A multi-agent based energy management solution for integrated buildings and microgrid system

Amjad Anvari-Moghaddam, Ashkan Rahimi-Kian, Maryam S. Mirian, Josep M. Guerrero

A practical framework for coordinated DR and DG management is proposed. An ontology-driven multi-agent based energy management system is presented. Efficient strategies for real-time management of batteries are proposed. Cost-effective and comfort-aware energy management solutions are presented.

Abstract

In this paper, an ontology-driven multi-agent based energy management system (EMS) is proposed for monitoring and optimal control of an integrated homes/buildings and microgrid system with various renewable energy resources (RESs) and controllable loads. Different agents ranging from simple-reflex to complex learning agents are designed and implemented to cooperate with each other to reach an optimal operating strategy for the mentioned integrated energy system (IES) while meeting the system’s objectives and related constraints. The optimization process for the EMS is defined as a coordinated distributed generation (DG) and demand response (DR) management problem within the studied environment and is solved by the proposed agent-based approach utilizing cooperation and communication among decision agents. To verify the effectiveness and applicability of the proposed multi-agent based EMS, several case studies are carried out and corresponding results are presented.

1. Introduction

The steady increase in the price of conventional energy sources and concerns about pollutants emissions along with the needs for improved operational efficiency, introduces smart renewable microgrids as promising solutions. These systems which are capable of working in standalone or grid-tied modes [1], accept different kinds of energy sources as input and meet the end-user’s demand with minimal human intervention. However, to provide energy of the required quality in a reliable, clean and economical way, different distributed energy resources (DERs) within the microgrid must be operated in a coordinated manner [2,3]. On the other hand, given the persistent trend in modernization and urbanization, growth in residential energy demand is expected to stay high, which in turn necessitates demand response (DR) and demand side management (DSM) policies for optimal operation of the system [4–6].

In order to draw the best performance of such integrated energy systems (IESs), smart system optimizers (SSOs) have to be designed and implemented. The SSOs must take both real-time information and forecast data into account and optimally schedule operating set-points based on the system’s objectives and constraints. So far, several contributions on optimal dispatch of IESs and related control strategies have been made. The authors in [7,8] provided details about the control tasks and strategies involved in the IES management with a review on the main types of controls proposed in the literature. The most straightforward solution to fulfill the mentioned control objective is deemed to be a centralized SSO implementation. For example, Olivares et al. [9] proposed a centralized energy management system (EMS) to economically dispatch an isolated microgrid in presence of both schedulable and non-schedulable distributed generators (DGs). Although, the proposed EMS strategy decomposed the main
problem into unit commitment (UC) and optimal power flow (OPF) sub-problems to avoid nonlinearity in formulation, it introduced high level of required coordination among DERs, which made this strategy inefficient for real-time implementation. Yuan et al. [10] developed a penny-wise energy scheduling approach for residential microgrids with high penetration of renewable energy sources (RESSs) and applied a two-stage optimization process to determine optimal utilization of DERs. However, that paper neglected the interaction among controllable energy sources at demand and supply sides for a multi-period model. Research works in [11–14] mainly focused on DER management from a canaled perspective (i.e., system operator’s viewpoint) and introduced minimum cost of operation for the examined IES as an objective. Other research works (e.g., [15–17]) made efforts on developing integrated DSM strategies for optimal energy management within residential microgrids considering user’s preferences as objectives. However, references [12–17] did not develop optimum operating strategies under sudden changes of working conditions due to the presence of uncertain parameters in the environment. Moreover, the proposed DR and DG management strategies in [14–17] were not optimized together, although these aspects are interdependent and the execution of one can greatly affect the other. In the above-mentioned works, there are also some technical issues which need to be addressed suitably. For example in the proposed centralized schemes (e.g., [9–12,14,16]), a central entity derives all the elements within the network, observes the environment, performs the calculations and sends back the control signals to the actuators, thus the whole system suffers from a single point of failure. Moreover, it can be easily observed that the computational complexity increases exponentially as the system size increases and considerable communication expenditure is accordingly needed to fulfill the requirements. From the information security viewpoint, the proposed centralized database might be also exposed to unauthorized access, disclosure, disruption or modification.

An alternative approach for SSO implementation within a typical IES is a decentralized scheme that utilizes distributed controllers for energy management and optimization [18,19]. Most of the research works in this area have focused on hierarchical control architecture using multi-agent systems (MASs) [20–33]. In [21] a MAS-based optimal energy management solution was proposed for smart grids where interactive operation of generation units and DR was formulated as an optimization problem. In that work, although each system participant was assigned with an energy management agent, the proposed problem was solved by the system operator in a centralized market-oriented scheme. Similarly, authors in [22,23] elaborated on multi-level management and control schemes for microgrid systems taking into account the interaction among agents at different levels, however they failed to satisfy system-level objectives such as social-welfares or economic operation of DG units. In [24], a multi-agent framework was developed to automate building energy optimization and to support distributed decision making with limited engineering effort. However, some issues related to a robust MAS design and hardware implementations were not considered. Also, the proposed multi-agent control algorithm had some limitations on dealing with some types of equipment such as heating, ventilation and air conditioning (HVAC) systems that have multiple operating modes and their optimal control becomes a mixed-integer programming problem that cannot be solved with the proposed algorithm. The work in [25] presented an efficient consumption scheduling framework for schedule consumption plan in small residential areas. By using a decentralized game theoretic method and decomposing the centralized optimization, authors demonstrated that the computational complexity can be distributed among the individual home demand management units. However, they failed to show the effectiveness and applicability of the proposed model on larger test systems where the scheduling optimization might not converge to an equilibrium. Similarly, authors in [26] introduced a decentralized agent-based approach for optimal residential demand planning. Although they tackled the problem of scalability and complexity of computation for larger scale systems (which was a remaining issue in previous works) through a tree topology for the proposed MAS, they failed to construct a fault-tolerant topology with self-organization mechanisms. Other distributed agent-based solutions to energy management were also presented for grid-tied microgrids in [27,28], islanded microgrids in [29,30], and multiple microgrids in [31]. Motivated by the idea of decentralized control, authors of [32,33] also presented MAS-based management and control strategies for integrated energy systems. Although the reviewed decentralized schemes demonstrated more robust operation (e.g., [20,21,26,30–33]), less complexity (e.g., [20,24,25,27]) and fewer communication requirements ([22–24,29]) compared to the centralized ones, they can still suffer from degradation of performance on large networks due to the increased communication frequency and network induced delays (e.g., [25,28–30]), increased use of database space (e.g., [21,23,25,32]) and complex use and administration (e.g., [24,26–29,33]).

This paper proposes a practical framework for coordinated DR and DG management in an integrated building and microgrid system (here named as a residential microgrid) using MAS concept within a local area network. In this framework, the SSO is not conceived as a single system to operate and control but as a cluster of self-contained entities that nevertheless collaborate effectively. This scheme also offers a distributed monitoring and control architecture for the emerging smart microgrids, where communication among different nodes with different tasks is necessary for optimal management of energy generation and consumption in real-time. Moreover, within the proposed framework, similar types of energy-related production and consumption units are grouped and controlled by local SSOs, while global coordination among different groups is achieved through a centralized coordinator. It is noteworthy that the term “energy management” in this work refers to the process of energy conservation and optimal use of energy sources within a residential microgrid which is the key to meet the system’s objectives. The main contributions of this paper can be summarized as follows:

- A practical framework is proposed for optimal demand response and dispersed generation management in a typical IES where multiple objectives and different hard/soft constraints need to be satisfied simultaneously,
- A fault-tolerant ontology-driven agent-based energy management solution is proposed for real-time monitoring and optimal control using standard configurations and communication languages for agents,
- An efficient strategy for real-time management of energy storage devices is proposed to optimally compensate any power mismatch in the IES and to mitigate the effects of uncertain parameters on system operation.

The remainder of this paper is structured as follows: Section 2 presents the system configuration and specifications as well as the proposed MAS architecture. Section 3 introduces the EMS design and mathematical modeling. Evaluation of the functionality and applicability of the proposed MAS framework for efficient energy management in a residential microgrid is performed in Section 4. Finally, Section 5 concludes this paper.
2. System presentation

Layout of the studied buildings and microgrid system is shown in Fig. 1. The system includes different means of dispersed generation and energy storage as well as controllable loads. It is assumed, each residential building is equipped with a micro-combined heat and power generator (m-CHP), a domestic hot water system, a radiant floor heating/cooling system (RFS), and energy storage units. The electric demand can be provided by the utility, centralized energy sources within the microgrid, distributed m-CHPs and energy storage systems at homes. Likewise, the thermal demand in each building is supplied by the m-CHP and RFS. Since centralized RESs (such as wind and solar) are shared by the whole community, each household has its subscription rate denoting the amount of power that can be extracted from these energy sources.

To optimally manage energy and comfort level in the examined community, a MAS-based structure is designed and developed as follows:

- **Central Coordinator Agent (CCA):** CCA is responsible for collecting and sharing information, such as real-time energy prices (RTPs) and meteorological data with corresponding agents. It also serves as a supervisory control agent that manages the energy monitoring and real-time operation of the residential microgrid.
- **Building Management Agent (BMA):** BMA is a goal-based agent that receives information about in-home task operating status, usage requests and network signals and sends control actions back to the smart controllable devices. It also collects relevant information from the dominated environment to identify solutions for different user’s objectives such as energy saving and a comfortable lifestyle.
- **RES Agent (RESA):** RESA collects the meteorological information, forecasts the output power of the RESs in short-time intervals using methods developed in [34,35], and sends related information to the requesting agents. Since two types of RESs, including wind turbine (WT) and photovoltaic system (PV), are considered in this paper, two types of RESA were created as WT-Agent and PV-Agent.
- **Battery Bank Agent (BBA):** To optimally compensate any real-time power mismatch in the IES (i.e., deviation of power flows from the scheduled values due to presence of uncertain parameters in the environment), another goal-based agent called BBA is designed and applied to control the charge/discharge states of the centralized battery bank based on a Bayesian learning (BL) algorithm which is detailed in Section 3.5.
- **Service Agent (SA):** The service agent provides other agents with special types of computations (e.g., optimization), when it is needed. This simple-reflex agent receives required information as input and delivers the optimal outputs based on a priority queue.
- In the proposed MAS architecture, the agents act cooperatively to achieve the following goals: (1) supplying the system loads continuously; (2) minimizing the energy cost of the residential community; (3) maintaining the residents’ comfort levels. Fig. 2 presents the communication network for the proposed MAS architecture. In the same figure, message passing structure based on the FIPA1-compliant agent communication language (ACL) is also shown.

Within the architecture, different ontologies are also introduced and used as references to give meaning to symbols in the message contents. These ontologies also help to define the names and types of data to be used in the exchange of messages while validating the information to be converted from the semantic point of view. Considering a given ontology the following key properties are included in the message content:

- **Cardinality** of a data frame which denotes the number of values the frame could have (e.g., 0, 1, N),
- **Allowed type** which represents the value type of a data frame (e.g., string, integer, or instance of a class),
- **Valid range** (VR) which shows the lower and upper boundaries for a numeric data frame (e.g., [0, 1]),
- **Identified/Anonymous frame** which accounts for a name-specific data frame (Identified) or a default type (Anonymous).

In addition to communication network, the agent management framework (AMF) should be defined. As illustrated in Fig. 2, the proposed AMF consists of several components as follows: the agent platform (AP), in which the agents and additional supporting software are deployed; agent container (AC), in which all the services needed for hosting and executing agents are available; directory facilitator (DF), which provides yellow pages services to other agents; agent management system (AMS), which is in charge of operation management such as creation, migration and deletion of agents; remote management agent (RMA), which serves as a graphical console for platform management and control; and message transport service (MTS) that supports FIPA-ACL message transportation between agents in the AP or between agents on different APs. Message passing among agents living in different containers of the same platform is done via internal message transport protocol (IMTP), while hypertext transfer protocol (HTTP) is applied for inter-platform communications. It is also observed from Fig. 2 that within a given platform, there is a main-container regarded as a bootstrap point. It is the first container that needs to be launched and all other containers must join thereafter via registering through the main-container. To make the proposed MAS architecture more robust, a fault-tolerant structure is proposed as depicted in Fig. 3. Within this structure, there are three main-containers (one is the master and the others are the slaves or replica backups), which are arranged in a unidirectional ring with each node monitoring its next neighbor. If one container fails, the others detect the failure event and take the appropriate recovery actions. In this regard, the level of fault tolerance, scalability and distribution of the platform could be controlled and a fully operational system in the event of a main-container failure can be guaranteed. It should be noted that to launch a fault-tolerant platform configured as that described above, it is assumed that each of the container nodes (including main and non-main containers) is to be initiated on different hosts. Also, the host with the main container must be launched with additional kernel-level services known as the address notification service (ANS) and the main container replication service (MCRS).

3. EMS math modeling for residential microgrid

In this section, mathematical models of different system’s components are presented and the optimal coordinated DR and DG management problem is explained.

3.1. Building-level distributed energy sources

3.1.1. Micro-cogeneration system (m-CHP Unit)

The electrical/thermal power output of the considered m-CHP system at each time step $h$ can be calculated as follows:

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1 Foundation for Intelligent Physical Agents.
\[ Pe_{\text{CHP}}(h)/\eta_e = P_{\text{th}}^{\text{h}}(h)/\eta_{\text{in}} = g_{\text{CHP}}(h) \]  
\[ Pe_{\text{CHP}}(h) \in [P_{\text{min}}^{\text{h}}, P_{\text{max}}^{\text{h}}] \]  
\[ |P_{\text{CHP}}^{\text{h}}(h) - P_{\text{CHP}}^{\text{h}}(h - 1)| \leq P_{\text{ramp}}^{\text{h}} \]  
\[ |P_{\text{CHP}}^{\text{h}}(h) - P_{\text{CHP}}^{\text{h}}(h - 1)| \leq P_{\text{ramp}}^{\text{h}} \]  
where \( g_{\text{CHP}} \) represents the total gas flow into the unit and \([P_{\text{min}}^{\text{h}}, P_{\text{max}}^{\text{h}}]\) is the allowed electrical (thermal) output range of the CHP unit. \( P_{\text{ramp}}^{\text{h}} \) is the maximum allowable electrical (thermal) ramp rate, and \( \eta_e, (\eta_{\text{in}}) \) is the electric (thermal) efficiency of the system. For an additional auxiliary boiler, the same thermal constraints must be met as well [36]. For a hot water storage system connected to a given m-CHP unit, the following updated temperature function is used to model the equivalent thermal energy of the hot water inside the tank:

\[ T_{st}(h+1) = (V_{cw}(h)T_{cw} - T_A(h))/V_{tot} + (V_{cw}(h) + P_{\text{aux}}^{\text{h}}(h)/(V_{cw}C_{w}) - (A_t(V_{cw}C_{w}R_{ct}))(T_A(h) - T_{b}(h)) + P_{\text{ramp}}^{\text{h}}(h - 1)\]

\[ T_A(h) \in [T_{\text{min}}, T_{\text{max}}] \]  
where \( V_{tot} \) and \( V_{cw}(h) \) are the total tank volume and hourly hot water demand, and \( P_{\text{aux}}^{\text{h}}(h) \) is the auxiliary boiler thermal output power. \( T_{cw} \) and \( T_{b}(h) \) are the entering cold water and basement temperatures at hour \( h \), respectively. Likewise, \( A_t \) is the surface area of the tank; \( R_{ct} \) is the R-value of the tank insulation material. Due to users’ needs and comfort levels, the hot water temperature \( T_{st}(h) \) within the storage tank must be kept within an acceptable range, which is defined by (6).

3.1.2. Energy storage system (ESS)

The behavior of a given battery-based ESS can be described mathematically through the following equation:

\[ SOC(h + 1) = SOC(h) + (h_{\text{step}} \{ p_{\text{ESS}}^{\text{h}}(h) - p_{\text{ESS}}^{\text{dch}}(h) \})/E_{\text{ESS}} \]  
\[ SOC(h) \in [SOC_{\text{min}}, SOC_{\text{max}}] \]  
where \( SOC(h) \) is the battery’s state of charge at each time step \( h_{\text{step}} \) bounded by an upper limit \( SOC_{\text{max}} \) and a lower limit \( SOC_{\text{min}} \). \( E_{\text{ESS}} \) denotes the battery capacity in kWh. The charging (discharging) power of an ESS is also bounded according to the following constraints:

\[ p_{\text{ESS}}^{\text{h}}(h) \leq P_{\text{max}}^{\text{h}} \eta_{\text{ch}} u_{\text{ESS}}(h) \]  
\[ p_{\text{ESS}}^{\text{dch}}(h) \leq P_{\text{max}}^{\text{dch}} (1 - u_{\text{ESS}}(h))/\eta_{\text{dch}} \]  

where \( P_{\text{max}}^{\text{h}} (P_{\text{max}}^{\text{dch}}) \) is the battery’s maximum charging (discharging) power; \( \eta_{\text{ch}} (\eta_{\text{dch}}) \) is the battery’s charging (discharging) efficiency; and \( u_{\text{ESS}} \) is a binary variable denotes charging (“1”) or discharging (“0”) status at each time step.
3.1.3. Radiant floor heating/cooling system (RFS)

In a RFS, the amount of thermal power supplied (or absorbed) to (or from) the house floor at each time step is calculated as follows:

\[
Q_{HC}(h) = \left( u_{HC}(h) \eta_H(h) - (1 - u_{HC}(h)) \eta_C(h) \right) P_{HC}(h)
\]  

(10)

\[
P_{HC} \in [0, P_{HC,max} \eta_H] \in [\eta_H^m, \eta_H^M], P_{HC} \in [\eta_C^m, \eta_C^M]
\]  

(11)

Fig. 2. Proposed MAS architecture - communication network and agent management ontology (AMO).

Fig. 3. Topology of the proposed fault tolerant platform.
where $P_{HC}(h)$ is the heat pump electrical power consumption at hour $h$, $u_{HC}$ is a binary variable representing the operating mode of the RFS (heating ("1") or cooling ("0")), and $\eta_{HC}$ is the performance coefficient of the mentioned system in heating (cooling) mode.

3.2. Thermal model of a building envelope

To characterize the thermal behavior of a building envelope in terms of temperature update functions, different heat flows should be considered as follows:

$$T_{in}(h) = T_{in}(h - 1) + h_{\text{step}} \cdot \left( Q_{fi}(h) + Q_{si}(h) + Q_{ihg}(h) - Q_{io}(h) \right) / m_{i}c_{pi}$$

$$T_{in}(h) \in [T_{in}^{\text{min}}, T_{in}^{\text{max}}]$$

$$T_{f}(h) = T_{f}(h - 1) + h_{\text{step}} \cdot \left( Q_{HC}(h) + Q_{sf}(h) - Q_{fg}(h) - Q_{fi}(h) \right) / m_{f}c_{pf}$$

$$T_{f}(h) \in [T_{f}^{\text{min}}, T_{f}^{\text{max}}]$$

where $Q_{fi}$, $Q_{si}$, $Q_{fg}$ are the heat flows between two nodes; namely, indoor air-outdoor, floor-indoor air and floor-ground through the equivalent thermal resistances, respectively [37,38].

$Q_{iHg}$ is the internal heat gain of a building estimated according to the heat generated by the occupants ($Q_{occ}$) [37,39], lights and appliances ($Q_{etc}$) [40,41], $Q_{o}$ is the heat flow into an exterior surface of a building subject to solar radiation [37], $Q_{fg}$ is the amount of heat obtained directly from solar radiation when it enters through the glazing and absorbed by the house floor [37,39]. Similarly, $c_{pi}$ ($c_{pf}$) and $m_{i}$ ($m_{f}$) are the specific heat capacity coefficient and mass of the floor (indoor air), respectively. $T_{in}$ and $T_{f}$ also denote indoor air and floor temperatures, respectively.

3.3. Load scheduling for residential DR

Generally, a number of household appliances are schedulable and their usages can be controlled during the period under consideration. Each schedulable load (task) $j$ has several parameters, which is required to be set by the users for efficient scheduling. As shown in Fig. 4, these parameters mainly include: power rating ($P_{s,j}$), valid start/stop times ($h_{v,j} = [h_{st,j}, h_{et,j}]$) during which task $j$ is valid for scheduling, desired start/stop times ($h_{d,j} = [h_{he,j}, h_{hl,j}]$) during which task $j$ is better to be scheduled according to the user’s preferences, cycle duration ($D_{h,j}$) and priority ($x_{j} \in \{1, 2, 3\}$; “1” for the lowest priority task and “3” for the highest one). Apart from these settings, several operating constraints must be considered for schedulable household appliances. First, the operation of each controllable task must be completed within a valid time period:

$$\sum_{h|h_{st,j}} u_{j}(h) = \Delta h_{j}$$

where $u_{j}(h)$ is a binary variable showing the ON ("1") or OFF ("0") state of appliance $j$ at hour $h$. Second, some devices must operate continuously (i.e., without any stop) during the runtime:

$$\sum_{h|h_{st,j}} |u_{j}(h) - u_{j}(h - 1)| \leq 2$$
Table 1
Operating parameters for the DG units.

<table>
<thead>
<tr>
<th>Building-level m-CHP Unit</th>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>PeCHP</td>
<td>[0.3, 1.5]</td>
<td>kW</td>
<td></td>
</tr>
<tr>
<td>Ptemp</td>
<td>0.9</td>
<td>kW/h</td>
<td></td>
</tr>
<tr>
<td>gCHP</td>
<td>92.4 × 10⁻³</td>
<td>m³/h</td>
<td></td>
</tr>
<tr>
<td>ηe, ηth, ηaux</td>
<td>30, 70, 86</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>Tst</td>
<td>[60, 80]</td>
<td>°C</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preamp</td>
<td></td>
<td>l</td>
</tr>
<tr>
<td>Vtot</td>
<td>200</td>
<td>m³</td>
</tr>
<tr>
<td>Rst</td>
<td>2.818</td>
<td>°C/W</td>
</tr>
<tr>
<td>Ast</td>
<td>1.99</td>
<td>m²</td>
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</table>

<table>
<thead>
<tr>
<th>Building-level ESS</th>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>EESS</td>
<td>24</td>
<td>kWh</td>
<td></td>
</tr>
<tr>
<td>Pch, Pdch</td>
<td>3.3, 3.3</td>
<td>kW</td>
<td></td>
</tr>
<tr>
<td>SOC</td>
<td>[20, 80]</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>ηch, ηdch</td>
<td>87, 90</td>
<td>%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Radiant Floor Heating/Cooling System</th>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>pCHP</td>
<td>2</td>
<td>kW</td>
<td></td>
</tr>
<tr>
<td>ηH</td>
<td>[100, 400]</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>Tset</td>
<td>25</td>
<td>°C</td>
<td></td>
</tr>
<tr>
<td>ηC</td>
<td>[100, 300]</td>
<td>%</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Centralized Battery Bank</th>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
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<tbody>
<tr>
<td>EBB</td>
<td>250</td>
<td>kWh</td>
<td></td>
</tr>
<tr>
<td>Pch, Pdch</td>
<td>35, 35</td>
<td>kW</td>
<td></td>
</tr>
<tr>
<td>SOC</td>
<td>[20, 80]</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>ηch, ηdch</td>
<td>89, 93</td>
<td>%</td>
<td></td>
</tr>
</tbody>
</table>

(a) Fig. 7. Hourly base-load electricity demand and hot water usage profiles: (a) weekend, (b) weekday.
Third, operation of a given task \(n\) may depend on the completion of another task (e.g., task \(j\)):

\[
\sum_{h=h_{\text{hs},n}}^{h_{\text{eh},n}} u_i(h) \cdot H(\zeta - \Delta h_j + \sum_{h=h_{\text{hs},n}}^{h_{\text{eh},n}} s_j(h)) = \Delta h_n
\]

where \(h_{\text{hs}}\) is the earliest start time, \(\zeta\) is a positive number smaller than 1, and \(H(\cdot)\) is a Heaviside step function. Finally, parallel operation of several tasks at each time step must meet the power consumption limit of a house \(P_{D,\text{max}}\) as follows:

\[
\sum_{j \in M} P_{ij}(h) u_i(h) + \sum_{k \in N} P_{kj}(h) \leq P_{D,\text{max}}
\]

where \(M\) and \(N\) are the sets of schedulable and non-schedulable loads with the power ratings of \(P_{ij}\) and \(P_{kj}\), respectively.

### 3.4. Energy and comfort management

The energy usage cost of a typical residential building (CRBi) can be expressed as follows:

\[
\text{CRBi} = \sum_{i \in K} \rho_{\text{grid}}(h) P_{\text{grid},i}(h) + \rho_{\text{gas}}(u_{\text{CHP},i}(h) g_{\text{CHP},i}(h) + u_{\text{aux,i}}(h) g_{\text{aux,i}}(h))
\]

where \(P_{\text{grid},i}(h)\) is the amount of power exchange between the \(i\)th building and the utility at hour \(h\), and \(\rho_{\text{grid}}\) and \(\rho_{\text{gas}}\) are the real-time grid electricity and natural gas prices, respectively. \(g_{\text{aux,i}}(h)\) is the total amount of gas consumed by the \(i\)th auxiliary boiler at hour \(h\) and \(u_{\text{aux},i}(h)\) is the ON/OFF state of the corresponding unit; \(T\) is the optimization time horizon and \(K\) is the set of all households within the residential microgrid.

Moreover, user's convenience level about household task scheduling (TSCi) and in-home thermal comfort level (TCi) can be modeled as follows:

\[
\text{TSCi} = \sum_{j \in M} (s_{i,j} SL_i(h, j))
\]

\[
\text{TCi} = \sum_{h \in T} CL_i(h)
\]

where \(SL_i(h, j)\) is the \(i\)th user's satisfaction level when task \(j\) is executed at hour \(h\) and \(CL_i(h)\) is the level of thermal comfort observed by the inhabitants of the \(i\)th house at each time step. To measure the \(i\)th user's SL and CL, two preference functions are defined as depicted in Fig. 5. The \(SL_i(h, j)\) utility function is shaped based on the desired start/stop times \(h_{\text{ss}}, h_{\text{es}}\) for each schedulable household appliance \(j\) (as discussed in Section 3.3) and reflects the \(i\)th user's satisfaction degree when a task is executed at different times. Similarly, the \(CL_i\) utility function is formed based on the \(i\)th user's living habits and preferences for indoor temperature and quantifies his/her level of thermal comfort. In this figure, \(T_{\text{set}}\) is the user-specified set-point for indoor temperature and \(\Delta T_{\text{in}}\) is the threshold temperature difference. \(\epsilon^o\) and \(\epsilon^r\) are very small numbers used to avoid division by zero error once we develop a mixed objective function \(f_i\) for each user as follows:

\[
\text{Min} \left\{ f_i = \text{CRBi} \cdot (\psi_{i,1} \frac{TSC_i}{SL_{\text{max}}} + \frac{TC_i}{CL_{\text{max}}})^{-1} \right\}
\]

where \(\psi_{i,1}\) and \(\psi_{i,2}\) are the weighting coefficients set by the \(i\)th user and reflect the significance of the normalized satisfaction degree and comfort level from his/her point of view. It's noteworthy that the proposed multi-objective mixed-integer programing problem takes into account not only lower cost of energy consumption for each building, but also higher comfort levels in electrical and thermal zones for inhabitants.

The above-mentioned optimization problem should be solved for each building unit subject to (22) and all the previously mentioned technical/operational constraints for available building-level devices and units:

\[
P_{\text{grid},i}(h) + P_{\text{CHP},i}(h) + \delta_i P_{\text{ESS},i}(h) - P_{\text{RES},i}(h) = P_{D,\text{in}}(h)
\]

in which, \(\delta_i\) is the user’s subscription rate denoting the share of \(i\)th household from RESs within the microgrid according to the ratios of investment and \(P_{\text{RES}}\) denotes the amount of available power from those energy sources.

### 3.5. Centralized battery bank management

To compensate any real-time power imbalances within the residential microgrid economically, BBA should observe the environment, make a fast decision and act accordingly based on the learned optimal policy of charge/discharge of the battery bank. As a model-free decision making algorithm, reinforcement learning (RL) is widely used in numerous applications [42]. However, by using Bayesian RL (BRL) framework, it is possible to partition the multi-modal perceptual space into reasonable number of distinct states and choose the actions that maximize the task performance.
in the presence of uncertainty [43]. In this paper, the battery bank energy management problem is formulated as a Markov decision process and the BBA is trained with a BRL method to optimize the real-time operation. The system state space at each decision time is described as:

\[ s^{(k)} = [p^{(k)}_{\text{grid}}, p^{(k)}_{\text{r}}, \text{SOC}^{(k)}_{\text{b}}]^T \]  

(23)

where \( p_{\text{r}} \) is the net energy content of the microgrid, and \( \text{SOC} \) is the state of charge of the centralized battery bank. The action is to charge (or discharge) \( \beta \) percent of \( p_{\text{r}} \) into (or from) the battery bank.

**Fig. 9.** Performance comparison of the simulated MAS-based EMSs in different working scenarios.
at each time considering charging/discharging capacity as well as the SOC limit:

\[ P_{BB}^{(k)} = \beta^{(k)} \cdot |P_{r}^{(k)}| \]

The reward function for taking action \( \beta \) is configured based on the cost saving for charging/discharging as well as the system reliability with battery backup energy. In case of positive energy content (i.e., the amount of electricity generation inside the microgrid

Fig. 10. Interactive process among agents within the proposed MAS.
exceeds the demand), the surplus of energy can be stored in the battery bank or sold to the power utility considering the following reward function:

\[ r^{(k)} = \zeta_1 - \rho_{BB}[^{(k)}] \cdot P_r^{(k)} + \rho_{grid}^{(k)} (1 - \beta^{(k)}) \cdot P_r^{(k)} + \zeta_2 \cdot SOC^{(k+1)} \]  

(25)

where \( \rho_{BB} \) is the charging/discharging cost of the battery bank, \( \zeta_1 \) and \( \zeta_2 \) are weighting factors to make a trade-off between normalized cost reduction and back-up energy, \( \rho_{grid}^{\text{max}} \) (\( \rho_{grid}^{\text{min}} \)) is the maximum (minimum) value of the time-varying grid electricity price, and \( P_{r,\text{max}} \) (\( P_{r,\text{min}} \)) is the maximum (minimum) possible value for the net energy content of microgrid.

Similarly, in case of negative energy content, extra demand can be supplied either by the battery bank or the local grid considering the following reward function:

\[ r^{(k)} = \zeta_1 - \rho_{BB}[^{(k)}] \cdot P_r^{(k)} - \rho_{grid}^{(k)} (1 - \beta^{(k)}) \cdot P_r^{(k)} + \zeta_2 \cdot SOC^{(k+1)} \]  

(26)

To make the power management strategy more adaptive, another BRL framework, as illustrated in Fig. 6, should be applied to handle two possible situations: (1) if \( \beta = 100\% \) and the battery bank does not reach the SOC limit, (2) if the battery bank is at the SOC limit. The first case denotes a condition in which the battery bank not only absorbs (or supplies) the whole \( P_r \), but also it has a tendency to further increase (or decrease) the SOC level considering the current and future situations. To this end, battery itself can exchange energy with the local grid through the following action and related reward function taking all the operating constraints into account:

\[ P_{BB}^{(k)} = u_{BB} \cdot (\gamma^{(k)} \cdot P_{BB,\text{ch}} \cdot \eta_{BB,\text{ch}} + (1 - u_{BB}) \cdot (\gamma^{(k)} \cdot P_{BB,\text{dis}} \cdot \eta_{BB,\text{dis}})) \]  

(27)

\[ r^{(k)} = u_{BB} \left\{ \zeta_1 \left( \frac{\gamma^{(k)} \cdot P_{grid}^{(k)} + \rho_{BB}^{(k)}}{P_{grid}^{\text{max}} + \rho_{BB}} \right) + \frac{\zeta_2 \cdot SOC^{(k+1)}}{1 - u_{BB}} \right\} 
\]  

(28)
where \( \gamma \) is the action stated based on percentage, \( P_{\text{max, BB}} \) \((P_{\text{max, BB}})\) is the battery’s maximum charging (discharging) power, \( \eta_{\text{BB, ch}}(\eta_{\text{BB, dch}}) \) is the battery bank’s charging (discharging) efficiency, and \( u_{\text{BB}} \) is a binary variable showing the charging/discharging action at each decision period. In a similar way, power exchange with the grid can be introduced as a solution to the second case, where the battery is almost full (or empty) and there is no capacity to store (or supply) \( \beta P_{\text{Per}} \).

4. Simulation case study

The examined IES is considered as a grid-connected microgrid with 10 houses as shown in Fig. 1. Each residential unit is simulated based on a real single-zone low-energy house in Sydney (latitude 33.86°S and longitude 151.21°E) which is oriented north, fully exposed to solar insolation and has a floor area of 201.2 m². Both the walls and the flat roof of the simulated houses are comprised of the same structural insulated panels with R-value of 6.25. It is also assumed that all sides of the houses are equipped with double-glazed windows to the outside environment with areas of 15 m² and 7 m² on the North and the South sides, and 4 m² on the East/West sides, respectively. Further information regarding the constructional elements of the building units can be found in [44]. Different kinds of distributed heat and electricity generation units as well as schedulable tasks/loads are also considered for the mentioned integrated buildings and microgrid system. The specifications of these units are summarized in Table 1.

Ten sets of home energy profile data, representing the hourly household electricity demands and hot water usages during weekends and weekdays, were also generated as shown in Fig. 7. Other parameters such as meteorological information (as shown in Fig. 8) and electricity prices for the examined location are adopted from [45,46], respectively.

To examine the validity, effectiveness and applicability of the proposed energy monitoring and optimization system, several scenarios in different time frames (i.e., weekdays and weekends), climate (i.e., hot and cold), pricing schemes (i.e., RTP, time of use (TOU) and flat rate (FR)), are considered. Moreover, different levels

<table>
<thead>
<tr>
<th>Task</th>
<th>( h_s )</th>
<th>( h_d ) (Weekday)</th>
<th>( h_d ) (Weekend)</th>
<th>( \Delta h )</th>
<th>( P_s ) (kW)</th>
<th>( \omega )</th>
</tr>
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<tr>
<td>WMN</td>
<td>S*: 07:00</td>
<td>08:00</td>
<td>13:00</td>
<td>2</td>
<td>0.50</td>
<td>1</td>
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<tr>
<td></td>
<td>E**: 21:00</td>
<td>14:00</td>
<td>19:00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DWR</td>
<td>S*: 09:00</td>
<td>14:00</td>
<td>17:00</td>
<td>2</td>
<td>0.70</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>E*: 22:00</td>
<td>18:00</td>
<td>21:00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DRY</td>
<td>S*: 09:00</td>
<td>11:00</td>
<td>16:00</td>
<td>1</td>
<td>1.80</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>E*: 21:00</td>
<td>17:00</td>
<td>21:00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IRN</td>
<td>S*: 01:00</td>
<td>05:00</td>
<td>08:00</td>
<td>1</td>
<td>1.10</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>E*: 13:00</td>
<td>07:00</td>
<td>11:00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VCL</td>
<td>S*: 08:00</td>
<td>09:00</td>
<td>15:00</td>
<td>1</td>
<td>0.65</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>E*: 20:00</td>
<td>12:00</td>
<td>19:00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MWV</td>
<td>S*: 08:00</td>
<td>11:00</td>
<td>13:00</td>
<td>1</td>
<td>0.90</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>E*: 19:00</td>
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<td>16:00</td>
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<td></td>
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</tr>
<tr>
<td>RCR</td>
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<td>16:00</td>
<td>2</td>
<td>0.30</td>
<td>3</td>
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<tr>
<td></td>
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<td>19:00</td>
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<tr>
<td>ELK</td>
<td>S*: 04:00</td>
<td>06:00</td>
<td>08:00</td>
<td>1</td>
<td>1.00</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>E*: 12:00</td>
<td>07:00</td>
<td>10:00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOS</td>
<td>S*: 01:00</td>
<td>06:00</td>
<td>07:00</td>
<td>1</td>
<td>0.80</td>
<td>3</td>
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<tr>
<td></td>
<td>E*: 10:00</td>
<td>08:00</td>
<td>09:00</td>
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</tbody>
</table>

S*: Start Time.
E**: End time.
of intelligence for BMAs (as key players in the proposed agent-based energy management process) are studied as follows: Smart BMA: it not only aims at reducing energy consumption cost, but also ensuring optimal task scheduling and thermal comfort zone for inhabitants, Normal BMA: it manages the tasks in a cost-effective way under different pricing schemes; keeps the thermal comfort zone, however does not consider user’s preferences, Naïve BMA: it neither considers energy cost nor the user’s convenience level, but maintains the house within the comfortable temperature range.

The simulation platform is implemented in JAVA. Other third-party software packages such as MATLAB and GAMS are incorporated as computation engines for estimation, learning and optimization tasks. Moreover, to facilitate the development of an agent-based environment in compliance with the FIPA specifications, Java agent development framework (JADE) is utilized.

Simulation results in terms of total operation cost of the integrated buildings and microgrid system (TOC), average users’ convenience and thermal comfort rates (UCR and TCR), and the hybrid index (Mobj) as defined in (29) under different case studies are shown in Fig. 9. The interactive process among agents during the course of scenarios is also presented in Fig. 10.

\[
Mobj = \frac{TOC}{(Q SL_{max} CL_{max}) + \sum_{i=1}^{n} (\psi_{i1} TSC_i + \psi_{i2} TC_i)}
\]

It is clearly observed from the simulation results that the proposed EMS architecture which benefits from smart BMAs has superior performance in terms of Mobj index compared to naïve and normal approaches averaged over all working conditions. The results also imply that using smart BMAs not only save energy in buildings, but also assure desired comfort levels for inhabitants. From an economic viewpoint, the smart and normal BMAs make significant energy savings, however the naïve one fails to do so. On the other hand, the performance of the mentioned BMAs are quite competitive to each other in keeping a thermal comfort zone (regarding the TCR index); however, the normal BMA fails to fully satisfy the user’s task scheduling needs in terms of the UCR index.

Apart from the BMA’s intelligence, different weather conditions, time frames and pricing schemes could affect the EMS behavior. As can be seen in Fig. 11, for example, in a hot weather condition the cooling load of a building increases further mainly due to the sun’s direct and indirect effects (i.e., \( Q_{si} \) heat flow), which in turn necessitates further operation of cooling systems to fulfill user’s needs. The same trends can be observed in different time frames. As an example, during the weekends in a hot summer, cooling loads of the buildings might go higher compared to the ones in weekdays because of the excessive heat generated by the residents (\( Q_{occ} \)), lights and appliances (\( Q_{etc} \)) and impose more cost and less comfort to the occupants. Simulation results in this case for a typical household within our study show that \( Q_{occ} \) contributes up to 38% in internal heat gain of the building (\( Q_{ihg} \)) while the rest is made by \( Q_{etc} \) (see Fig. 12). The running costs of the residential microgrid can also be changed under different pricing schemes. As an illustration, by using RTP in a given weekday of a cold winter, the energy consumption cost of the community reduced around 5% and 13% compared to ones with TOU and FR schemes, respectively.

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Fig. 14. Coordinated system-level energy management and lower-level supply/demand side control.
With respect to the proposed MAS structure, three kinds of interactions among agents can be observed. The first type is a peer-to-peer interaction which is formed at the beginning of a new conversation when each agent within the platform registers itself to the DF and receives a valid identifier (AID) for future talks (message lines 2–12 in Fig. 10). This process follows by a set of communications that enables DF to update each node with the information about other agents’ services and corresponding AIDs (message lines 13–27, in Fig. 10). The second type is a hierarchical interaction within which a set of conversations is triggered based on a predefined scheme. For example, first CCA gets the available power output information from RESAs (message lines 28–37) and sends the related information to the distributed BMAs (message line 45). Then each BMA determines the optimal energy management solution for its related building unit based on the gathered data and other local information (message lines 46–48). Thereafter, the amount of power exchange with the grid is reported to the CCA (message line 49). Considering all the power exchanges with the local utility, CCA (in cooperation with the BBA) dispatches the centralized battery bank optimally based on the microgrid residual demand and electricity price in real-time (message lines 50–54). The third type of interaction can be realized in case of a faulty condition. If the master main container suddenly fails (e.g., main container #1 on host #1 is killed during a hierarchical interaction), it can be observed, that the MCRS/ANS services detect the change to the main container ring and keep the address list of all platform nodes up to date (message lines 37–45). AMS and DF agents are automatically recreated on a back-up main container (e.g., main container #2 on another host) and the proposed MAS-based EMS remains fully operational.

To get better insight into the coordinated energy and comfort management process, simulation results for optimal scheduling of household devices for a given building unit in a hot weekday under RTP scheme are also shown in Fig. 13. It is understood from Fig. 13 that during early hours of the day when RTP is relatively low, a major part of the residential load is supplied by the power utility; and the charging of the local battery is done with lower costs. Conversely, during the peak demand hours when RTP gets higher spikes, in-home units including the m-CHP and the battery, generate more electricity not only to meet the load economically, but also to make profits from selling energy to the utility. Besides, optimal scheduling of household appliances (e.g., washing-machine (WMN), dishwasher (DWR), tumble-dyer (DRY), Iron (IRN), vacuum-cleaner (VCL), microwave (MWV), rice-cooker (RCR), electric-kettle (EKL), and toaster (TOS)) is done effectively regarding to associated operational constraints and user’s preferences shown in Table 2. It is worthy to mention that a practical solution to implement such a cost-effective and comfort-aware strategy in a building unit lies on the use of fully-featured automation/energy management systems that benefit from several communication domains, including the smart meter domain (AMI), the internet domain and home area network (HAN). Moreover, it is of high significance to well design and set up lower-level controllers at supply/demand sides in order to meet the system’s stability and hard real-time system’s constraints. In other words, coordinated system-level energy management and lower-level supply/demand side control such as one shown in Fig. 14 is the true architecture that is needed in reality for the safe and optimal operation of an IES. In this architecture, the leading actor is the energy management system that manages the operation of domestic energy-related production (e.g., controllable DG units) and consumption units (e.g., schedulable household devices) optimally and provides required information such as set points and reference signals for local controllers. Within this structure, the inner-loop control at lower-level control layer aims at regulating the output power of the DG unit by using typical proportional integral (PI) controllers [47]. Primary control loop can also be separately
designed to generate appropriate reference current signals based on the received set-points from the home automation/EMS system.

It was mentioned earlier that BBA is responsible for real-time operation management of the centralized battery bank with regard to the system state space at each decision period. In this frame, BBA's perceptual domain is a bounded three-dimensional space within which the agent's action is discretized into 21 distinct categories with a step granularity of 5%. Moreover, the learning rate of the agent in both BRL algorithms is set to 0.9 initially and reduced gradually to 0.1 during the learning phase. All the choices on parameters are made based on the system size as well as the trade-off between agent’s training time and the level of precision. In this regard, Fig. 15 shows the performance of the proposed approach (BRL) in comparison with a dual-iterative Q-learning (D-I QL) method proposed in [48] and a time-based reinforcement learning (TRL) method proposed in [49,50] in terms of the achieved average reward, learning rate and distribution of learned components during the first and the second learning phases. In this comparative study, we assume that the reward functions, the structures of the actions and critic networks, which implement the D-I QL and TRL algorithms, be the same as those in the proposed BRL.

As the figure shows, our proposed method demonstrates faster learning and higher rewards during the stages of learning which is quite important in practical applications. As an example, BRL learning is achieved during the first phase in 162 episodes compared to 217 in case of D-I QL and 253 in case of TRL. The second learning phase is also completed in 103 episodes for BRL while this achieved after 158 and 209 episodes for D-I QL and TRL, respectively. In a like manner, the average reward that BRL could get at the end of the first learning phase is 7.2% and 13.4% higher than those of D-I QL and TRL, respectively. Similar trend exists for the second learning phase where BRL could collect more rewards than the other methods (nearly 7% and 16% more rewards compared to D-I QL and TRL, respectively). Also, the distribution of the learned components shows that the proposed algorithm controls the density of the components properly. When the optimal actions are the same, fewer components are generated but more are produced once a wide exploration is intended. This adaptive generation of components is the main reason for faster convergence and for gaining more rewards during early stages of learning.

Optimal operation of the centralized battery bank in a typical test day is shown in Fig. 16. In the same figure, real-time electricity prices and the hourly net energy content of the microgrid ($P_r$) which is calculated based on the difference between scheduled powers and real measurements in the examined day are also plotted. Simulation results indicate that any unexpected load change during the early hours of the day is mainly compensated by the utility due to the lower electricity prices compared to the marginal cost of operation for the battery bank (which is considered 5.8¢/kWh), while different trend can be observed in other hours of the day. As an example, in the midday battery bank absorbs more energy not only to increase the SOC level in an economic way but also to provide back-up energy for the peak hours. Such a behavior is clearly understood during 16:00–19:00 when BBA decides to further increase the back-up energy by taking the second action. By doing so, the running cost of the microgrid decreases around 5% at the end of the day which is equal to 390¢. It is noteworthy that in the previous calculations the value of back-up power has not been taken into account.

5. Conclusion

In this paper, a fault-tolerant ontology-driven multi-agent control structure was proposed for coordinated energy and comfort management in integrated buildings and microgrid system. Within the mentioned structure, several cooperative agents were introduced and trained in a way to reach a global coordination, meet the system’s objectives and satisfy related constraints. The optimal control and management problem in the mentioned system was also mathematically formulated as a multi-objective optimization problem and solved under different operating conditions. It was demonstrated through a number of simulations that the proposed architecture has the capability to reduce system’s operation cost and to ensure user’s needs under different weather conditions, time frames and pricing schemes. It was also observed that through an agent-based control of storage options it is possible to mitigate the effects of uncertain parameters in the environment and guarantee the secure and optimal operation of the system.
References


