Energy Conversion and Management 86 (2014) 831–847

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

# A cognitive decision agent architecture for optimal energy management of microgrids

Rosemarie Velik *, Pascal Nicolay

CTR Carinthian Tech Research, Europastrasse 4/1, 9524 Villach, Austria

ARTICLE INFO

*Article history:*
Received 28 March 2014
Accepted 15 June 2014
Available online 5 July 2014

*Keywords:*
Photovoltaic energy
Battery storage
Energy management
Variable grid prices
Microgrids
Optimization

ABSTRACT

Via the integration of renewable energy and storage technologies, buildings have started to change from passive (electricity) consumers to active prosumer microgrids. Along with this development come a shift from centralized to distributed production and consumption models as well as discussions about the introduction of variable demand–supply-driven grid electricity prices. Together with upcoming ICT and automation technologies, these developments open space to a wide range of novel energy management and energy trading possibilities to optimally use available energy resources. However, what is considered as an optimal energy management and trading strategy heavily depends on the individual objectives and needs of a microgrid operator. Accordingly, elaborating the most suitable strategy for each particular system configuration and operator need can become quite a complex and time-consuming task, which can massively benefit from computational support. In this article, we introduce a bio-inspired cognitive decision agent architecture for optimized, goal-specific energy management in (interconnected) microgrids, which are additionally connected to the main electricity grid. For evaluating the performance of the architecture, a number of test cases are specified targeting objectives like local photovoltaic energy consumption maximization and financial gain maximization. Obtained outcomes are compared against a modified simulating annealing optimization approach in terms of objective achievement and computational effort. Results demonstrate that the cognitive decision agent architecture yields improved optimization results in comparison to the state of the art reference method while at the same time requiring significantly less computation time.



## 1. Introduction

In developed countries, approximately 40% of the total energy consumption stems from buildings [1]. Accordingly, the optimization of buildings' energy production, consumption, and exchange have been identified as important factors in resource saving and climate protection and are a market with high growth potential [2–4]. Via integration of renewable energy (e.g. photovoltaics systems) and storage technologies (e.g. batteries), buildings have started to change from passive (electricity) consumers to active prosumer (producer + consumer) microgrids [5]. Microgrids in general are low voltage distribution networks comprising energy consumers, energy generators, and energy storage elements [6,7] and can either operate in island mode or are connected to other microgrids and/or the main grid [8]. In recent years, they have gained increasing importance due to their promise to provide reliable, safe, efficient, and sustainable energy from distributed renewable energy sources [9–11]. As a consequence, distributed energy production and consumption models are beginning to replace the so far dominating centralized approaches [12,13]. Furthermore, the introduction of variable demand–supply-driven grid electricity prices is discussed [14]. Via the integration of upcoming information, communication, and automation technologies, these developments pave the way for a wide range of novel energy management and energy trading concepts to optimally use available energy resources [15–17]. However, what is considered as an optimal energy management and trading strategy heavily depends on the individual objectives and needs of a microgrid operator. Depending on the particularities of microgrid configurations, the surrounding and infrastructure they are embedded in, regulatory policies, and the needs and objectives of their operators, different solutions will be required. For instance, in remote areas where no grid connection exists, autonomy could be the basic driver for building and neighbourhood microgrids. In areas where security of grid energy supply is low, the bridging of power outages might be the principal goal. Triggered by regulatory policy changes now financially rewarding photovoltaics (PV) energy self-consumption

* Corresponding author. Tel.: +43 424256300; fax: +43 42425300400.
*E-mail address:* rosemarie.velik@ctr.at (R. Velik).

http://dx.doi.org/10.1016/j.enconman.2014.06.047
0196-8904/

instead of PV grid feedin, developing strategies to maximize the self-consumption of produced energy can become of relevance. Furthermore, to support the main electricity grid operator, strategies to cut off peak loads and to provide balancing energy can be of interest. With the predicted introduction of variable grid prices, operators will additionally become motivated to employ strategies to achieve a profit maximization via energy trading. Operators might also wish to optimally combine certain primary and secondary objectives (e.g., achieving a good financial profit as primary objective while at the same time trying to take into account environmental sustainability aspects as secondary objective). Accordingly, elaborating the most suitable strategy for each particular operator need and microgrid configuration can become quite a complex and time-consuming task, which can massively benefit from computational support.

In this article, we introduce a bio-inspired cognitive decision agent architecture for optimized, goal-specific energy management in microgrids. These microgrids – each containing loads, a PV system, and a battery storage – emulate typical prosumer household buildings and are arranged in a neighbourhood. They are connected to the main grid as well as to each other. For evaluating the performance of the architecture, a number of test cases are specified, which target objectives like local PV energy consumption maximization and financial gain maximization in different configurations over a test period of 30 days. Obtained results are compared against a state of the art modified simulating annealing optimization approach in terms of objective achievement and computation effort. In own prior work [18,19], it has been demonstrated that for the application targeted in this article, modified simulated annealing is a powerful approach for finding globally or very close to globally optimal solutions with very restricted computation effort. This fact qualifies modified simulated annealing as a high-standard reference method for benchmarking the novel cognitive decision agent approach proposed here.

## 2. Related work

Identifying the best suited energy management and control strategy for a non-trivial microgrid configuration can be considered as a large-scale optimization problem [12,20–22]. In the last decades, a wide range of optimization techniques have been developed for the operation and control of different types of power systems [23] and microgrids [24]. In principle, it can be distinguished between single objective optimization and multi objective optimization problems [21]. The operation and control of microgrids usually falls into the category of multi-objective optimization [25]. [26,27] describe the problem of energy management in microgrids as the searching of the optimal or near optimal unit commitment and dispatch of the available sources and energy storage systems so that certain selected criteria (reliability, security, environmental compatibility, cost efficiency, etc.) are achieved.

When attempting to provide a categorization of so far suggested optimization methods, various different classifications are possible. In the field of power system control and sustainable energy management, a classification scheme reappearing in scientific literature distinguishes between (1) traditional/conventional optimization methods and (2) Artificial Intelligence (AI) based optimization methods [20–25].

*Traditonal/conventional methods* applied for such problems include linear programming [28], integer programming [29], mixed integer linear programming [8,30–32], nonlinear programming [33], dynamic programming [34–36], and constrained programming [37]. However, with an increasing complexity of energy system configurations, finding an optimal solution with conventional optimization methods has turned out to often lead

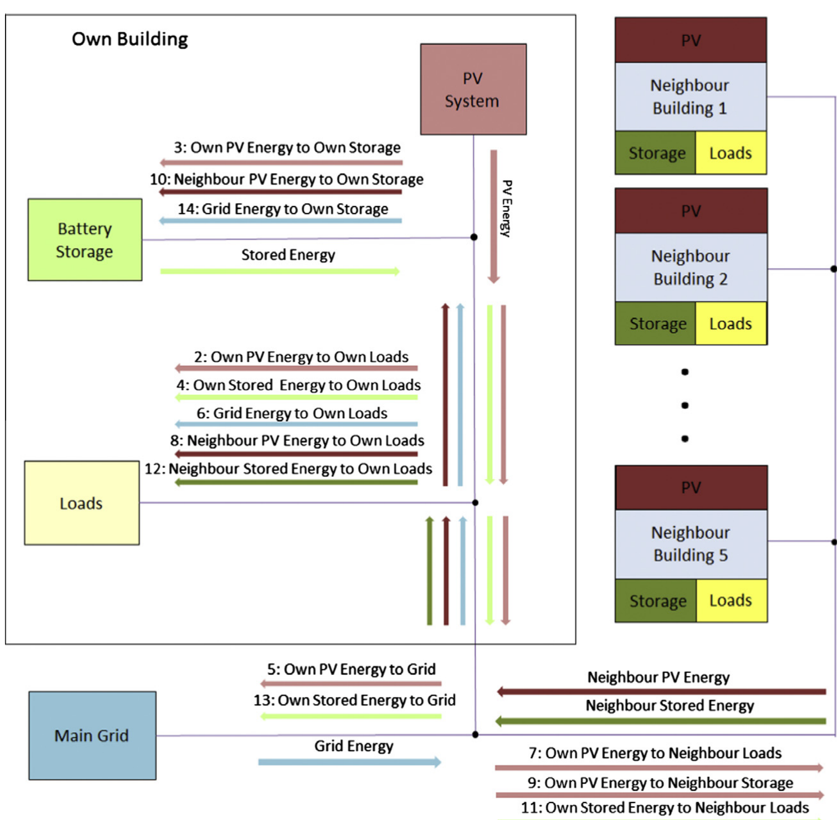


**Fig. 1.** System topology of microgrid representing a typical prosumer building ("own building") including connections to neighbouring microgrids ("neighbour building 1–5") and the main electricity grid ("main grid"). Arrows between components indicate energy exchange possibilities within the system.

**Table 1**
Energy exchange "actions" between microgrid system components.

| Action ID | Action description | Execution pre-conditions |
|---|---|---|
| 1 | Do no more activity | None |
| 2 | Own PV energy to own loads | Own PV energy remaining & Own loads still need energy |
| 3 | Own PV energy to own storage | Own PV energy remaining & Own storage is not full |
| 4 | Own stored energy to own loads | Own storage is not empty & Own loads still need energy |
| 5 | Own PV energy to grid | Own PV energy remaining |
| 6 | Grid energy to own loads | Own loads still need energy |
| 7 | Own PV energy to neighbour loads | Own PV energy remaining & Neighbour loads still need energy & Mutual agreement for according energy exchange |
| 8 | Neighbour PV energy to own loads | Neighbour PV energy remaining & Own loads still need energy & Mutual agreement for according energy exchange |
| 9 | Own PV energy to neighbour storage | Own PV energy remaining & Neighbour storage is not full & Mutual agreement for according energy exchange |
| 10 | Neighbour PV energy to own storage | Neighbour PV energy remaining & Own storage is not full & Mutual agreement for according energy exchange |
| 11 | Own stored energy to neighbour loads | Own storage is not empty & Neighbour loads still need energy & Mutual agreement for according energy exchange |
| 12 | Neighbour stored energy to own loads | Neighbour storage is not empty & Own loads still need energy & Mutual agreement for according energy exchange |
| 13 | Own stored energy to grid | Own storage is not empty |
| 14 | Grid energy to own storage | Own storage is not full |

**Table 2**
Characteristics of generated PV, load, and grid electricity price data.

| | |
|---|---|
| Number of households | 6 |
| Generated curves | 6 different load consumption curves, 6 identical PV production curves, 1 grid price curve |
| Time duration | 30 days |
| Time resolution | 1 h |
| Load consumption/household | 480 kW h in 30 days; 16(±6) kW h per day |
| PV production/household | 480 kW h in 30 days; 16(±10) kW h per day |
| Grid electricity price range | 1, 2, or 3 units/kW h |
| Average grid electricity price over a day | 2 units/kW h |

to computation times that are simply too high for a targeted application. Accordingly, in recent years, *Artificial Intelligence based methods* have gained popularity for energy system optimization with the objective to derive near-optimum solutions in shorter periods of time [22,23,25,38]. [23] underlines the capability of AI techniques to adapt to the nonlinearities and discontinuities commonly found in power systems and points out that the best-known algorithms for such purposes include simulated annealing [39], evolution programming [40], genetic algorithms [41–43], tabu search [44], and neural networks a [45,46,47]. [21,22,25] furthermore mention (particle) swarm optimization [48], fuzzy set theory [49,50], ant/bee colony search algorithms [51,52], artificial immune systems [53], and rule-based approaches [54] as feasible solutions.

In addition to this, several publications suggest to employ *game theory* for smart grids and microgrids [55,56]. Applications mentioned in this context are cooperative energy exchange between microgrids [57], distributed control of loads and sources [58], control of the usage of stored energy [59,60], and demand side management [60–63]. Furthermore, [9,64] investigate the feasibility of applying a hierarchical multi-agent system for microgrid operation and management, specifically for switching between island mode and grid-connected mode.

Despite the many efforts spent and progresses achieved in the field of power system and energy management optimization, research in this domain is today by no means completed. The steadily increasing complexity of systems requires the development of further more capable and more efficient approaches [22].

The main novelty of the article at hand is the presentation and validation of a novel multi-objective optimization method for finding user-specific optimal microgrid operation strategies not only featuring energy trading with the main grid under time-variable grid price conditions but additionally allowing energy exchange with five neighbouring storage-augmented mircrogrids according to agreed energy exchange conditions. A particularity of the optimizer is that it is not only capable of finding one optimal operation mode but can provide different alternating energy management strategies for different situations (e.g. different alternating grid prices). Finding optimal solutions in such a setup requires the search through a relatively large search space. Accordingly, an optimization method had to be developed that is on the one hand capable of finding an optimal solution in a large search space without suffering from the common problem of getting easily "trapped" in non-optimal local minima. On the other hand, the optimization method had to be computationally inexpensive to yield fast optimization results and not suffer from the "curse of dimensionality" [31]. These demands were fulfilled by developing a comprehensive architectural framework that allows it to apply different filter mechanisms for search space limitation before starting to analyse the remaining search space for the globally optimal solution. The expected benefit of the proposed cognitive decision agent architecture is thus to obtain improved optimization results within reduced processing time in comparison to state of the art approaches while at the same time offering a flexible framework for intuitively modelling the decision-relevant aspects of microgrid energy management systems.

## 3. Materials and methods

### 3.1. System topology

Fig. 1 gives a schematic overview about the system topology used for the studies performed in this article. It represents a "network" of neighbouring buildings. Each building represents a microgrid constituting a typical prosumer household with (1) a photovoltaics system, (2) a battery storage, (3) loads, (4) a connection to the main grid, and (5) connections to five neighbouring prosumer buildings. Via the connections to the neighbours, PV energy and stored energy can be exchanged within the neighbourhood. In practice, such connections could either be realized with physical cable connections between buildings, or, more economically, via an agreement with the main grid operator to only charge/remunerate for the absolute amount of energy (purchased grid energy versus fed-in PV/stored energy) exchanged between the neighbourhood and the main grid.

The arrows in Fig. 1 indicate the principally supported directions of energy exchange between system components. These options of energy exchange, in the following referred to as "selectable actions", have to be ranked in an optimal order to result in an optimal energy management strategy for each microgrid according to its specified objectives. To search for the optimal ranking of actions is the task of the cognitive decision agent architecture presented in this article.

In Table 1, the actions as well as the pre-conditions for their execution are summarized. The action with the ID 1 ("Do No More Activity") refers to the case that, usually after having already selected a certain set of actions, no further actions shall be carried out. Accordingly, actions ranked after action 1 remain without execution. For the rest of the actions listed in Table 1, the principle of "maximal energy exchange" is pursued. This means that always the maximal possible amount of energy is exchanged between a selected source and sink before the next action is considered. For instance, for action 2 "Own PV Energy to Own Loads", this could result in the following two cases: (1) If more own PV energy is available than needed by the own loads, the loads are fully supplied by the own PV energy. (2) If less own PV energy is available than required by the own loads, all available PV energy is directed to the own loads;

### 3.2. Test data

For the 6 prosumer households making up the interconnected microgrids configuration, test data were acquired using a simple "prosumer and grid price data generator" developed during the research project "Smart City Villach – Vision Step I" [65,66]. This data generator can generate realistic PV production, load consumption, and grid electricity price profiles for households based on the specification of certain key parameters (see Table 2). Data were acquired for a duration of 30 days. To limit memory and computation requirements, data were acquired with a resolution of 1 h.

Over the period of 30 days, each household produced the same amount of energy as it needed to supply its loads.

An option of load shifting was not considered in the experiments. Each household used the same PV-production curve, which corresponds to the case that each house has the same roof orientation, tilt angle, and number of installed PV modules. Each household also got the same information about the current grid electricity price, which was in average 2 units/kW h per day but varied between the discrete values 1 unit/kW h, 2 units/kW h, and 3 units/kW h over the day. The grid electricity price was considered to be "bidirectional", i.e. valid in both directions (for purchasing energy from the grid and selling energy to the grid).

### 3.3. Test scenarios

To validate the cognitive decision agent architecture's capacity to find optimal, goal-specific energy management and trading strategies, 10 different test scenarios were specified (see Table 3). These test scenarios can be categorized in three classes:

(1) Environmentalist group scenarios.
(2) Business (wo)man group scenarios.
(3) Mixed group scenarios.

In the *environmentalist scenarios*, each of the six neighbouring buildings has the main objective to maximize the local consumption of locally produced PV energy within the neighbourhood.

In the *business (wo)man scenarios*, each prosumer building has the main objective to maximize its financial gain, which it can achieve via energy trading with neighbours and/or the main grid:

$$(\text{Financial gain} = \text{Money earned by selling energy} \\ - \text{money spent on purchasing energy})$$

In the *mixed group scenarios*, the neighbourhood consists of three buildings following the environmentalist strategy and three buildings aiming at financial gain maximization.

Each of the three scenario groups is divided into further sub-scenarios. The reason for creating sub-scenarios was to investigate how different options for selectable actions influence the energy management strategy determined by the cognitive decision agent architecture.

Table 3 indicates what actions are selectable for each of these sub-classes. In the scenarios 1 and 3, only energy exchange with the main grid is supported but no trading with neighbours. This represents the current default case where buildings act individually. In contrast to this, the scenarios 2, 4, and 5 additionally support energy trading with neighbours, an option that might gain importance in the nearer future.

Furthermore, sub-scenarios can be distinguished according to the usage options of their battery storage. Here, it is distinguished between "internal" and "external" storage use. The 'a' scenarios represent the current default case, which supports only "internal" storage use, which means that buildings can charge their storage only with PV energy produced by themselves or their neighbours. A discharge is only possible by directing their stored energy to the own or the neighbour loads. In addition to this, the 'b' scenarios support an "external" storage use meaning that also a charging of the storage with grid energy and a discharging of the storage by feeding stored energy into the grid are possible. With improving storage technology and decreasing storage investment costs, this option might in future gain significant importance.

### 3.4. System modelling and implementation

The specified system topology (see Section 3.1) and energy management optimization approaches (see Section 3.5) were implemented using Visual Studio C++. System components were assumed with an ideal efficiency and without performance degradation over time. On the one hand, this limited the modelling and simulation complexity and allowed for an easier interpretation and validation of results. On the other hand, this allowed it to investigate the theoretically possible upper limits of what can be achieved

**Table 3**
Test scenarios and corresponding selectable actions.

| Scenario ID | Description | Selectable actions | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1: Do no more activity | 2: Own PV energy to own loads | 3: Own PV energy to own storage | 4: Own stored energy to own loads | 5: Own PV energy to grid | 6: Grid energy to own loads | 7: Own PV energy to neighbour loads | 8: Neighbour PV energy to own loads | 9: Own PV energy to neighbour storage | 10: Neighbour PV energy to own storage | 11: Own stored energy to neighbour loads | 12: Neighbour stored energy to own loads | 13: Own stored energy to grid | 14: Grid energy to own storage |
| *Environmentalist group scenarios – local PV energy consumption maximization* | | | | | | | | | | | | | | | |
| 1a | Internal storage use, no exchange with neighbours | x | x | x | x | x | x | | | | | | | | |
| 1b | Internal and external storage use, no exchange with neighbours | x | x | x | x | x | x | | | | | | | x | x |
| 2a | Internal storage use, exchange with neighbours | x | x | x | x | x | x | x | x | x | x | x | x | | |
| 2b | Internal and external storage use, exchange with neighbours | x | x | x | x | x | x | x | x | x | x | x | x | x | x |
| *Business (wo)men group scenarios – financial gain maximization* | | | | | | | | | | | | | | | |
| 3a | Internal storage use, no exchange with neighbours | x | x | x | x | x | x | | | | | | | | |
| 3b | Internal and external storage use, no exchange with neighbours | x | x | x | x | x | x | | | | | | | x | x |
| 4a | Internal storage use, exchange with neighbours | x | x | x | x | x | x | x | x | x | x | x | x | | |
| 4b | Internal and external storage use, exchange with neighbours | x | x | x | x | x | x | x | x | x | x | x | x | x | x |
| *Mixed group scenarios – group consisting of environmentalists and business (wo)men* | | | | | | | | | | | | | | | |
| 5a | Internal storage use, exchange with neighbours | x | x | x | x | x | x | x | x | x | x | x | x | | |
| 5b | Internal and external storage use, exchange with neighbours | x | x | x | x | x | x | x | x | x | x | x | x | x | x |

with different energy management strategies independent of any specific currently available technology. As technologies in the targeted field are currently changing and improving very rapidly, emulating scenarios for any particular technology would only have yielded results of short term significance.

Battery storage elements were assumed with an effective storage capacity of 16 kW h, which equaled the average daily amount of produced and consumed energy of each household. Batteries were empty at system startup. Energy exchange with the main electricity grid was performed according to the variable grid electricity prices specified in Section 3.2. Energy exchange with neighbours always followed after a mutual energy exchange agreement and was carried out according to fixed prices, which were 1 unit/kW h for direct PV energy and 2 units/kW h for stored energy.

### 3.5. Energy management optimizer approaches

As outlined in Section 3.1, the main objective of an efficient energy management and trading system as introduced in this article is to decide about the prioritization of energy flows within the system in each time instant. For this purpose, this article presents a novel cognitive decision agent architecture, which is described in detail in Chapter 4. The outcome of this approach is compared against a modified simulated annealing optimizer method. As outlined by [20], simulated annealing is one of the best-known algorithms for (microgrid) power optimization problems. In prior own work [18,19], we demonstrated the effectiveness of such a modified simulated annealing approach in terms of both optimization accuracy and computation time for the described experiments. Accordingly, the results obtained in this prior work serve as basis for benchmarking the performance of the novel cognitive decision agent architecture approach.

## 4. Cognitive decision agent architecture

Fig. 2 gives a schematic overview about the structure of the cognitive decision agent architecture as used for the application described in this article. A first version of this architecture was developed during a multiannual interdisciplinary research project carried out at the Vienna University of Technology in which engineers and computer scientists collaborated with brain researchers in order to develop a novel, flexible, and computationally implementable model for autonomous decision making based on latest insights about mechanisms and concepts involved in human decision making [67–69]. This architecture was initially designed and evaluated based on a virtual environment in which autonomous mammal-like creatures had to take decisions about how to interact with their surrounding (hunt for food, avoid threads, collaborate with partners, defend themselves against enemies, etc.) in order to survive as long as possible individually and/or as a group [70,71].

In this article, this architecture is adapted and particularized in order to employ it for determining optimal, goal-specific energy management strategies in (interconnected) microgrids. The architecture consists of different interconnected modules and interfaces between these modules. The depicted arrows indicate information and/or control flows between the different units. The architecture is guided by two core concepts:

The first core concept is that cognitive decision-making bases on a combination of low-level and high-level mechanisms. Low-level mechanisms are mainly predefined, very fast, but not always completely accurate and have the main objective to prevent the system from harm. High-level mechanisms are not predefined and thus slower but can cover more complex situations and be more accurate. The second core concept concerns the use of particular evaluation and prioritization mechanisms and the use of different kinds of memory to efficiently reduce the number of possibilities from which the most suitable solution has to be chosen. In the following sections, a brief outline of the working principles of the different modules of the architecture is given.

### 4.1. Environment, internal states, sensors, actuators, body, and mind

Starting point for decision-making are processes going on in the **environment** of the system or within the system itself (**internal states**). These processes are detected via **sensors** and influenced via **actuators**. Together, the sensors, actuators, and internal states constitute the **body** of the system.

For the energy management applications targeted in this article, the **environment** of the system corresponds to (1) the building (the energy consumed depends on the particularities of the building and its occupants), (2) the surrounding of the building (weather and light conditions influence the energy that is produced and consumed), and (3) the interfaces to the neighbour buildings and the main grid.

The **body** corresponds to the physical components of the system necessary for the energy management and trading application (PV modules, batteries, inverters, loads, connection to main grid, connection to neighbour buildings, sensors, actuators). **Internal states** represent the "status" of the body (battery status, active

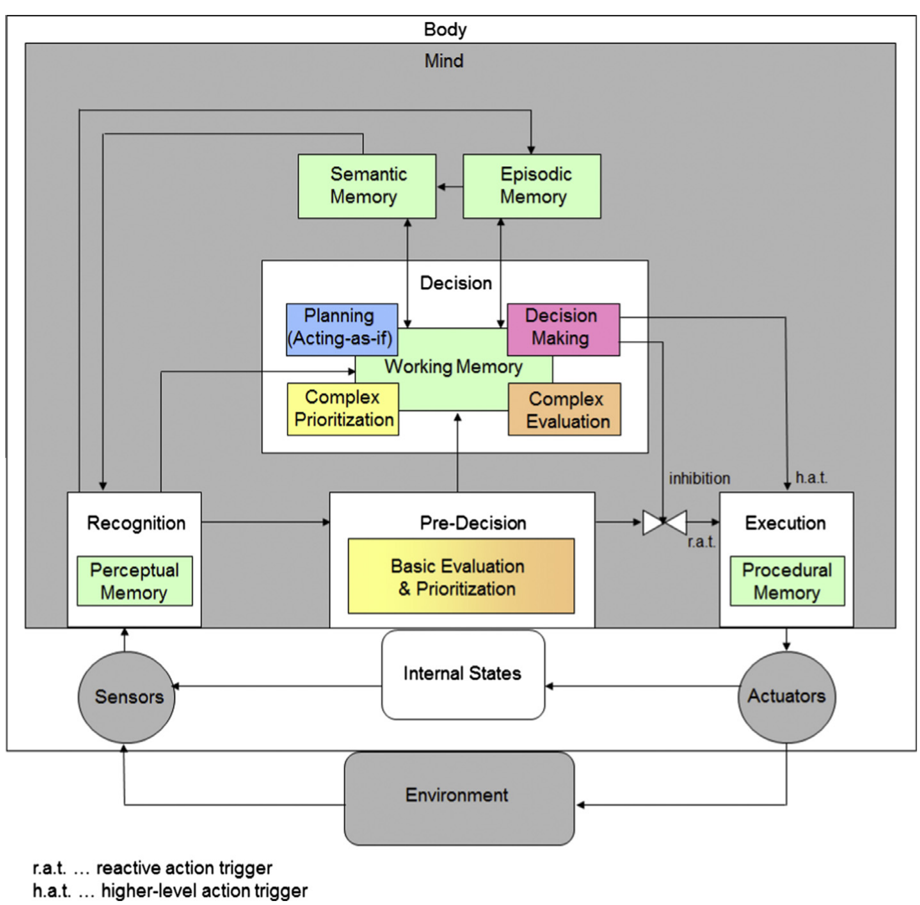


**Fig. 2.** Schematic overview of cognitive decision agent architecture.

**Table 4**
Pre-decision unit's evaluation criteria, their prioritization, and their triggered reactions.

| Evaluation criterion | Prioritization | Reaction |
|---|---|---|
| Battery is "empty" | 1 | Stop/inhibit discharging |
| Battery is "full" | 2 | Stop/inhibit charging |
| Set charging current $I_{Charge}$ is too high | 3 | Limit $I_{Charge}$ to $I_{ChargeMax}$ |
| Set discharging current $I_{Discharge}$ is too high | 4 | Limit $I_{Discharge}$ to $I_{DischargeMax}$ |

**Table 5**
Sub-objectives and their prioritization for environmentalist scenarios.

| Sub-objective | Optimization variable | Target value | Priority |
|---|---|---|---|
| All active loads need to be supplied with sufficient energy | Energy_Necessary_to_Obtain | 0 | 1 |
| No PV energy should remain unused | PV_Energy_Remaining | 0 | 2 |
| Direct consumption of PV energy produced within neighbourhood should be maximized | Direct_Local_PV_Consumption | MAX | 3 |
| Direct consumption of PV energy produced by own building should be maximized | Direct_Own_PV_Consumption | MAX | 4 |
| Stored PV energy should be used within the neighbourhood | Local_Storage_Consumption | MAX | 5 |
| Storing surplus PV energy within the own storage is preferred to storing surplus PV energy in the neighbour storages | Own_Storage_Loading | MAX | 6 |

**Table 6**
Sub-objectives and their prioritization for business (wo)men scenarios.

| Sub-objective | Optimization variable | Target value | Priority |
|---|---|---|---|
| All own active loads need to be supplied with sufficient energy | Remaining_Necessary_Load_Energy | 0 | 1 |
| Financial gain obtained through energy trading with neighbours and the main grid should be maximal | Financial_Gain | MAX | 2 |
| No PV energy should remain unused | PV_Energy_Remaining | 0 | 3 |

loads, produced PV energy). **Sensors** have the purpose to acquire information about the environment and the internal states of the system. They include volt-, ampere-, and watt-meters for measuring PV production, load consumption, battery status, energy exchange with neighbours, and energy exchange with the main grid.

**Actuators** in the system are (variable) switches to control the direction and amount of the energy exchange between system components.

Furthermore, the system comprises communication channels via which energy exchange offers/requests to/from neighbours are sent/received. In addition to this, the system receives PV production, load consumption, and grid price prognoses. Like the sensor and actuator information, incoming information of this kind is processed in the recognition unit and outgoing information in the execution unit.

Based on the information provided from the environment and the body, all information processing, planning, decision-making, and control tasks of the system take place in the architecture's "**mind**", which constitutes the central element of the decision agent architecture. The four main components of the mind are the **recognition** unit, the **execution** unit, the **pre-decision** unit, and the **decision** unit.

### 4.2. Recognition unit and execution unit

For the energy management application targeted in this article, the implementation of the recognition unit and the execution unit is quite straightforward. The task of the **recognition** unit is to extract and merge the relevant data coming from the sensors and communication channels (battery status, PV production, active loads, energy requests from neighbours, information from the grid, etc.). The **execution** unit is responsible for translating selected actions into the appropriate actuator commands (control of switches, sending of messages to components, neighbours, and the grid, etc.).

### 4.3. Pre-decision unit

The main task of the **pre-decision** unit is to protect the system from harm by assuring a fast predefined reaction in critical situations. To detect critical conditions and react to them, information about the environment and internal states reach the pre-decision unit. Rather than considering the information about the whole situation, the pre-decision unit just takes into account certain parameters from this information. In the **basic evaluation and prioritization** unit, it is evaluated if the values of one or a combination of parameters match with parameter sets defined as critical. This can then either lead to the immediate triggering of actions or it can be signified to the decision unit that a further increase/decrease of a certain parameter will lead to actions if not corrected in time. In case that several critical conditions occur at the same time and the system is not able to react to all of them concurrently or the reactions contradict each other, a prioritization of necessary actions is performed and the action with highest priority is carried out first. One particularly critical component in the microgrid system depicted in Fig. 2, which could easily be damaged and lead to safety issues, is the battery storage. Batteries are in general sensitive to overcharge, undercharge, and too high charging or discharging currents. Accordingly, for our energy management application, assuring that operation parameters of the battery do not exceed their limits is the crucial task assigned to the pre-decision unit. Table 4 summarizes the specified evaluation criteria and reactions of the pre-decision unit for the purpose of battery protection.

### 4.4. Decision unit

The **decision** module has the task to work out solutions for appropriate actions in situations where selecting the appropriate actions is not a simple straightforward specification process. For this purpose, the decision unit receives information from the **recognition** unit about ongoing situations and states in and around the system, hourly prognostications about PV production, load consumption, grid electricity price curves, and neighbour energy exchange offers/requests. Additionally, it can receive information from the **pre-decision** unit (in case that certain internal values are about to exceed critical limits that will require the pre-decision unit to react if not corrected in time).

Based on the described input information and the specified objectives of the microgrid operator, the decision unit has to select a sequence of actions which corresponds to the most beneficial energy management and trading strategy in the given constellation. The modules most relevant for this process are the **complex prioritization** unit, the **semantic memory** unit, the **episodic memory** unit, the **planning** unit, the **complex evaluation** unit, and the **decision-making** unit (see Sections 4.4.1–4.4.4). The streamlining of information between units is performed via the **working memory** unit. The main task of the prioritization unit, the semantic memory unit, and the episodic memory unit is to limit the search space within which an optimal solution has to be searched. In case they provide no (or not enough) information, the decision module has to start its **planning** unit and begin with simulations covering all possible (remaining) energy exchange action combinations. The outcome of these simulations is evaluated via a goal-specific "optimization metric" provided by the **complex evaluation** unit (see Section 4.4.4). Simulating all possible action combination would however mean to process an enormous amount of information. As shown in [18], the amount of action sets to be analysed for the specified environmentalist scenarios would be $x!$ in which $x$ is the number of selectable actions. In case of the business (wo)men scenarios, the computational effort is proportional to $(x!)^3$ [19]. Here, the 3rd power results from the fact that optimal action rankings are grid price dependent and that in this case a separate action set has to be determined for each of the 3 possible discrete grid electricity prices. Accordingly, for scenarios with more than a few selectable actions, searching through all possible combinations of actions without prior "filtering" leads to computational efforts not manageable by current machines in a reasonable amount of time. Therefore, the "search space" has to be reduced by the mentioned mechanisms before the planning unit can be started. The filter mechanisms applied for this purpose are described in the Sections 4.4.1–4.4.3.

#### 4.4.1. Complex prioritization unit

The first step in the abovementioned "filtering" process is performed by the **complex prioritization** unit, which as a result provides a partial action order to be used for further processing. This partial action order is determined by the following working principle:

Depending on the specified scenario goal, the complex prioritization unit contains a prioritized list of sub-objectives that shall be achieved by the system to lead to the overall goal fulfillment. The Tables 5 and 6 give an overview about the sub-objectives to be fulfilled for the environmentalist and business (wo)men scenarios including corresponding variable names, target values, and priorities.

Based on these sub-objective lists, a partial action order is determined for each scenario. Table 7 exemplarily illustrates this partial ranking process for the environmentalist scenario 2b. The other scenarios follow the same principle.

**Table 7**
Determination of partial action order performed by complex prioritization unit for environmentalist scenario 2b.

| Priority | Sub-objective | Beneficial actions | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1: Do no more activity | 2: Own PV energy to own loads | 3: Own PV energy to own storage | 4: Own stored energy to own loads | 5: Own PV energy to grid | 6: Grid energy to own loads | 7: Own PV energy to neighbour loads | 8: Neighbour PV energy to own loads | 9: Own PV energy to neighbour storage | 10: Neighbour PV energy to own storage | 11: Own stored energy to neighbour loads | 12: Neighbour stored energy to own loads | 13: Own stored energy to grid | 14: Grid energy to own storage |
| 1 | All active loads in neighbourhood need to be supplied with sufficient energy | | • | | • | | • | • | • | | | • | • | | |
| 2 | No PV energy should remain unused | | • | • | | • | | • | • | • | • | | | | |
| 3 | Direct consumption of PV energy produced within neighbourhood should be maximized | | • | | | | | • | • | | | | | | |
| 4 | Direct consumption of PV energy produced by own building should be maximized | | • | | | | | | | | | | | | |
| 5 | Stored PV energy should be used within the neighbourhood | | | | • | | | | | | | • | • | | |
| 6 | Storing surplus PV energy within the own storage is preferred to storing surplus PV energy in the neighbour storages | | | • | | | | | | | | | | | |
| Resulting partial action order | | 7a | 1 | 5 | 3a | 6a | 4 | 2a | 2b | 6b | 6c | 3b | 3c | 7b | 7c |

**Table 8**
Determination of partial action order performed by complex prioritization unit in combination with semantic memory unit for business (wo)men scenario 4b.

| | | Beneficial actions | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1: Do no more activity | 2: Own PV energy to own loads | 3: Own PV energy to own storage | 4: Own stored energy to own loads | 5: Own PV energy to grid | 6: Grid energy to own loads | 7: Own PV energy to neighbour loads | 8: Neighbour PV energy to own loads | 9: Own PV energy to neighbour storage | 10: Neighbour PV energy to own storage | 11: Own stored energy to neighbour loads | 12: Neighbour stored energy to own loads | 13: Own stored energy to grid | 14: Grid energy to own storage |
| *Rules from semantic memory unit* | | | | | | | | | | | | | | | |
| Grid price 1 | •: Get cheap energy (from PV, grid) and store it in battery for later use<br>x: Do not use stored energy, as it is more expensive than purchasing PV/grid energy | | | • | x | | | | | • | • | x | x | x | • |
| Grid price 2 | •: Try to use PV energy for load supply as it is cheaper than energy from storage or grid | | • | | | | | • | • | | | | | | |
| Grid price 3 | •: Use cheaper stored energy instead of grid energy for own/neighbours loads supply<br>•: Sell surplus stored energy to grid to achieve financial gains<br>X: Do not store energy in battery as selling surplus energy is financially most beneficial now | | | x | • | | | | | x | x | • | • | • | x |
| *Sub-objectives from complex prioritization unit* | | | | | | | | | | | | | | | |
| Priority 1 | All own active loads need to be supplied with sufficient energy | | • | | • | | • | | • | | | | • | | |
| Priority 2 | Financial gain obtained through energy trading with neighbours and the main grid should be maximal | | | | | | | | | | | | | | |
| Priority 3 | No PV energy should remain unused | | • | • | | • | | • | • | • | • | | | | |
| Resulting partial action order (grid price 1) | | 6 | 3a | 1a | x | 5a | 4 | 5b | 3b | 1b | 1c | x | x | x | 2 |
| Resulting partial action order (grid price 2) | | 5a | 1a | 4a | 3a | 4b | 3b | 2 | 1b | 4c | 4d | 5b | 3c | 5c | 5d |
| Resulting partial action order (grid price 3) | | 6 | 3a | x | 1a | 5a | 4 | 5b | 3b | x | x | 2a | 1b | 2b | x |

In Table 7, the sub-objectives to be fulfilled for the environmentalist scenarios are listed according to the prioritization specified in Table 5. For fulfilling each sub-objective, always a number of particular actions are beneficial. These beneficial actions are marked with a black dot in the corresponding line of Table 7. For instance, for sub-objective 1 "All active loads in neighbourhood need to be supplied with sufficient energy", all actions that contribute to supplying the own or the neighbour loads with energy are beneficial. For sub-objective 2 "No PV energy should remain unused", all actions that assure that produced PV energy is directed and used/stored somewhere are beneficial.

Now, to perform a ranking of actions for determining the partial action order, first, actions are considered that are marked as beneficial for the sub-objective with priority 1. Next, actions are taken into account, which are (additionally) supportive for sub-objective 2, and so on. In case of ambiguity, i.e. that several actions are not

**Table 9**
Determination of partial action order before and after applying episodic memory rules for business (wo)men scenario 4b.

| Grid price | Partial action order determined by complex prioritization unit & semantic memory unit | | | | | | | | | | | | | | Partial action order determined after additionally applying rules from episodic memory unit | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1: Do no more activity | 2: Own PV energy to own loads | 3: Own PV energy to own storage | 4: Own stored energy to own loads | 5: Own PV energy to grid | 6: Grid energy to own loads | 7: Own PV energy to neighbour loads | 8: Neighbour PV energy to own loads | 9: Own PV energy to neighbour storage | 10: Neighbour PV energy to own storage | 11: Own stored energy to neighbour loads | 12: Neighbour stored energy to own loads | 13: Own stored energy to grid | 14: Grid energy to own storage | 1: Do no more activity | 2: Own PV energy to own loads | 3: Own PV energy to own storage | 4: Own stored energy to own loads | 5: Own PV energy to grid | 6: Grid energy to own loads | 7: Own PV energy to neighbour loads | 8: Neighbour PV energy to own loads | 9: Own PV energy to neighbour storage | 10: Neighbour PV energy to own storage | 11: Own stored energy to neighbour loads | 12: Neighbour stored energy to own loads | 13: Own stored energy to grid | 14: Grid energy to own storage |
| 1 | 6 | 3a | 1a | x | 5a | 4 | 5b | 3b | 1b | 1c | x | x | x | 2 | 7 | 3 | 1a | x | 6 | 5 | x | 4 | 1b | 1c | x | x | x | 2 |
| 2 | 5a | 1a | 4a | 3a | 4b | 3b | 2 | 1b | 4c | 4d | 5b | 3c | 5c | 5d | 6a | 1 | 5a | 4a | 5b | 4b | 3 | 2 | 5c | 5d | x | x | 6b | 6c |
| 3 | 6 | 3a | x | 1a | 5a | 4 | 5b | 3b | x | x | 2a | 1b | 2b | x | 8 | 4 | x | 1 | 7 | 6 | x | 5 | x | x | 3a | 2 | 3b | x |

distinguishable in their ranking based on the sub-objectives, actions are left on ex-aequo positions.

In Table 7, beneficial actions for fulfilling sub-objective 1 are the actions with the IDs 2, 4, 6, 7, 8, 11, and 12. As a consequence, they will assume the first 7 places in the ranking. To further distinguish their ranking, sub-objective 2 is considered, according to which the actions with the IDs 2, 7, and 8 remain in question for the places 1 to 3. Taking furthermore into account the sub objectives 3 and 4, action 2 gets assigned place 1 as it is marked as beneficial action in all four cases. The actions 7 and 8, which are both marked as beneficial for the first three sub-objectives, remain ex-aequo on place 2 and get assigned the ranking 2a and 2b, respectively. Following this principle, all other rankings are performed. Like before for the action 7 and 8, in case of ambiguity, actions are left on ex-aequo positions. In Table 7, this concerns the action triples with the IDs (4, 11, 12), (5, 9, 10), and (1, 13, 14). Their optimal ranking against each other has to be determined by applying either further "filtering" mechanisms from semantic and/or episodic memory or by directly performing simulations of all remaining possible action combinations in the planning unit (see Section 4.4.4). In case of the environmentalist scenario 2b, after the prioritization process described in Table 7, 2!·3!·3!·3! = 432 different action combinations remain to be investigated. This is a very manageable number, which does not require any further filtering. Accordingly, a further processing using semantic/episodic memory was not pursued for this scenario. However, in cases where the partial action ordering performed by the prioritization unit does not sufficiently reduce the search space, an additional integration of semantic knowledge and episodic knowledge, stored in the semantic/episodic memory unit, is recommended for further search space limitation. The corresponding working principles are illustrated in the next two sections for scenario 4b.

### 4.4.2. Semantic memory unit

As described in [69], in principle, the **semantic memory** contains useful facts and rules about the "body" and the "environment" of the system. This can for instance include information about actions that are beneficial to choose in a certain situation and for a certain scenario. Similarly, it can also contain information about actions that are not useful or counterproductive to choose under certain conditions. In Table 8, the working principle of the semantic memory unit as applied in this article is demonstrated using the business wo(men) scenario 4b. As illustrated in Table 8, for determining a partial action order, information from semantic memory about beneficial (•) and counterproductive ($x$) actions is combined with the sub-objective prioritization from the complex prioritization unit according to Table 6. As can be seen from Table 8, for sub-objective 2 "Financial gain obtained through energy trading with neighbours and the grid should be maximal" of the prioritization unit, no generally applicable beneficial action could be specified. This results from the fact that what is considered as a beneficial action depends on the current grid electricity price, which can vary between the discrete values 1, 2, and 3. To overcome this shortcoming, a small set of rules was specified in the semantic memory unit for the unified business (wo)men group scenarios about beneficial and counterproductive actions for the different grid prices. Now, determining a partial action order works according to the same principle as described in Section 4.4.1 with the only difference that for the business (wo)men scenarios, one partial action order has to be determined for each of the three grid prices. Actions marked as beneficial by the semantic memory for a certain grid price get the highest priority in the corresponding ranking. Action marked as counterproductive are excluded from the ranking. Afterwards, prioritizations from the complex prioritization unit are considered.

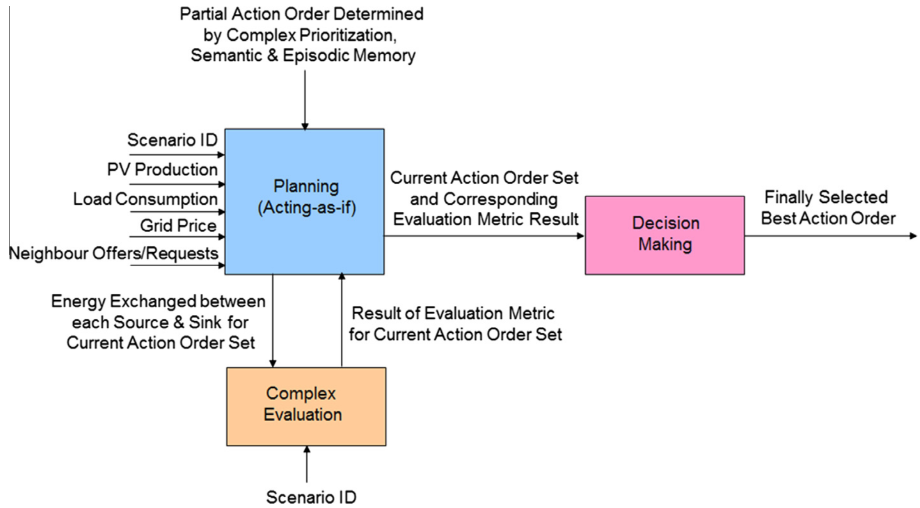


**Fig. 3.** Interaction of planning unit with the complex evaluation and the decision-making unit to evaluate remaining possible action combinations after the "filter" processes of the complex prioritization, semantic memory, and episodic memory unit have been applied.

For scenario 4b, the "filtering" processes provided by the complex prioritization unit and the semantic memory unit lead to a search space reduction as follows: Without any search space limitation method, $(14!)^3 = 6.6256E+32$ possible action combinations would have to be analysed by the planning unit. The performing of a pre-ranking in the complex prioritization unit alone would reduce this amount to $(2!\cdot3!\cdot5!\cdot4!)^3 = 4.1278E+13$ combinations. Combining the information from the complex prioritization unit and the semantic memory unit as specified in Table 8 confines it to $(3!\cdot2!\cdot2!)\cdot(2!\cdot3!\cdot4!\cdot4!)\cdot(2!\cdot2!\cdot2!\cdot2!) = 2.6542E+6$ combinations. This is already a quite manageable amount for computational simulations. If the search space shall be further reduced, this can be done by additionally applying episodic memory in a next step.

*4.4.3. Episodic memory unit*

As described in [69], in principle, episodic memory contains information about previously experienced events and situations and their outcome. This can for instance be observations about what actions have in the past been beneficial, counterproductive, or just without any effect to be executed after certain other actions. In the following, the working principle of applying episodic memory for search space reduction is illustrated for scenario 4b. For this purpose, a list of extracted system observations is applied to the partial action order determined in Table 8. This list of rules is also valid for all other specified scenarios and is actually quite evident from a logical standpoint considering the pursued principle of "maximal energy exchange" described in Section 3.1.

(1) If action 5 "Own PV Energy to Grid" has been called, all actions after this action involving the direction of own PV energy somewhere lead to no further change in results (as no further PV energy is remaining).
(2) If action 6 "Grid Energy to Own Loads" has been called, all actions after this action involving the direction of energy to the own loads lead to no further change in results (as the loads need no further energy).
(3) If action 13 "Own Stored Energy to Grid" has been called, all subsequent actions that attempt to direct energy from the storage to some other source lead to no further results (as the storage is empty) until an action is selected that (partly) charges the storage again.
(4) If action 14 "Grid Energy to Own Storage" has been called, all following actions that attempt to further charge the storage lead to no further results (as the storage is already full) until an action is selected that (partly) discharges the storage again.

For scenarios, in which the neighbourhood consists of a unified group of neighbours all following the same optimization strategy (scenarios 1–4), the following further rules were extracted from system observations concerning energy exchange between neighbours:

(5) Action 7 "Own PV Energy to Neighbour Loads" will only be executed once action 8 "Neighbour PV Energy to Own Loads" has also been called and vice versa.
(6) Action 9 "Own PV Energy to Neighbour Storage" will only be executed once action 10 "Neighbour PV Energy to Own Storage" has also been called and vice versa.
(7) Action 11 "Own Stored Energy to Neighbour Loads" will only be executed once action 12 "Neighbour Stored Energy to Own Loads" has also been called and vice versa.

These rules are again quite evident considering the fact that neighbours always have to mutually agree on a particular energy exchange option (one has to send the offer and the other one the request) before the energy transfer can take place.

In Table 9, the results of employing the abovementioned rules to the partial action order from Table 8 are presented. Via the application of episodic memory, the number of remaining action combinations to be analysed in scenario 4b is reduced from 2.6542E+6 combinations to 3456. These remaining combinations can now be further analysed by the planning unit in collaboration with the complex evaluation unit and the decision-making unit.

*4.4.4. Planning, complex evaluation, and decision-making units*

As described in the former sections, if the complex prioritization, semantic memory, and episodic memory units are not sufficient to conclude about a final action ranking, this process is taken over by the planning (*acting-as-if*) unit in collaboration with the complex evaluation and decision-making units by simulating remaining possibilities for action combinations and their expected outcomes.

**Table 10**
Pseudo-code description of algorithms running in the planning, complex evaluation, and decision-making units.

*Planning unit*

```
Do (Permute through all remaining possible action order combinations)
    For each time instant i and each building j
      Perform energy exchange between components according to current action order set
      Protocol the amount of energy directed from each source to each sink and the corresponding ''energy trading gain'' made in the
   variables:
      energy_source_x_to_sink_y[i][j] = amount_of_exchanged_energy;
      gain_source_x_to_sink_y[i][j] = amount_of_money_spent_received;
    End
    Calculate amount of energy exchanged between each source and sink and the corresponding trading gain as an average value per day and
   building
    Send results to Complex Evaluation Unit and wait for it to return the calculated evaluation metric value
    Send current action order set and current evaluation metric value to Decision Making Unit
While(Possible action order combinations remain to be analysed)
```

*Complex evaluation unit*

```
If(Scenario ID == Environmentalist Scenario)
  w1=1000; w2=100; w3=10; w4=1;
  Calculate the sub-objective variables
    Energy_Necessary_to_Obtain,
    PV_Energy_Remaining,
    Direct_Local_PV_Consumption,
    Direct_Own_PV_Consumption,
    Local_Storage_Consumption,
    Own_Storage_Loading
  from the variables energy_source_x_to_sink_y received from the Planning Unit
  Calculate Evaluation Metric:
      If((Energy_Necessary_to_Obtain==0) AND (PV_Energy_Remaining==0))
        Evaluation_Metric=w1*Direct_Local_PV_Consumption+w2*Direct_Own_PV_Consumption+
        w3*Local_Storage_Consumption+w4*Own_Storage_Loading;
      Else
        Evaluation_Metric=0;
    End
Else If(Scenario ID == Business (Wo)men Scenario)
  AVERAGE_LOAD_CONSUMPTION_PER_DAY=16; AVERAGE_PV_PRODUCTION_PER_DAY=16;
  w1=1000; w2=100; w3=1;
  Calculate the sub-objective variables
    Remaining_Necessary_Load_Energy,
    Financial_Gain,
    PV_Energy_Remaining
    from the variables energy_source_x_to_sink_y and gain_source_x_to_sink_y received from the Planning Unit
    Calculate Evaluation Metric:
        Evaluation_Metric=w1*(AVERAGE_LOAD_CONSUMPTION_PER_DAY-Remaining_Necessary_Load_Energy)+
        w2*Financial_Gain+w3*(AVERAGE_PV_PRODUCTION_PER_DAY-PV_Energy_Remaining);
End
Return Evaluation_Metric;
```

*Decision making unit*

```
Best_Evaluation_Metric_Value=0;
Best_Action_Order_Set=Undefined;
Do(Compare Current_Evaluation_Metric_Value received from Complex Evaluation Unit with Best_Evaluation_Metric_Value):
  If(Current_Evaluation_Metric_Value>Best_Evaluation_Metric_Value)
      Best_Evaluation_Metric_Value=Current_Evaluation_Metric_Value;
      Best_Action_Order_Set=Current_Action_Order_Set
  End
While(New Data are received from Planning Unit)
```

The corresponding information flow between these units is depicted in Fig. 3. Table 10 illustrates the corresponding implemented algorithms in the different modules in pseudo code form.

Based on the partial action order determined by the complex prioritization, semantic memory, and episodic memory units, the **planning** unit sequentially simulates the remaining possible action combinations and calculates a set of variables for each of them. Variables calculated concern the amount of energy directed from each source to each sink over the 30 days recording period and the money earned or spent for this purpose. For each action combination, this information is then sent to the **complex evaluation** unit for calculating a scenario-specific evaluation metric. This metric is determined as a weighted sum of the sub-objective variables specified in the Tables 5 and 6. The specified evaluation metrics correspond to the optimization functions used by the modified simulated annealing reference algorithm.

For the *environmentalist scenarios*, the evaluation metric is determined as follows:

$$\begin{aligned}&\text{If}((\text{Energy\_Necessary\_to\_Obtain} == 0)\ \text{AND}\ (\text{PV\_Energy\_Remaining}\\&\quad == 0))\ \ \text{Evaluation Metric} = w_1 \cdot \text{Direct\_Local\_PV\_Consumption}\\&\quad + w_2 \cdot \text{Direct\_Own\_}\mathit{PV}\text{\_Consumption}\\&\quad + w_3 \cdot \text{Local\_Storage\_Consumption} + w_4 \cdot \text{Own\_Storage\_Loading}\\&\text{Else}\\&\quad \text{Evaluation Metric} = 0\end{aligned}$$

In this metric, the two sub-objectives with highest prioritization (Energy_Necessary_to_Obtain and PV_Energy_Remaining) are translated into pre-conditions for yielding an evaluation metric consisting of the weighted sum of the four remaining sub-objectives. If a certain action order is NOT able to achieve that those

**Table 11**
Action orders that led to an optimal result numbers in brackets () indicate actions excluded by episodic memory.

| Scenario ID | | Action orders | |
|---|---|---|---|
| | | Modified simulated annealing | Cognitive decision agent architecture |
| 1a | | 2 4 3 6 5 1 | 2 4 6 3 5 1 |
| 1b | | 2 3 4 5 6 1 X X | 2 4 6 3 5 1 X X |
| 2a | | 2 7 8 4 3 6 12 11 10 9 5 1 | 2 8 7 4 11 12 6 3 9 10 5 1 |
| 2b | | 2 8 7 4 3 6 12 11 10 9 5 1 X X | 2 8 7 4 11 12 6 3 9 10 5 1 X X |
| 3a | GP = 1 | 3 6 2 4 5 1 | 3 2 6 5 1 X |
| | GP = 2 | 3 5 2 4 6 1 | 2 4 6 3 5 1 |
| | GP = 3 | 4 6 2 5 1 X | 4 2 6 5 1 X |
| 3b | GP = 1 | 3 5 4 13 6 2 14 1 | 3 14 2 6 5 1 X X |
| | GP = 2 | 14 5 3 13 6 1 X X | 2 6 4 5 3 13 1 X |
| | GP = 3 | 3 13 6 5 1 X X X | 4 13 2 6 5 1 X X |
| 4a | GP = 1 | 3 6 5 4 12 9 11 8 10 7 2 1 | 9 3 10 2 (8) 6 5 (7) 1 X X X |
| | GP = 2 | 10 8 3 7 2 4 6 5 9 1 X X | 2 8 7 4 6 (12) 10 3 5 9 1 X |
| | GP = 3 | 5 2 8 7 10 4 12 9 3 11 6 1 | 4 12 11 2 (8) 6 (7) 5 1 X X X |
| 4b | GP = 1 | 8 2 6 14 9 3 4 12 5 10 7 11 1 X X | 9 3 10 14 2 (8) 6 5 (7) 1 X X X X |
| | GP = 2 | 7 6 10 14 13 3 1 X X X X X X X | 2 8 7 6 4 (12) 9 10 5 3 14 13 1 X |
| | GP = 3 | 9 14 4 11 5 10 7 3 13 12 2 8 6 1 | 4 12 13 11 2 (8) 6 (7) 5 1 X X X X |
| 5a | GP = 1 | 6 8 11 4 3 10 2 9 7 5 12 1 | 3 10 9 8 2 6 5 7 1 X X X |
| | GP = 2 | 5 4 8 3 6 1 X X X X X X | 8 2 4 6 12 10 5 3 11 1 X X |
| | GP = 3 | 8 4 5 6 3 9 7 12 11 10 1 X | 8 4 12 11 2 6 10 5 1 X X X |
| 5b | GP = 1 | 8 10 6 12 9 13 14 4 7 5 2 11 3 1 | 9 10 3 14 8 2 6 7 5 11 1 X X X |
| | GP = 2 | 10 3 5 11 9 8 6 12 14 13 2 7 4 1 | 8 2 6 12 4 10 5 3 13 1 X X X X |
| | GP = 3 | 8 5 10 2 12 9 3 4 6 7 13 11 1 X | 8 12 4 13 11 2 6 10 5 1 X X X X |

first two sub-objective variables have the value zero, the evaluation metric will get assigned the value zero. The weights (w1–w4) of the evaluation metric reflect the prioritization of the sub-objectives 3–6. For our simulations, a factor of always 10 was chosen between each weight (w1 = 1000; w2 = 100; w3 = 10; w4 = 1), which proved to yield the desired results.

For the *business (wo)men scenarios*, the evaluation metric is calculated as:

$$
\begin{aligned}
\text{Evalution Metric} = (&w_1 \\
&\cdot (\text{AVERAGE\_LOAD\_CONSUMPTION\_PER\_DAY} \\
&- \text{Remaining\_Necessary\_Load\_Energy}) + w_2 \\
&\cdot \text{Financial\_Gain} + w_3 \\
&\cdot (\text{AVERAGE\_PV\_PRODUCTION\_PER\_DAY} \\
&- \text{PV\_Energy\_Remaining})
\end{aligned}
$$

According to the specification from Table 2, the variables AVERAGE_LOAD_CONSUMPTION_PER_DAY and AVERAGE_PV_PRODUCTION_PER_DAY have the value 16 kW h. The weights (w1–w3) correspond to the prioritization of the sub-objective as assigned in Table 6. For the simulations, a setting of the weights to the values w1 = 1000, w2 = 100, w3 = 1 proved to yield well-performing results.

After having calculated the evaluation metric value, the complex evaluation unit sends this information back to the planning unit, which then transmits this information to the **decision-making** unit together with the corresponding action order set that led to this result. In the decision-making unit, the result of the evaluation metric corresponding to the current action order set is compared to the best result achieved so far. In case the result is better, the current action order set is taken over as new reference solution. Once all remaining action order combinations have been analysed this way, the decision-making unit initiates the execution of the best determined action order set by forwarding it to the execution unit.

## 5. Results and discussion

In this chapter, the results of the cognitive decision agent architecture are presented and compared against a modified simulated annealing optimizer approach having been developed and described in detail in [18,19].

### 5.1. Determined action orders and corresponding evaluation metric values

The Tables 11–13, summarize the achieved results of the cognitive decision agent architecture and compare it to the modified simulated annealing reference approach. Table 11 illustrates the optimal action orders found by both methods. The action order numbers correspond to the action IDs specified in Table 1. It turned out during simulations that usually more than one action order set can lead to the same result. However, due to limitations in space, always only one such optimal set is listed in Table 11. Actions prioritized after the action ID 1 (''Do No More Activity'') are represented by an 'X' and are not executed. Numbers in brackets (see scenarios 4a and 4b) indicate actions that were identified by the episodic memory unit to not bring additional benefits and can thus be excluded. For the environmentalist scenarios (scenarios 1 and 2), the determined action order set is independent of the grid price (GP). For the business (wo)men scenarios (scenarios 3 and 4), for each grid price, a specific optimal action order had to be determined. For the mixed group scenarios (scenarios 5a and 5b), Table 11 only lists the determined strategy of the business (wo)men microgrids. The environmentalist microgrids employed the same strategy as found by the cognitive decision agent architecture in the scenarios 2a and 2b, respectively.

Based on the action orders presented in Table 11, Table 12 summarizes the values of the overall evaluation metric and its sub-objective variables for the different investigated environmentalist scenarios. Table 13 presents the corresponding results for the business (wo)men scenarios. Next to the comparison of the cognitive decision agent architecture with the modified simulated annealing optimizer, the tables additionally indicate the global optimization error of both methods by comparing their evaluation metric values

**Table 12**
Values of individual sub-objective variables and overall evaluation metric for environmentalist scenarios.

| Scenario ID | Modified simulated annealing | | | | | | | | Cognitive decision agent architecture | | | | | | | | Achieved improvement for cognitive decision agent architecture in relation to modified simulated annealing approach | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Not provided load supply (kW h) | PV energy waste (kW h) | Direct local PV energy consumption (kW h) | Direct own PV energy consumption (kW h) | Local storage consumption (kW h) | Own storage loading (kW h) | Evaluation metric value | Deviation of evaluation metric value (%) from global optimum calculated via total state space search [18] | Not provided load supply (kW h) | PV energy waste (kW h) | Direct local PV energy consumption (kW h) | Direct own PV energy consumption (kW h) | Local storage consumption (kW h) | Own storage loading (kW h) | Evaluation metric value | Deviation of evaluation metric value (%) from global optimum calculated via total state space search [18] | Evaluation metric value (%) | Local PV energy consumption (%) |
| 1a | 0.00 | 0.00 | 5.47 | 5.47 | 8.82 | 8.96 | 6113 | 0.00 | 0.00 | 0.00 | 5.47 | 5.47 | 8.82 | 8.96 | 6113 | 0.00 | 0.00 | 0.00 |
| 1b | 0.00 | 0.00 | 5.47 | 5.47 | 8.82 | 8.96 | 6113 | 0.00 | 0.00 | 0.00 | 5.47 | 5.47 | 8.82 | 8.96 | 6113 | 0.00 | 0.00 | 0.00 |
| 2a | 0.00 | 0.00 | 5.77 | 5.47 | 8.58 | 8.72 | 6409 | 0.03 | 0.00 | 0.00 | 5.77 | 5.47 | 8.77 | 8.72 | 6411 | 0.00 | 0.03 | 1.34 |
| 2b | 0.00 | 0.00 | 5.77 | 5.47 | 8.58 | 8.72 | 6409 | 0.03 | 0.00 | 0.00 | 5.77 | 5.47 | 8.77 | 8.72 | 6411 | 0.00 | 0.03 | 1.34 |

to results obtained in own prior work [18,19] by a total state space search approach. This shall demonstrate that the modified simulated annealing optimizer is already a very powerful method for finding (very close to) globally optimal solutions for our target application and thus can serve as a first-choice reference method for benchmarking our novel cognitive decision agent architecture.

In accordance with the results from the Tables 12 and 13, Fig. 4 graphically illustrates the (positive or negative) percentage improvement of the cognitive decision agent architecture in comparison to the modified simulated annealing reference approach. For the environmentalist scenarios (scenarios 1 and 2), the comparison was made in terms of the overall locally produced PV energy that could be consumed within the neighbourhood. For the business wo(men) scenarios (scenarios 3, 4, and 5), the comparison was made in terms of the obtained financial gain of the neighbours following the business (wo)men strategy. As can be seen from Fig. 4, the cognitive decision agent architecture achieved in 5 out of 10 cases up to 1.99% better results than the modified simulated annealing approach. In 4 scenarios, the result was equal. Only in scenario 3a, a slightly less optimal result (−0.57%) was obtained.

### 5.2. Computation effort

Table 14 compares the computing effort (number of iteration to find the optimal solution) of the cognitive decision agent architecture with the modified simulated annealing approach for the different analysed scenarios. As can be seen, the cognitive decision agent architecture needed in all investigated scenarios significantly less iterations than the modified simulated annealing approach. Summed up over all scenarios, this overall computation effort was 45.8 times lower.

### 5.3. System behaviour analyses

The Figs. 5 and 6 illustrate and compare system behaviour aspects of the environmentalist and the business (wo)men group when following the energy management and trading strategies determined by the cognitive decision agent architecture.

Fig. 5 illustrates how the PV energy produced by the building microgrids pursuing an environmentalist strategy is distributed between sources and sinks. As described in Section 3.3, the overall objective of environmentalist buildings is to maximize the local consumption of locally produced energy within the neighbourhood. As can be seen from Fig. 5, the achieved amount of local PV use within the neighbourhood was between 89% and 98% depending on the particular scenario. In case that no energy trading with neighbours was possible (scenarios 1a and 1b), the achieved local PV use was 89%. This could be achieved by storing own surplus PV energy for later use when enough PV energy was produced. For the scenarios 2a and 2b, this amount increased to 91%, which was achieved by additionally exchanging PV energy and stored energy between neighbours. For the scenarios 5a and 5b, a further improvement to 98% could be achieved, which resulted from the fact that the environmentalist buildings were now embedded into a mixed neighbourhood group in which business (wo)men had the preference to purchase PV and stored energy from environmentalist neighbours instead of using their own energy if this brought them financial benefits.

Fig. 6 compares the achieved financial gain (in units per day and building) in the different business (wo)men scenarios. In the scenarios 5a and 5b, in which the neighbourhood consisted of a mixed energy trading group with business (wo)men agents and environmentalist agents, the financial gain is illustrated separately for both agent types. Additionally, the average value is shown. As can been seen from Fig. 6, the financial gain achieved by the

**Table 13**
Values of individual sub-objective variables and overall evaluation metric for business (wo)men scenarios.

| Scenario ID | Modified simulated annealing | | | | | Cognitive decision agent architecture | | | | | Achieved improvement for cognitive decision agent architecture in relation to modified simulated annealing approach | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Financial Gain (Units) | Not provided load supply (kW h) | PV energy waste (kW h) | Evaluation metric value | Deviation of evaluation metric value (%) from global optimum calculated via total state space search [19] | Financial Gain (Units) | Not provided load supply (kW h) | PV energy waste (kW h) | Evaluation metric value | Deviation of evaluation metric value (%) from global optimum calculated via total state space search [19] | Evaluation metric value (%) | Financial gain (%) |
| 3a | 9.60537 | 0.00 | 0.00 | 16976.0 | 0.00 | 9.55107 | 0.00 | 0.00 | 16971.1 | 0.03 | -0.03 | -0.57 |
| 3b | 134.421 | 0.00 | 0.00 | 29458.1 | 0.00 | 134.421 | 0.00 | 0.00 | 29458.1 | 0.00 | 0.00 | 0.00 |
| 4a | 9.77849 | 0.00 | 0.00 | 16993.8 | 0.03 | 9.82182 | 0.00 | 0.00 | 16998.2 | 0.00 | 0.03 | 0.44 |
| 4b | 134.421 | 0.00 | 0.00 | 29458.1 | 0.00 | 134.421 | 0.00 | 0.00 | 29458.1 | 0.00 | 0.00 | 0.00 |
| 5a | 12.52 | 0.00 | 0.00 | 17268.1 | 0.14 | 12.7687 | 0.00 | 0.00 | 17292.9 | 0.00 | 0.14 | 1.99 |
| 5b | 141.667 | 0.00 | 0.00 | 30182.7 | 0.26 | 142.443 | 0.00 | 0.00 | 30260.3 | 0.00 | 0.26 | 0.55 |

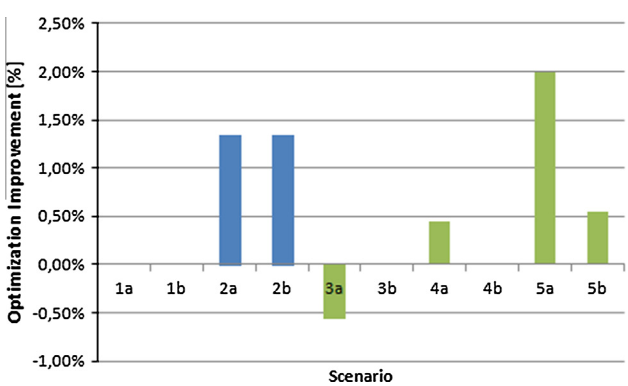


**Fig. 4.** Achieved optimization improvement of cognitive decision agent architecture in relation to modified simulated annealing reference method; (evaluation variable for the scenarios 1–2: achieved local PV energy self-consumption of environmentalists; evaluation variable for the scenarios 3–5: achieved financial gain of business (wo)men).

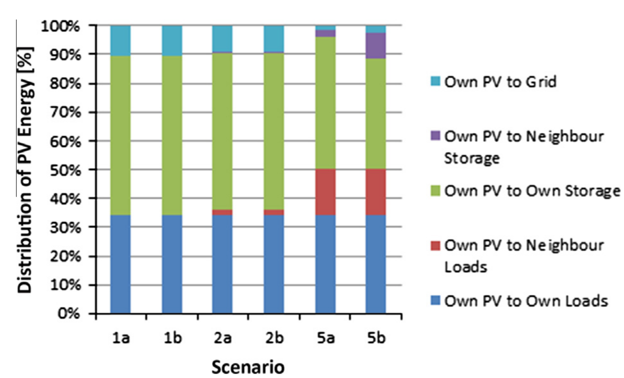


**Fig. 5.** Distribution of produced PV energy between sources and sinks for buildings following an environmentalist strategy.

business (wo)men group is significantly higher in scenarios where an energy exchange of stored energy with the grid was facilitated ('b' scenarios). Furthermore, when comparing scenario 4a and 4b with scenario 5a and 5b, it turned out that the achieved financial gain of business (wo)men was notably higher in the mixed neighbourhood group (scenarios 5a and 5b).

Taking a closer look at Figs. 5 and 6 concerning the mixed neighbourhood groups scenarios 5a and 5b, it can be observed that both the environmentalist and the business (wo)men could achieve improved results concerning their individual objectives (maximization of local PV energy use/financial gain). This demonstrates that acting in energy trading groups in which participants have disparate objectives can lead to a win–win situation for the different parties.

**Table 14**
Comparison of computational effort of modified simulated annealing approach and cognitive decision agent architecture.

| Scenario ID | Number of selectable actions | Number of iterations | |
|---|---|---|---|
| | | Modified simulated annealing | Cognitive decision agent architecture |
| 1a | 6 | 404100 | 1 |
| 1b | 8 | 538800 | 6 |
| 2a | 12 | 808200 | 72 |
| 2b | 14 | 942900 | 432 |
| 3a | 6 | 1211400 | 4 |
| 3b | 8 | 1616400 | 24 |
| 4a | 12 | 2421396 | 288 |
| 4b | 14 | 2828700 | 3456 |
| 5a | 12 | 2416752 | 13824 |
| 5b | 14 | 2828658 | 331776 |

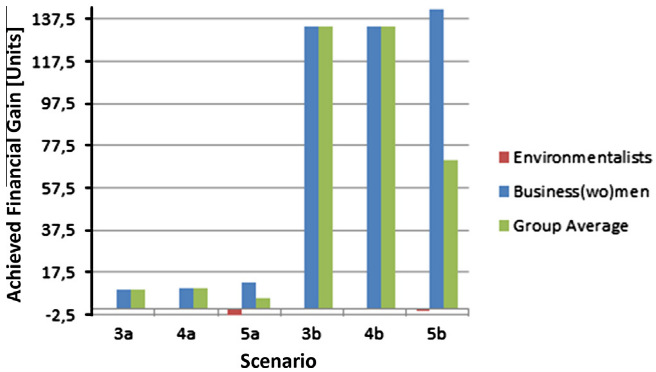


**Fig. 6.** Average achieved financial gain per building and day in business (wo)men scenarios.

## 6. Conclusion and outlook

In this article, a cognitive decision agent architecture was presented for finding goal-specific energy management strategies in interconnected microgrids, which were additionally connected to a main grid featuring variable grid electricity prices. Specifically, the architecture was used for identifying (1) financial gain maximization strategies and (2) local PV energy self-consumption maximization strategies in different system configurations. The cognitive decision agent architecture was based on concepts and function principles borrowed from human decision making like different hierarchical evaluation and prioritization mechanisms and the use of semantic and episodic knowledge. The performance of the architecture was compared in terms of both optimization result and processing time against the outcomes obtained from a modified simulated annealing optimizer approach. The study showed that with the introduced cognitive decision agent architecture, an improvement of optimization results in the percentage range could be achieved together with a significant reduction of the computational processing effort, which was in sum 45.8 times lower than for the chosen state of the art reference method. Accordingly, it was demonstrated that the proposed cognitive decision agent architecture is a powerful and efficient method for determining optimal or close to optimal energy management strategies in non-trivial interconnected microgrid configurations. Due to the modular structure of the architecture, the system furthermore provides good adaptability and scalability properties.

A minor disadvantage of the cognitive decision agent architecture in comparison to the modified simulated annealing approach is a slightly increased design effort in cases where semantic memory facts and rules shall be specified for search space filtering. In future, this drawback could be circumvented by integrating mechanisms into the system that can automatically extract such facts and rules from some source. Further interesting research topics for extending the functionality of the architecture in future include (1) mechanisms for system behaviour modelling to predict longer term PV production, load consumption, and grid price curves as well as neighbour behaviour and (2) the application of game theory for concurrently finding optimal energy management strategies for a larger set of interconnected microgrids with disparate operation objectives.

## Acknowledgement

The work reported in this article has been co-funded by the European Commission within the INTERREG Program for supporting small and medium sized companies (SME) in Italy and Carinthia (Austria) and the Austrian Research Promotion Agency (FFG) within the program Fit4Set (project Vision Step I).

## References

[1] Velik R. Cognitive architectures as building energy management system for future renewable energy scenarios – a work in progress report. IJSEI Int J Sci Eng Invest 2013;2(17):68–72.
[2] Nanomarkets, Sensors for the smart grid: market opportunities 2010 to 2017, Market Report, December, 2009.
[3] Zhang L, Gari N, Hmurcik L. Energy management in a microgrid with distributed energy resources. Energy Convers Manage 2014;78:297–305.
[4] Kang S, Park J, Oh K, Noh J, Park H. Scheduling-based real time energy flow control strategy for building energy management system. Energy Build 2014;75:239–48.
[5] Zhang D, Shah N, Papageorgiou L. Efficient energy consumption and operation management in a smart building with microgrid. Energy Convers Manage 2013;74:209–22.
[6] Costa L, Kariniotaki G. A stochastic dynamic programming model for optimal use of local energy resources in a market environment. IEEE Lausanne Power Tech 2007:449–54.
[7] Basu A, Panigrahi T, Chowdhury S, Chowdhury S, Chakraborty N, Sinha A, et al. Key energy management issues of setting market clearing price (MCP) in micro-grid scenario. In: 42nd International universities power engineering conference; 2007. p. 854–860.
[8] Parisio A, Rikos E, Tzamalis G, Glielmo L. Use of model predictive control for experimental microgrid optimization. Appl Energy 2014;115:37–46.
[9] Xiao Z, Li T, Huang M, Shi J, Yang J, Yu J, et al. Hierarchical MAS based control strategy for microgrid. Energies 2010;3(9):1622–38.
[10] Mohammadi M. Review of simulation and optimization of autonomous and grid-connected hybrid renewable energy systems as micro-grids. Isesco J Sci Technol 2013;9(16):60–7.
[11] Zakariazadeh A, Jadid S, Siano P. Stochastic multi-objective operational planning of smart distribution systems considering demand response programs. Electric Power Syst Res 2014;111:156–68.
[12] Stluka P, Godbole D, Samad T. Energy management for buildings and microgrids. Decis Control Eur Control Conf 2011:5150–7.
[13] Mendes G, Ioakimidis C, Stadler M, Marnay C. Multi-building microgrids for a distributed energy future in Portugal. Int Conf Appl Energy ICAE; 2012. 14 pages.
[14] Ilic D, Da Silva P, Karnouskos S, Griesemer M. An energy market for trading electricity in smart grid neighbourhoods. In: Proc. 6th IEEE International Conference on Digital Ecoxystems Technologies; 2012.
[15] Velik R. Renewable energy self-consumption versus financial gain maximization strategies in grid-connected residential buildings in a variable grid price scenario. IJARER Int J Adv Renew Energy Res 2013;2(6).
[16] Velik R. Battery storage versus neighbourhood energy exchange to maximize local photovoltaics energy consumption in grid-connected residential neighbourhoods. IJARER Int J Adv Renew Energy Res 2013;2(6).
[17] Velik R. The influence of battery storage size on photovoltaics energy self-consumption for grid-connected residential buildings. IJARER Int J Adv Renew Energy Res 2013;2(6).
[18] Velik R, Nicolay P. Energy management in storage-augmented, grid-connected prosumer buildings and neighbourhoods using a modified simulated annealing optimization. Comput Operat Res 2014 [Submitted for publication].
[19] Velik R, Nicolay P. Grid-price-dependent energy management in microgrids using a modified simulated annealing triple-optimizer. Appl Energy 2014;130:384–95.
[20] Zeng Y, Cai Y, Huang G, Dai J. A review on optimization modeling of energy systems planning and GHG emission mitigation under uncertainty. Energies 2011;4:1624–56.
[21] Kádár P. Application of optimization techniques in the power system control. Acta Polytechnica Hungarica 2013;10(5).
[22] Vale Z, Venayagamoorthy G, Ferreira J, Morais H. Computational intelligence applications for future power systems. Comput Int Eng Syst, Int Syst, Control Autom: Sci Eng 2011;46:176–93.
[23] Soliman S, Mantawy A. Modern optimization techniques with applications in electric power systems. Energy Systems Springer Science+Business Media; 2012.
[24] Gu W, Wu Z, Bo R, Liu W, Zhou G, Chen W, et al. Modeling, planning and optimal energy management of combined cooling, heating and power microgrid: a review. Int J Electr Power Energy Syst 2014;54:26–37.
[25] Narkhede M, Chatterji S, Ghosh S. Trends and challenges in optimization techniques for operation and control of microgrid – a review. In: 1st International conference on power and energy in NERIST (ICPEN); 2012. p. 1–7.
[26] Tomoiaga B, Chindris M, Sumper A, Marzband M. The optimization of microgrids operation through a heuristic energy management algorithm. Adv Eng Forum Sustain Develop Energy Env 2013:8–9(2).
[27] Hawkes Al, Leach M. Modelling high level system design and unit commitment for a microgrid. Appl Energy 2009;86:1253–65.
[28] Privitera G, Day A, Dhesi G, Long D. Optimising the installation costs of renewable energy technologies in buildings: a linear programming approach. Energy Build 2011;43(4):838–43.
[29] Liu P, Gerogiorgis D, Pistikopoulos E. Modeling and optimization of polygeneration energy systems. Catal Today 2007;127(1–4):347–59.
[30] Ikegami T, Iwafune Y, Ogimoto K. Development of the optimum operation scheduling model of domestic electric appliances for the supply-demand

adjustment in a power system. IEEE Trans Power Energy 2010;130(10):877–87.
[31] Morais H, Kádár P, Faria P, Vale Z, Khodr H. Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. Renewable Energy 2010;35(1):151–6.
[32] Sechilariu M, Wang B, Locment F. Supervision control for optimal energy cost management in DC microgrid: design and simulation. Int J Electr Power Energy Syst 2014;58:140–9.
[33] Borghetti A, Bosetti M, Grillo S. Short-termscheduling and control of active distribution systems with high penetration of renewable resources. IEEE Syst J 2010;4(3):313–22.
[34] Löhndorf N, Minner S. Optimal day-ahead trading and storage of renewable energies: an approximate dynamic programming approach. Energy Syst 2010;1(1):61–77.
[35] Marano V, Rizzo G, Tiano F. Application of dynamic programming to the optimal management of a hybrid power plant with wind turbines, photovoltaic panels and compressed air energy storage. Appl Energy 2012;97:849–59.
[36] Wang Y, Lin X, Pedram M, Park S, Chang N. Optimal control of a grid-connected hybrid electrical energy storage system for homes. Des Autom Test Eur Conf Exhib 2013: 881–6.
[37] Cai Y, Huang G, Yang Z, Lin G, Tan Q. Community-scale renewable energy systems planning under uncertainty: an interval chance-constrained programming approach. Renew Sustain Energy Rev 2009;13(4):721–35.
[38] Zheng Y, Chen S, Lin Y, Wang W. Bio-inspired optimization of sustainable energy systems: a review. Math Prob Eng 2013. 12 pages.
[39] Ekren O, Ekren B. Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing. Appl Energy 2010;87(2):592–8.
[40] Hemmati M, Amjady N, Ehsan M. System modeling and optimization for islanded micro-grid using multi-cross learning-based chaotic differential evolution algorithm. Int J Electr Power Energy Syst 2014;56:349–60.
[41] Chen C, Duan S, Cai T, Liu B, Hu G. Smart energy management system for optimal microgrid economic operation. Renewable Power Gen 2011;5(3):258–67.
[42] Lu H, Alanne K, Martinac I. Energy quality management for building clusters and districts (BCDs) through multi-objective optimization. Energy Convers Manage 2014;79(March):;525–533.
[43] Mohamed F, Koivo H. Online management genetic algorithms of microgrid for residential application. Energy Convers Manage 2012;64(December):562–8.
[44] Naama B, Bouzeboudja H, Allali A. Solving the economic dispatch problem by using tabu search algorithm. Energy Procedia 2013;36:694–701.
[45] Calderaro V, Conio G, Galdi V, Massa G, Piccolo A. Active management of renewable energy sources for maximizing power production. Int J Electr Power Energy Syst 2014;57:64–72.
[46] Matallanas E, Castillo-Cagigal M, Gutiérrez A, Monasterio-Huelin F, Caamaño-Martín E, Masa D, et al. Neural network controller for active demand-side management with PV energy in the residential sector. Appl Energy 2012;91(1):90–7.
[47] Rossi F, Velázquez D, Monedero I, Biscarri F. Artificial neural networks and physical modeling for determination of baseline consumption of CHP plants. Expert Syst Appl 2014;41(10):4658–69.
[48] Ganesan T, Elamvazuthi I, Zilati K, Shaari K, Vasant P. Swarm intelligence and gravitational search algorithm for multi-objective optimization of synthesis gas production. Appl Energy 2013;103:368–74.
[49] Li Y, Li Y, Huang G, Chen X. Energy and environmental systems planning under uncertainty: an inexact fuzzy-stochastic programming approach. Appl Energy 2010;87(10):3189–211.
[50] Kyriakarakos G, Dounis A, Arvanitis K, Papadakis G. A fuzzy logic energy management system for polygeneration microgrids. Renewable Energy 2012;41:315–27.
[51] Ketabi A, Alibabaee A, Feuillet R. Application of the ant colony search algorithm to reactive power pricing in an open electricity market. Int J Electr Power Energy Syst 2010;32(6):622–8.
[52] El-Zonkoly A. Optimal placement and schedule of multiple grid connected hybrid energy systems. Int J Electr Power Energy Syst 2014;61:239–47.
[53] Lakshmi K, Vasantharathna S. Gencos wind–thermal scheduling problem using artificial immune system algorithm. Int J Electr Power Energy Syst 2014;54:112–22.
[54] Trovão J, Pereirinha P, Jorge H, Antunes C. A multi-level energy management system for multi-source electric vehicles: an integrated rule-based meta-heuristic approach. Appl Energy 2013;105:304–18.
[55] Saad W, Han Z, Poor H, Bas T. Game theoretic methods for the smart grid: An overview of microgrid systems, demand-side management, and smart grid communications. IEEE Signal Processing Magazine, Special Issue on Signal Processing Techniques for the Smart Grid 2012;29(5):86–105.
[56] Fadlullah Z, Nozaki Y, Takeuchi A, Kato N. A survey of game theoretic approaches in smart grid. Int Conf Wireless Commun Signal Process 2011:1–4.
[57] Saad W, Han Z, Poor H. Coalitional game theory for cooperative micro-grid distribution networks. IEEE Int Conf Commun Workshops 2011:1–5.
[58] Weaver W, Krein P. Game-theoretic control of small-scale power systems. IEEE Trans Power Delivery 2009;24(3):1560–7.
[59] Maity I, Rao S. Simulation and pricing mechanism analysis of a solar-powered electrical microgrid. IEEE Syst J 2010;4(3):275–84.
[60] Vytelingum P, Voice T, Ramchurn S, Rogers A, Jennings N. Agent-based micro storage management for the smart grid. In: Proc. of 9th int. conf. on autonomous agents and multiagent systems; 2010.
[61] Mohsenian-Rad A, Wong V, Jatskevich J, Schober R, Leon-Garcia A. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE Trans Smart Grid 2010;1(3):320–31.
[62] Agarwal T. Noncooperative games for autonomous consumer load balancing over smart grid. Master thesis, Texas A&M University; 2010.
[63] Ibars C, Navarro M, Giupponi L. Distributed demand management in smart grid with a congestion game. First IEEE Int Conf Smart Grid Commun 2010:495–500.
[64] Dou C, Liu B. Hierarchical management and control based on MAS for distribution grid via intelligent mode switching. Int J Electr Power Energy Syst 2014;54:352–66.
[65] Velik R, Schmid S, Rittsteiger W, Karitnig A, Wilhelmer D, Smole E. The smart energy demo project vVision Step I – Smart City Villach. In: 11th Austrian photovoltaic conference; 2013.
[66] Velik R, Kafka K, Neumaier L, Schmid J, Pairitsch H, Egger W, Silva-Martinz J. Design of a PV-supplied, grid-connected storage test bed for flexibly modeling future energy scenarios. Smart Grids Week Salzburg 2013.
[67] Roesener C. Adaptive behavior arbitration for mobile service robots in building automation. Ph.D. Thesis. Vienna University of Technology, Vienna, Austria; 2007.
[68] Palensky B. From neuro-psychoanalysis to cognitive and affective automation systems. Ph.D. Thesis. Vienna University of Technology, Institute of Computer Technology, Vienna, Austria; 2008.
[69] Velik R, Zucker G, Dietrich D. Towards automation 2.0: A neuro-cognitive model for environment recognition, decision-making, and action execution. EURASIP Journal on Embedded Systems. Special Issue on Networked Embedded Systems for Energy Management and Buildings 2011; 2011: 11 pages.
[70] Deutsch T, Lang R, Pratl G, Brainin E, Teicher S. Applying psychoanalytic and neuro-scientific models to automation. In: Proceedings of the 2nd IET international conference on intelligent environments; 2006. p. 111–8.
[71] Velik R. Brain-like artificial intelligence for automation: Foundations, concepts and implementation examples, BRAIN. Broad Res Art Intell Neurosci 2013;4:26–54.