning, optimizing, controlling, and high-level communication as well as learning as optional functionality (marked with a dashed frame) imparting the mentioned attributes reactiveness, proactiveness and social ability.

Reasoning

In contrast to optimizers and controllers, agents should be able to perform tasks that were not explicitly defined and programmed at design time. Thus, agents are capable of reaching the programmer's defined goals by processing sequentially different tasks that they develop from a knowledge base of their environments. This process can be illustrated with a real-life scenario: suppose you have a meeting on the other side of city and that you usually take your bike. How would you behave if your bike was broken? You would think (reason) about other vehicles you might be able to use by checking the logical relation between bikes and other known objects, such as cars, tricycles, and walls. Understanding that walls are not vehicles is something taken for granted by humans. For computers, this is a non-trivial task. However, "practical reasoning" [2] enables agents to explore tasks or actions from a logical knowledge of their environments that suit the situation to be solved. After finding a set of possible alternatives, which can also stem from cooperation with other agents, the agents need to make the decision of which task or action they want to perform to reach their goals.

Optimization

Usually, agents make this decision by some sort of performance measurement. [44] describes the idea of associating “utilities with states of the environments”. Utility is a numeric value which shows how “good” an agent’s envisaged task/alternative is. Thus, the agent tries to find one alternative out of the set of explored alternatives that promises the highest utility. This does not imply that agents always act on basis of a single utility function to reach their goals. Sometimes they act on zero or multiple coexisting utility functions. This is illustrated in the above example: through reasoning you figured out that you have three alternative transportation options that will get you to your meeting: by car, by tricycle, or by foot. Thus, you can reach your goal either by choosing the cheapest (by foot) or the most comfortable alternative (the car). But if you have no preference it is irrelevant which vessel (task/alternative) you choose unless you reach your goal “arriving at the meeting place”. This is similar to agents. Agents can either realize the optimal task or choose a task randomly. Expressing this example in a mathematical form, the parallels between optimizers and “decision making”, as it is usually entitled by agent scientists becomes apparent (cf. section 3.1):

$$u(v_1) \leq u(v_2) \text{ for all } v \in V \quad (\mathbf{2})$$

while

$$u : V \rightarrow \mathbb{R}$$

and

$v_{1,2}$ = vehicle one/two, V = Pool of alternative vehicles, u = Cost of transport

Learning

Based on this example, we further want to illustrate the learning ability of agents. Agents, like humans, can recognize changes to their environmental constraints. They can identify new alternatives, such as vehicles that are faster, cheaper, or both. The ability to recognize changes in the environment is vital for reaching the agent’s goal, but also proves to be very difficult. This is because such learning requires - much like reasoning - knowledge about the logical relations of objects in the environment in which the agent is embedded. However, the learning system of an agent modifies the number of alternatives which the reasoning functionality can process and thereby it also modifies the optimizer’s pool of alternatives V, indirectly. As mentioned before, the agent’s ability to expand and modify its behavior via learning is not a mandatory functionality for an agent but it constitutes – when implemented – an essential distinguishing feature of an agent compared with controllers or optimizers.

Controlling

After determining which tasks should be realized, agents give commands (set points) to their technical system for which they are responsible (considering the car as technical system in our example, a command could be "start the motor and drive at a certain velocity"). Furthermore, agents need to check if the command is performed correctly and, if not, to take corrective actions. This is what closed-loop controls do, roughly. As mentioned before, closed-loops try to arrange a given set point by reacting based on the control variable's feedback.

High-level Communication

The most distinctive attribute of agents compared to other technical control systems is really an agent's social ability. Social ability does not only include the interaction with humans as done with expert systems [44], it also encompasses the freedom to interact with any valuable communication partner, be it a human, superior entity (e.g. server, market), or other agents. This freedom to automatically and flexibly establish communication at run-time makes a high-level communication interface and language necessary. Such a language is specified by the Foundation for Intelligent Physical Agents (FIPA). Within the FIPA-Specification a high-level communication language is formalized and specified. FIPA-Agents Communication Language (ACL) comprises generic messages classes, so called performatives. These performatives express the type or class of a message without specifying the content and the content language (e.g. the performative "request" is used by agents asking other agents to submit any information) [10]. Thus, agents can establish communication with any kind of content at run-time and are not limited to communication interfaces defined at design time (e.g. web-services) [14], [33]. As described in section 5, this functionality will likely bring valuable advantages and it is indispensable when agents are part of a multi-agent based control systems.

4. "Multi-Agent Systems" in Recent Smart Grid Projects

In this section, we review the most recent smart grid research projects labeled with the term 'agent' or 'multi-agent'. We do not claim to provide a complete listing of all smart grid multi-agent systems. Rather, we intend to carve out common interpretations and implementations of the agent technology by illustrating some representative examples. Therefore, we only considered the domain of distributed agent-based control systems (as defined in [24]). Furthermore, we refer to the more general term 'control entity' (CE) to describe the diverse systems (and their differing interpretations of agent systems) instead of using the term 'agent'. Subsequently, in section 5, we discuss under which circumstances CEs and control systems can be understood as multi-agent control systems.

The majority of previous multi-agent labeled systems consist of distributed CEs, which are responsible for trading energy on local electricity markets (LEM) by sending bids. In distributed CEs scenarios, CEs calculate energy sales or energy purchase prices based on their individual cost functions. The cost functions for CEs are composed of the specific power device's (e.g. combined heat and power plant, photovoltaic system, or simply a dwelling with different loads) cost function for which the CE is responsible. After calculating the cost-minimal operation of the power equipment, the CEs send bids to their dedicated LEMs. The LEMs subsequently match the CEs' energy offers and demands and send the auctions outcome. CEs can either act as sellers or buyers at the local energy market [4], [5], [18], [21], [23], [34], [42].

The general structure of these systems is depicted in Figure 5. In addition to the descripted basic market-oriented structure (continuous lines) a further upper trading level is visualized in the figure (dashed lines). In this level, LEMs can trade energy at an upper electricity market (EM). However, they only do so if they were not able to locally match all supplies and demands of the CEs. Such a cascading system can be found in [18] and [43]. With few exceptions, such as [22], these market-oriented systems usually are non-predictive systems. Thus, they only calculate energy for the next time intervals that range between 500 milliseconds [42], [43] and several minutes [22], and do not calculate a cost optimal schedule (e.g. for the next 24 hours). In most all market-oriented systems labeled as MAS, control entities are only connected to their dedicated local energy market. Hence, these MAS are not programmed to search or adapt their strategies to other local or global markets. Furthermore, current market-oriented multi-agent systems are mainly programmed for one dedicated market type. For example, the above-mentioned systems can handle only bids within an auction based, active power market. However, an agent should be capable of handling all types of markets (e.g. active, reactive, and spinning reserve markets) and all offered products (e.g. spot deals or forward transactions).

Grid-oriented systems constitute the second important application field of multi-agent based distributed control systems in the smart grid. These control systems are primarily responsible for ensuring a grid operation in a normal state, which implies an operation within the standardized voltage, power, and frequency limitations of the grid. For example, [21] extends the market-oriented approach of [43] with a local frequency measurement and adjustment. [32] developed a voltage control system implementing a central CE that optimizes reactive power injection of distributed energy systems (DES). Therefore, the CEs are responsible for the DESs only receiving a set point from the central CE.

Furthermore, in previous grid-oriented projects, distributed control systems capable of performing an automatic reconfiguration of their control parameters in case of grid topology changes were developed. Grid topology[2] changes can arise either by an activation of circuit breakers and (e.g. to increment or decrement the voltage level), or from connection, or disconnection, from the main grid:

a) of either single Distributed Energy Resources (DER) at any instant or
b) of entire grid sections, due to an occurring fault like a short circuit. [30]

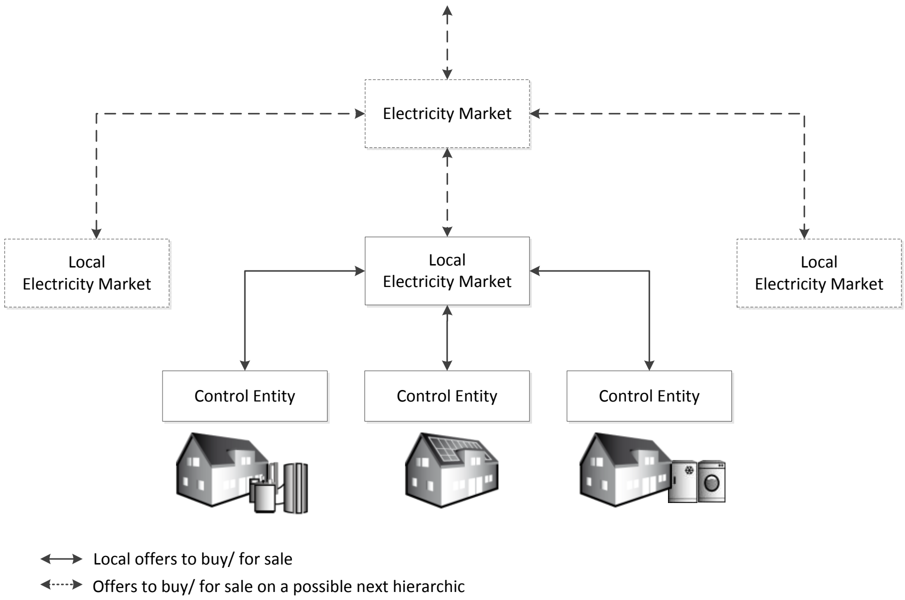

Fig. 5. Common structure of systems labeled as MAS applying an auction based active power spot market.

While the activation of circuit breakers, and the connection and disconnection of DERs, require "solely" the reconfiguration of distributed control entities, the control of separated grid sections is particularly challenging. These so called micro-grids require several non-trivial tasks like fault detection and localization, coordination of the islanded grid section's voltage, and frequency control as well as synchronization when reconnecting to the main grid [30]. [26] and [29] developed distributed control systems, responsible for reliable operation in the normal grid state as well as for automatic and secure transition from the normal grid state, to the island state

[2] Within this paper grid topology is understood as defined in electrical engineering. Thus, a change of any grid parameter (e.g. change of a load, change of impedances, and activation of switches) is regarded as topology change. It encompasses not only the restructuring of electrical grids.

and back. Switches and distributed energy systems (e.g. photovoltaic system, electricity storages, loads, etc.) equipped with interconnected CEs are capable of communicating in a many-to-many manner, and thus may coordinate the grid in every state without passing information via a dedicated central control entity.

5. Agents' Assets and Suitable Application Fields

Comparing the distinction of agents developed in this paper (Section 3) and recent smart grid projects labeled as multi-agent systems (Section 4), we claim that most projects implemented control systems exhibiting some, but not all, agent functionalities in a stricter sense. Although these multi-agent control systems have proved to be very effective, some smart grid applications do not necessitate multi-agent systems as a control system. In the following, we discuss where the usage of (the notion of) multi-agent systems and the application of holistic agents might be valuable assets in the smart grid. We structured this section according to the main smart grid domains: grid-oriented and economic-oriented approaches. While grid-oriented approaches control DERs in a way that reliable grid operation is ensured (e.g. distributed voltage control via reactive power injection), the economic-oriented approaches control DERs grid independently (e.g. virtual power plants).

5.1. Economic-oriented Control Systems

As mentioned above and posed by Jennings and Bussmann, multi-agent systems should demonstrate CEs which have the capability "to initiate (and respond to) interactions that were not foreseen at design time" [15]. Although, the investigated market-oriented systems (in section 4, paragraph 2) constitute decentralized and negotiating CEs, the systems cannot be deemed agent systems in a stricter sense (cf. section 3). This is because:

First, the negotiation of CEs in market-oriented MAS is mainly limited to only one negotiation partner, the local electricity market. Second, the investigated market-oriented MASs demonstrate CEs which are dedicated to only one market type (e.g. real time markets or active energy spot markets) and they are not capable of automatically initiating contracts (for example) on other market types (e.g. forward-markets and reactive energy (spot) markets) or to conclude a direct, bilateral, over-the-counter contract. Both seem to contradict the agent definition and somehow also the legal requirement of being able to freely choose any energy supplier[3]. In contrast, a multi-agent system, in a stricter sense, should allow agents to negotiate energy with any other agent, and thereby enter into any contracts with any

[3] Based on the Liberalization of EU's electricity supply system

partner, either of a local energy market or a gird neighbor who offers or sells energy bidirectionally over the counter.

Further, CEs in economic-oriented systems labeled as multi-agent system should have the freedom to cooperate and to dynamically form subgroups ("holons") with other CEs. Applied in the smart grid, this would enable dynamic and automatic composition (and decomposition) of energy communities. These communities would, for example, try to match electricity production and consumption within their community first, before entering negotiations with external agents or other electricity communities. In addition, it is conceivable that agents would form groups with the purpose of acting as a virtual power plant that appears as a whole, such as when trading energy at the operating reserve market [6], [39].

However, the flexibility to interact at unpredictable times, for unforeseen reasons with other unpredictable CEs makes what social ability embodies evident. **CEs, like those mentioned above** (cf. section 4), are bound to a single web-service enabling bidding at a dedicated LEM, **cannot be deemed "social" and proactive**. (cf. [14]). In combination with a single possibility to modify the bids - which makes reasoning needless - the alleged agents demonstrate more of the characteristics of communicating optimizers. However, what social ability and proactiviness applied in economic-oriented MAS should imply is illustrated by an example: Imagine a rural low-voltage grid with four nodes representing four households with different energy systems. As depicted in Figure 6., the first household is equipped with a combined heat and power plant (CHP), the second and fourth with a photovoltaic system (PV), and the third with a heat pump (HP). All energy systems are controlled by agents responsible for the technical and economical efficient operation. The agent goals, which are usually cost-minimal energy supply and profit-oriented generation, are defined at design time. Other than current control systems, agents are not bound to one control strategy in achieving these goals. Thus, the HP agent might proactively ask the CHP agent and the PV Agent – without dedicate command of a human – if they are interested in cooperating within an energy community. If the other agents agree in that cooperation, all agents need to adapt their control parameters in order to achieve the joint objective of the energy community (social ability): profit maximization while ensuring a reliable energy supply. Further, it is conceivable that the community may decide proactively to participate in the operating reserve market because they assume a higher profit. Such a machine-to-machine decision makes a social interaction and an automatic adjustment of the control parameters indispensable. Figure 6. shows examples of different possibilities through which agents can achieve their goals. While (a) depicts agents that fend for themselves, in (b) and (c) agents are cooperating for either the purpose of self-consumption or to appear as one party on energy markets.

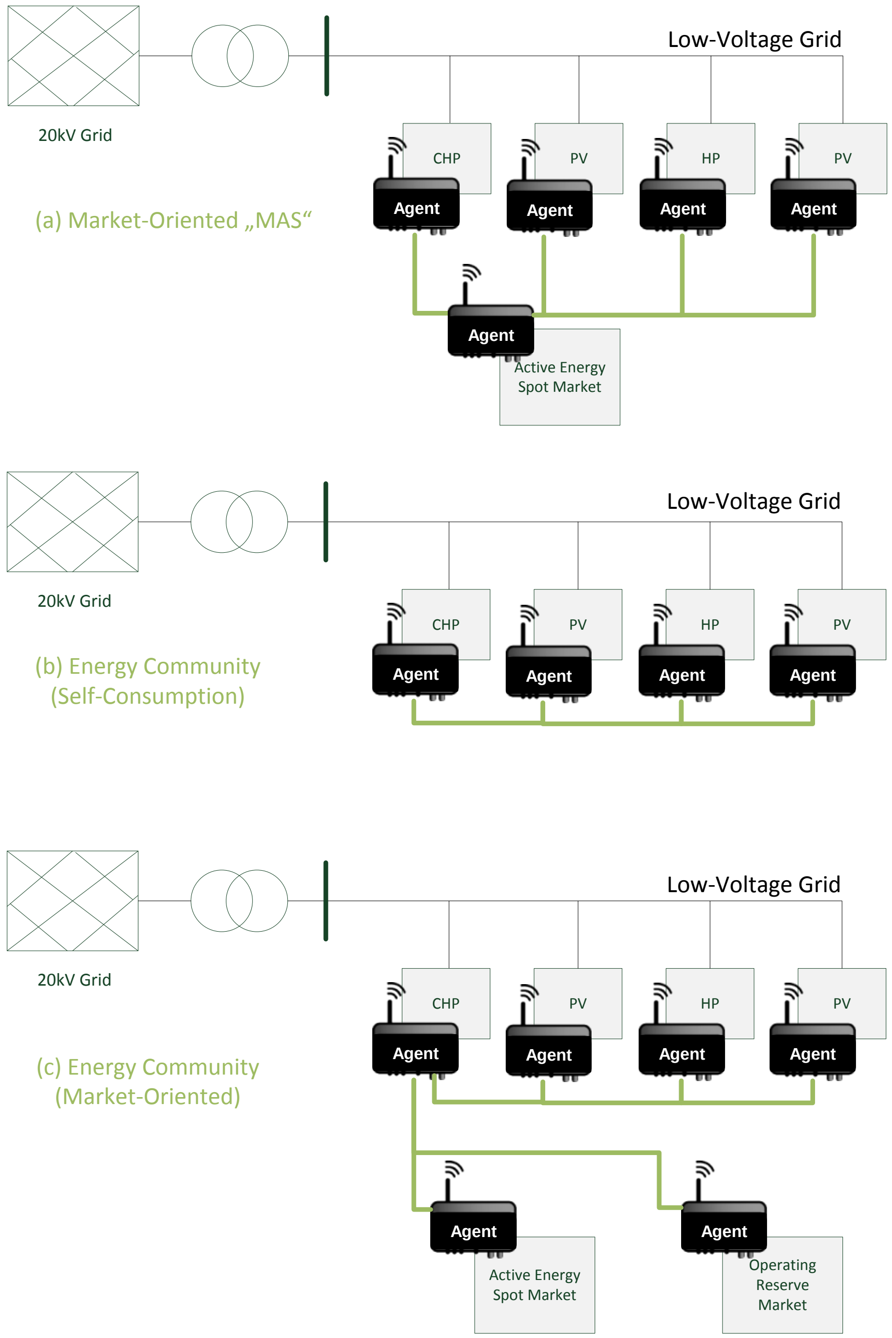

Fig. 6. Examples of how agents (in a low-voltage grid) can organize themselves.

5.2. Grid-oriented Multi-Agent Systems

The development of distributed renewable systems obliges network operators to extend their (sub-)transmission control systems to the distribution and low-voltage grids. To preserve operational personal from workload increase, which even today necessitates automation [15], multi-agent systems could be a suitable solution. Industrial manufacturing and industrial process automation already demonstrate that agent-based systems bring sizable advantages when applied as a control system for uncertain, difficult to predict and varying environments. Biological wastewater treatment plants or production systems with repetitive plugging of equipment are the most noteworthy example which Metzger et al. surveyed [25]. These conditions seem – in a weakened form – also present in future electricity distribution grids. The following paragraphs discuss where agent technology in grid-oriented control is of value. Since voltage and frequency control demonstrate the most important and most discussed grid values in smart grid research, we have subdivided this section accordingly. Further, we discuss micro-grid control systems within a separate paragraph, since it is responsible for all values which are important for stable and reliable grid operation.

Voltage Control in Distribution Grids

In addition to frequency control, network operators are responsible for controlling grid voltage. In contrast to the grid frequency, the voltage depends on the grid's topology, encompassing the grid impendency, grid structure, and the active and reactive energy flows of consumers and generators connected to the grid. Voltage control in distributed and low-voltage grids was not important in the past due to the unidirectional energy flows and the associated static drop of voltage along the power line. The transformers in low-voltage grids were adjusted in the way that the voltage was high enough even at the end of the grid. Over-voltage problems are assumed when the current static transformer parameterization remains unchanged while the number of distributed generators (e.g. photovoltaic systems or combined heat and power plants) rises. In order to keep the voltage in the permitted ranges, one approach is to involve the distributed systems in grid stabilization by means of dynamic adaptation of the active (P) and reactive power (Q) depending on the grid voltage. These distributed systems need to be coordinated to avoid voltage oscillation in the grid and to ensure a maximal production of renewable active energy. For this purpose, the **controllers can be extended to agents, capable of coordinating and negotiating injection of power**. To reduce the configuration efforts of the agents and to allow automatic adaptation when the grid structures change, agents should be capable of detecting grid position. These changes in grid structure can develop because, first, short circuits or earth faults need to be recovered, or, second due to an islanding of the grid section in which the agent is located. In both cases manual reconfiguration and coordination of the distributed controllers' parameters seems inappropriate. Thus, agents which realize automatic configuration may be valuable assets in this scenario. Especially in regions with a high percentage of overhead lines (as in the United States) automatic troubleshooting of electricity grid is of paramount interest.

Grid Frequency Control

The gradual substitution of conventional power plants with distributed renewable energy systems compulsorily increase the influence of distributed systems on the frequency. To ensure a stable and reliable grid in the future frequency control need to be coordinated among those millions of distributed systems, since large frequency changes can lead to an unstable power system.

In today's central European electricity grid (ENTSO–E[4] grid), the transmission grid operators are responsible for the frequency control. The frequency control is divided in three control levels which differ in their time of activation: a) primary control (frequency-response reserve), b) secondary control (spinning reserve), and c) tertiary control (replacement reserve). In case of a frequency deviation, the control levels are activated step-wise, beginning with the primary control, via the secondary control and ending at tertiary control (if the deviation still exists). The primary control reacts within a few seconds (max. 30 seconds) to frequency deviation by automatically adapting the power of some generation units in the electricity grid according to a given static. After one minute, the secondary control replaces the primary control and tries to restore the frequency to the nominal value (in Europe 50 Hz). If it is not possible to restore the frequency with the secondary control after five minutes, tertiary control is manual (e.g. via phone) requested by transmission operators. All forms of operating reserve (frequency-response reserve, spinning reserve and replacement reserve) are traded on the operating reserve market. Currently only larger power plants are allowed to participate on the operating reserve markets.

Assuming that the current operating reserve mechanism remains unchanged, while in the future small distributed generation units are also allowed to trade replacement reserve, **agents might be of value when enabling automated participation of distributed energy systems at the operating reserve market.** As a control entity for a distributed energy system (e.g. a combined heat and power plant) the agent would autonomously negotiate at the operating reserve market in order to operate its distributed energy system cost-optimally. [21] describes such a multi-agent system which controls the frequency via a market-oriented multi-agent system. A Balancing-Agent, which is responsible for the frequency, offers active energy for consumption when the frequency is about to drop and buys energy - which is left unused - when the frequency rises. Here, the Balancing-Agent appears as a central coordinating unit to which the other agents are

[4] European Network of Transmission System Operators

dedicated. As mentioned above, it is questionable if a control entity which is slowly connected to the operating reserve market server shall be deemed an agent in strictest sense. The automatic negotiation can also be implemented using web-services. But as described by [14] web-services are not agents. Hence, labeling negotiating control entities as agents would only make sense when they demonstrate proactiviness and social behavior as described in section 3. Consistently, proactiviness and social behavior are only feasible if alternative courses of action exist. It is the control entity which is capable of deciding, for example, to either offer at the operating reserve market or to any other energy market (cf. section 5.1), which would constitute a freedom, on the basis of which a control entity may develop its proactiviness. Furthermore, social behavior only evolves if other control entities and, with that, possibilities of cooperation (e.g. as virtual power plant) exist.

Besides the question of how distributed energy resources can participate passively at the frequency control via a replacement reserve market, it still remains unclear how they can participate actively[5], without causing grid destabilization. As mentioned above, recent photovoltaic inverters were configured to disconnect from the grid if the frequency reached the limit of 50.2 Hz. If a large amount of systems would react accordingly, this would cause serious grid problems [17]. Thus, the parameterization of the distributed energy system via cooperating agents – as applied for voltage control – would be conceivable. But other than the voltage, the frequency constitutes a grid-wide value. This would imply the coordination of millions of energy systems, which seems unrealistic mainly due the associated high communication traffic. Assuming that, in the future, only some power units are responsible for the supply of frequency-response and spinning reserve power, a multi-agent system might be an appropriate solution for an automatic, autonomous, and self-parameterizing control system of the power plants control, as described in [1].

Micro-Grid Control

Micro-grids seem to be the most appropriate smart grid domain for the applications of multi-agent based control systems regarding the recent numerous micro-grid projects [19]. [3] defines micro-grids as small, local distribution systems containing generation and loads that can be separated totally from the distribution grid. Micro-grids constitute, indeed, perfect environments for the application of MAS, for the following reasons: First, other than the main grid, the micro-grid demonstrates a small separate system comprising of a limited number of control entities. That makes the coordination and the assigned communication efforts manageable. Other than in the smart grid parameterization, for example, of the frequency

[5] Actively implies that the control units measure the frequency at their dedicated grid node and react directly to frequency deviations by adapting the injected active power, or reactive power.

controllers becomes feasible. Second, micro-grids in disconnected mode are fully responsible for the stable and reliable operation of the grid. That encompasses, besides the voltage control, the frequency control and protection issues as well. The indispensable energy balance needs to be ensured, while, caused by disconnection, only a reduced number of devices that can provide reserves exist. Likewise, the micro-grid control system needs to react to regular changes in the grid topology (e.g. disconnection of distributed energy resources or loads). Hence, as described in [30], MAS would be a valuable asset, because other than in a centralized micro-grid control system, no manual adaption of the central control algorithms/models is necessary. Within a MAS automatic adaption of the distributed control parameters takes place if topology changes occur. Numerous multi-agent based micro-grid control systems can be found in literature. [19] and [30] give a broad overview about recent multi-agent based micro-grid controls.

In this section we illustrated that the terms 'agent' and 'multi-agent' systems applied in the smart grid are of value when automatic, cooperative, and coordinated reconfiguration of distributed devices (e.g. distributed energy systems or grid equipment) is required during runtime. We discussed the application of multi-agent systems for frequency control, voltage, micro-grid control (grid-oriented), and economic-oriented control systems, since they constitute the major smart grid control domains. Further applications, such as the optimal coordination of an electric vehicle fleet or substation monitoring and diagnostic systems, can be considered as further possible applicable fields for multi-agent systems. However, it is recommended to carefully consider if either multi-agent systems or current state-of-the-art control technology should be applied, as the case pops up on a case by case basis. Furthermore, the term 'agent' should only be used if the control systems evince the above mentioned abilities: proactivity, reactivity and social behavior, and not only as a synonym for state-of-the-art control technologies.

6. Conclusion

This article has sought to justify why and when multi-agent systems are suited for smart grid applications. First, we have posed that state-of-the-art control technologies should not be understood as agents, but, in turn, agents should be understood as software artefacts that exhibit the functionalities of optimizers, controllers, and learning systems, accompanied by the capabilities of practical reasoning and social interaction. Second, we contrasted our understanding of agents with interpretations of recent smart grid projects labelled as multi-agent control systems. These projects have already demonstrated the effectiveness of multi-agent systems, although they implement agents only in the broadest senses: due to the decentralized structure, data is locally processed where it is produced and local negotiation effects a coordination of the distributed systems. However, to explore all agent benefits and to sharpen the notion, we suggest terming control entities as agents when they encompass all of the above mentioned functionalities. The assets are: i) automatic reconfiguration in case of time-invariant environment changes (e.g. grid topology changes); ii) automatic initiation of and participation in (economic) interest groups (virtual power plants); and iii) automatic adaption to changing control strategies (e.g. in case of grid islanding). Coordination of thousands of distributed, fluctuating, electricity generators and a robust operation of our electricity grids constitutes an enormous future control challenge. This dynamic, distributed, and widespread environment seems to be perfectly suited for the application of agent-based control systems.

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