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Smart grid and smart building inter-operation using agent-based particle swarm optimization

L.A. Hurtado*, P.H. Nguyen, W.L. Kling

Department of Electrical Engineering, Eindhoven University of Technology, The Netherlands

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ABSTRACT

Future power systems require a change from a *"vertical"* to a *"horizontal"* structure, in which the customer plays a central role. As buildings represent a substantial aggregation of energy consumption, the intertwined operation of the future power grid and the built environment is crucial to achieve energy efficiency and sustainable goals. This transition towards a so-called smart grid (SG) requires advanced building energy management systems (BEMS) to cope with the highly complex interaction between two environments. This paper proposes an agent-based approach to optimize the inter-operation of the SG–BEMS framework. Furthermore a computational intelligence technique, i.e. Particle Swarm Optimization (PSO), is used to maximize both comfort and energy efficiency. Numerical results from an integrated simulation show that the operation of the building can be dynamically changed to support the voltage control of the local power grid, without jeopardizing the building main function, i.e. comfort provision.

1. Introduction

Being responsible for about one-third of the energy consumed in cities [1], commercial and industrial buildings play a central role in the emerging energy supply chain by offering their flexibility of energy use. Through Demand Response (DR) programs, operation of buildings with a proper Energy Management System (BEMS) can improve the performance of electric power grid, reduce investment costs, and increase Renewable Energy Sources (RES) penetration, without jeopardizing the demand side activities. However, there is a lack of functional interaction between Smart Grid and Building Energy Management System (SG–BEMS) to fully invoke flexibility from the built environment to achieve energy efficiency and sustainability goals.

Several attempts have been made to enable the inter-operation of these highly complex systems. However, buildings and the power grid have been treated as independent and unique control systems, operated based on their own information while oversimplifying interaction from the other. For instance, a model for load shifting has been developed from the SG's perspective with a DR solution while the building thermal capacity is simplified [2]. On the contrary, a model for the smart operation of Heat, Ventilation and Air Conditioning (HVAC) system is presented to optimize the system's energy efficiency with an abstraction of the power grid [3]. Thus, there is a clear need to have a comprehensive integration framework to fully address a wide range of variables in different physical environments, on all time scales of the inter-operation of the SG–BEMS [4].

To cope with the complexity of this integration framework, a shift is evident from a centralized energy management systems to a decentralized structure with the introduction of computational and distributed intelligence. By dividing the general control problem into a number of smaller control areas, distributed intelligence reduces the control burden, while improving the flexibility and efficiency of the control system [5]. For instance, in [6], a distributed control strategy is used to integrate Distributed Energy Resources (DERs) in the built environment. In [7], a distributed control methodology to optimize exchanged power flow and energy among smart buildings by means of the multi-traveling salesmen problem optimization method is proposed. This tendency based on a bottom-up architecture can invoke flexibility from different levels of the built environment towards the SG. Throughout the literature, one of the most popular decentralized control approaches is based on Multi-Agent Systems (MAS), which is now being applied in a wide range of applications in the power systems, e.g. condition monitoring, system restoration, market simulation, network control and automation [8,9]. MAS is also widely studied in the area of building automation, building energy management, and building control and operation [10–14].

* Correspondence to: Den Dolech 2, 5612AZ Eindhoven, The Netherlands. Tel.: +31 40 247 3297; fax: +31 040 2450735.
E-mail addresses: l.a.hurtado.munoz@tue.nl (L.A. Hurtado), p.nguyen.hong@tue.nl (P.H. Nguyen), w.l.kling@tue.nl (W.L. Kling).

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Furthermore, advanced optimization methods are required to guarantee a global optimal solution, maximizing the welfare of both the building and the power grid. For this decision-making step, the research trend seems to be moving away from deterministic gradient based optimization methods, e.g. Newton–Raphson, to stochastic ones, e.g. Particle Swarm Optimization (PSO), along with the increasing availability of data measurements. Currently, stochastic optimization methods such as PSO have been utilized in a wide range of power grid operation and control applications [15–18]. However, the application of advanced optimization techniques on the customers side to reveal their benefits in the smart grid environment is still limited [19]. We researched on making use of the building thermal buffers and storage systems to dynamically adapt with the power grid requirements, without significantly affecting the building's comfort levels [20].

This paper proposes a SG–BEMS integration framework including a MAS based control scheme to optimize both comfort and energy efficiency. Developed hierarchical agent structure will allow lower level agents abstracting the information of their immediate environment into the form of single value information blocks for the higher level agents. In this way, data management complexity is reduced at each agent level, in order to exploit the demand flexibility potential within the built environment to support the power grid with voltage control service. A PSO optimizer is proposed to improve the MAS's capability in exploiting the building's flexibility for the SG. Finally, the performance of the MAS based SG–BEMS platform is tested in a Low Voltage (LV) test feeder, and the system's potential for voltage control is demonstrated.

The remainder of this paper is divided into five sections. Section 2 presents the SG–BEMS framework, as well as the problem description for the integrated system. Section 3 formulates the optimization problem and introduces PSO as a suitable optimization technique. Section 4 describes the implementation of the distributed control methodology. Section 5 describes the test systems used and the simulation results obtained. Finally, Section 6 summarizes and presents conclusions from this study.

2. SG–BEMS framework

Development of an intertwined operation of the SG and BEMS needs a common framework to address critical involved control blocks for both two domains. This SG–BEMS framework is based on a reference of the Smart Grid Architecture Model (SGAM) [21], with an extension onto the building consumer domain, as shown in Fig. 1. Exchanging information within and between the two domains allows each system to operate towards its own goal, while reducing unnecessary information exchange. However, this interoperation framework requires a common ontology, to allow the exchanged messages to be understandable by both domains.

Both the power grid, i.e. the distribution grid, and building domains are formed by four different layers in this framework [21]. The "Operation" layer, which is linked directly to the SG–BEMS interaction, hosts the power system control, e.g. Distribution Management Systems (DMS), the Energy Management Systems (EMS), and the building controls, e.g. the centralized management systems (CMS), zone management system (ZMS), and the device management system (dMS). These systems have the main purpose of monitoring and controlling the distribution system equipment and the building equipment based on the information available. At the "Field" layer, the equipment to monitor, control and protect the power system and the building installation can be found. Such equipment are intelligent devices with communication enabled controller to monitor and control the automated devices.

In the following subsections, the two domains in the SG–BEMS framework will be described in more detail: their context, ultimate goals for each system operation, as well as their constraints.

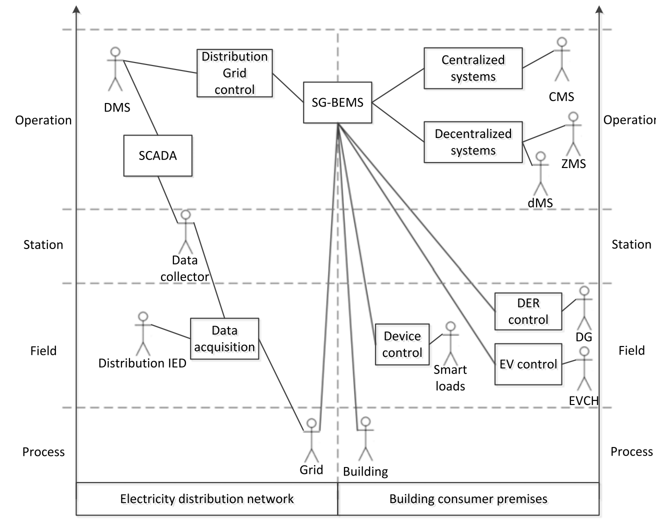

Fig. 1. SG–BEMS framework domains.

2.1. Distribution grid domain

The electric distribution grid is operated by the distribution system operator. Its main objective is to maintain reliable power supply to the customers. As the proliferation of RES and DER becomes larger, their intermittent and uncontrollable nature causes not only system balance issues, but also problems for the reliable operation of the distribution grid. Conventionally, the functioning block of distribution grid control must take place to support (a) prevention of overloading of assets; (b) regulation of voltage magnitude; (c) maintenance of the power quality and security.

Among them, voltage regulation is one of the biggest concerns of distribution system operators. Due to the high number and diversity of loads, voltage variations are higher in the LV networks than in the medium or high voltage networks. These voltage variations, Δu [$p.u.$], over a network feeder are formulated as a function of the active power, $P[W]$, the reactive power, $Q[var]$, and the line impedance $Z[\Omega] = R + jX$, as described by the following equation:

$$\Delta u = \frac{(P \cdot R + Q \cdot X) + j(P \cdot X + Q \cdot R)}{u_{base}}, \tag{1}$$

where u_{base} is the base or reference voltage, e.g. $u_{base} = 240$ V for LV networks.

As shown in the equation, the voltage variation depends not only on the power flow in the feeder but also on the network impedance. The X/R ratio will define whether it is the reactive or active power which has a greater impact on the voltage level. In the LV network, the impedance is mostly resistive, which means that active power control has a bigger impact on the voltage variations along the feeder.

2.2. Building consumer domain

The two main aspects of the building consumer domain are comfort management and energy consumption. In buildings, the central objective is to provide the occupants with a comfortable environment. About 50% of the total electrical energy consumed is used for comfort management [22]. This strong correlation is crucial to reveal flexibility from the built environment to offer to the SG.

The following subsections describe more in detail these two aspects of the building consumer domain.

2.2.1. Comfort formulation

Comfort is a complex and subjective human perception, which varies according to each person and each particular environmental context. Traditionally, it is controlled by a combination of a centralized management system and human interventions, e.g. lights in local zones. Different standards have been developed to guarantee comfort levels. For instance, *ASHRAE*55 and *ISO*7730, for thermal comfort; *ISO*8995 − 1, for visual comfort; and *ASHRAE*62.1, for indoor air quality.

As a building consists of a high number of components differing in characteristics and operation times, the building is usually divided into multiple zones, e.g. office rooms, common areas, halls, floors, etc. Nonetheless, each zone has a particular energy demand and control variables.

In this paper, comfort is conceptualized as a function of thermal comfort (i.e. temperature) [11] and extended to air quality (i.e. humidity).[1] Both are modeled through a Gaussian function representing the degree of satisfaction, with the average comfort value as the mean (μ) and a standard deviation (σ). This guarantees the operation of the system in a range instead of a single value, which is closer to the subjective nature of comfort perception, as expressed in the following equation:

$$comf = \underbrace{(\omega) e^{\left[\frac{-(T-\mu_T)^2}{2\sigma_T^2}\right]}}_{\text{Thermal comfort}} + \underbrace{(1-\omega) e^{\left[\frac{-(RH-\mu_{RH})^2}{2\sigma_{RH}^2}\right]}}_{\text{Air quality comfort}}, \tag{2}$$

where ω is a weight factor, T is the temperature, μ_T is the mean temperature, σ_T is the standard deviation for the thermal comfort, RH is the relative humidity, μ_{RH} is the mean humidity, and σ_{RH} is the standard deviation for air quality comfort.

The first part in (2) represents the thermal comfort, i.e. the change in time of the temperature in a zone. This change can be modeled applying the energy conservation principle, as shown in the next equation:

$$\frac{dT(t)}{dt} = \frac{1}{M\, c_p} \left(Q_{in} + Q_{HVAC} + Q_{heater} + Q_{loss}\right), \tag{3}$$

where, M is mass of the volume of air; c_p is the specific heat capacity of air; Q_{in} represents the internal gains due to the heat generation rate per person[2]; Q_{HVAC} represents the heat contribution by the HVAC system operation as a function of the volumetric supply air flow rate, i.e. $\dot{v}_s$ [23]. Due to the high costs involved in supplying the heat demand only by an air system, i.e. the HVAC system, a heat pump is added as the main heating source in this research. Therefore, Q_{heater} represents the heat contribution of the heat pump used as a function of the water flow, i.e. $\dot{v}_{s,h}$. Finally, Q_{loss} is used to model the heat losses through the envelope of the zone [24].

The second part in (2) represents the zone's relative humidity. From the energy conservation principle, the dynamic model of change of enthalpy in the air is given as follows [23]:

$$\frac{dRh(t)}{dt} = \frac{1}{M} \left(\dot{v}_s \rho_a \left(RH_s - RH\right) + M_o\right), \tag{4}$$

where, ρ_a the air density, RH_s is the supply air enthalpy, RH is the air enthalpy in the room, i.e. humidity ratio, and M_o is the Moisture load.

The CO_2 concentration levels are treated as a constraint of the system. Similarly to the dynamic model of temperature and humidity, the change in time of the CO_2 levels is given by [25]:

$$\frac{d\Phi(t)}{dt} = \frac{1}{V} \left(\dot{v}_s \left(\Phi_s - \Phi\right) + N\Phi_{gen}\right), \tag{5}$$

where V is the zone's air volume, Φ is the CO_2 concentration at time t, Φ_s is the CO_2 concentration in the supply air, and Φ_{gen} is the CO_2 production rate per person. The supply air's concentration is a function of the supply air flow and the return air flow $\dot{v}_r$, as follows:

$$\Phi_s = \frac{(\dot{v}_s - \dot{v}_r)\Phi_{out} + \dot{v}_r \Phi}{\dot{v}_s}. \tag{6}$$

2.2.2. Energy formulation

This paper categories energy consumption systems in the building into centralized and decentralized ones. Energy demand of a centralized system corresponds to the energy consumed by the comfort systems including the heat pump for heating purposes, E_{heater}, and the HVAC for air quality and supplementary heat, E_{HVAC}. Whereas, energy demand of a decentralized system corresponds to individual systems in local zones, E_i, e.g. lights and computers.

The total energy consumption of a building is expressed in the following equation:

$$E_{total} = \underbrace{E_{HVAC} + E_{heater}}_{\text{centralized}} + \underbrace{\sum_{i=1}^{N} E_i}_{\text{decentralized}}. \tag{7}$$

The energy consumed by a typical HVAC system is a function of the supplied air temperature and flow rate. In turn, air temperature and flow rates are functions of the individual systems that form the HVAC system as follows:

$$E_{HVAC} = E_{fan,s} + E_{fan,r} + E_{hcoil} + E_{ccoil}, \tag{8}$$

where, $E_{fan,s}$ and $E_{fan,r}$ are the energy consumed by the supply and return fans, which are proportional to $\dot{v}_s$ and $\dot{v}_r$ [26]. The energy consumed by the heating coil, i.e. E_{hcoil}, and the energy consumed by the cooling coil, i.e. E_{ccoil}, are a function of the air flow rates (supply and return), the difference in the indoor and outdoor temperatures, and their respective efficiencies.

The energy consumed by the heat pump is a function the required heat power and the coefficient of performance, *COP*, of the machine. The required heat is the energy used to compensate for the thermal losses, and it is proportional to the volumetric flow of water through the system, $\dot{v}_{s,h}$, the temperature of the supplied water, $T_{s,w}$, and the zone temperature, T_z. Finally, the *COP* describes the ratio between the useful heat produced and the work input.

$$E_{heater} = \frac{\dot{v}_{s,h} \rho_w c_{p,w} (T_{s,w} - T_z)}{COP}, \tag{9}$$

where, ρ_w is the water density and $c_{p,w}$ is the heat capacity of water.

3. Optimization problem formulation

The SG–BEMS framework involves multiple objectives which might be conflicting, i.e. comfort maximization and energy minimization, and a consideration to enable grid support services. The first objective relates to the problem described by (2), with $comf \in [0, 1]$. Thus, the maximization of comfort can be rewritten as the minimization of discomfort. The second objective is the minimization of the energy consumed in the building. In this work, we limit the energy optimization problem to the minimization of the energy consumed by the comfort systems. These two objective functions are represented by the following equations:

$$f_1(x) = discomf = 1 - comf, \tag{10}$$

$$f_2(x) = E_{total} = E_{HVAC} + E_{heater}, \tag{11}$$

where x is a solution vector formed by the thermal and air quality comfort control parameters, i.e. $\dot{v}_s$, $\dot{v}_{s,h}$ and $\dot{v}_r$.

[1] The carbon dioxide is considered as a constraint of the optimization problem.

[2] The solar gains are neglected in this work.

In order to support the grid without jeopardizing comfort provision, the SG–BEMS inter-operation needs to handle both optimization problems in (10) and (11) simultaneously under optimal conditions for the distribution network. Therefore, the optimization problem can be rewritten as follows:

Minimize

$$f(x) = (f_1(x), f_2(x)). \tag{12}$$

Subject to

$$\Phi_{CO_2}(t) \leq \Phi_{max} \tag{13}$$

$$comf \geq comf_{min} \tag{14}$$

$$u_{min} \leq u(t) \leq u_{max}, \tag{15}$$

where Φ_{CO_2} and Φ_{max} are CO_2 levels at instant t and at its maximum comfort, and $comf_{min}$ is the minimum comfort level acceptable. The first two constraints are used to not allow the comfort satisfaction fall out of the defined comfort ranges at all times. The last constraint aims to ensure that the voltage magnitude at the connection point stays within the allowed limits.

As the optimization objectives (10) and (11) are two different functions, it is a challenge to find a single optimal solution for the optimization problem in (12). Pareto-optimal solutions must be found to represent the best trade-off and/or the best compromise by using different approaches [27]. Here, the weighted aggregation method is used to aggregate all the objectives of the problem into a single one through a weighted combination. Thus, (12) can be rewritten as:

$$Wf_1(x) + (1 - W)\sigma f_2(x), \tag{16}$$

where W is a non-negative weight and σ is a normalization factor that allows the two objectives to be treated equally. The main advantage of this method is that it allows using a single objective algorithm and turning the weight W to adjust dynamically the important role of either $f_1(x)$ or $f_2(x)$. However, it requires the algorithm to be applied repeatedly to find the desirable number of non-dominated solutions.

As this problem includes both non-linear and linear functions, we used PSO as a suitable technique for tackling the optimization problem, as it is known to solve large-scale non-linear optimization problems. Additionally, it has a faster convergence than traditional methods because of being a free-gradient optimization method. Compared to more recent computational intelligence-based methods, e.g. genetic algorithm, PSO is also easier to implement, with more effective memory usage and fewer parameters to adjust [15].

3.1. Particle swarm optimization

PSO has been proven to be an alternative solution to deal with the non-linear and non-stationary systems with noise and uncertainties. PSO is a stochastic-based optimization method that has its roots in artificial life, social psychology, and computer science [28]. It uses a population of i particles to search for suitable solutions over a hyperspace, where i is a positive integer. In each iteration k, the particles find a new solution $x_i^{k+1} = \{\dot{v}_s, \dot{v}_r, \dot{v}_{s,h}\}$, by stochastically updating their flying trajectories, i.e. position x_i and velocity v_i. This update process is based on the historical data available from the swarm. Every time, the best solution is found for each particle, i.e. p_i^k, and a new leader, the best particle of the swarm, is selected, i.e. p_g^k. This is done until either certain conditions are met or the maximum number of iterations, i.e. k_{max}, has been reached. This process is described by the following rules [15,28]:

$$v_i^{k+1} = uv_i^k + \phi_1 rand_1 \cdot (p_i^k - x_i^k) + \phi_2 rand_2 \cdot (p_g^k + x_i^k), \tag{17}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}, \tag{18}$$

$$u = u_{max} - \frac{u_{max} - u_{min}}{k_{max}} k \tag{19}$$

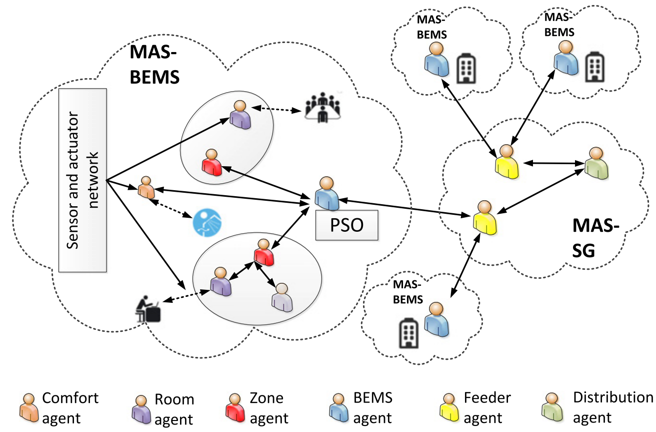

Fig. 2. SG–BEMS agent architecture diagram.

where, u is an inertia weight used to enhance the searching process by controlling the exploration of the search space,[3] and described by (19); ϕ_1 and ϕ_2 are two positive learning constants, which represent the learning ability to fly towards the particle's best position and to the swarm leader, respectively[4]; $rand_1$ and $rand_2$ are two random numbers with uniform distribution in the range [01]; p_i^k is the best position the particle i has achieved based on its own experience; p_g^k is the global best position based on overall swarm's experience; u_{max} and u_{min} are the maximum and minimum inertia values, respectively.

4. SG–BEMS agent structure

As aforementioned, the SG–BEMS inter-operation includes centralized and decentralized energy management systems with highly complex tasks. To deal with this challenge, computational and distributed intelligence has been highlighted as a suitable way to monitor and control the inter-operating energy systems, while improving reliability, flexibility and system efficiency. One of the most popular decentralized control approaches is agent based control, which is now being applied in a wide range of applications in the power systems and building automation. The agent's capability to tackle complex problems, based on cooperation, coordination and negotiation, has been revealed in different research works, e.g. in [8,29].

In this paper, a dual agent-based control system has been developed to address the inter-operation of both the distribution grid and the building. This platform includes two hierarchical systems: MAS-SG and MAS-BEMS, as illustrated in Fig. 2.

The MAS-SG system is represented by "feeder" agents to monitor continuously the voltage profile of the LV feeder, and by a "distribution" agent to monitor and control the distribution network operation. Based on the current status of the voltage, the feeder agent can create a request of support for the different flexible loads, i.e. smart buildings. Moreover, based on the general distribution grid information, the distribution agent can create request of support for the different feeder agents.

The MAS-BEMS is formed by three hierarchical management levels according to the building structure:

3 A higher value in the initial steps, e.g. 0.9, allows the free movement of the particles. Once the optimal region is found, this value can be decreased, e.g. 0.4, to narrow the search.

4 By changing these parameters, the responsiveness of the particle is controlled. By increasing these constants, the oscillations around the optimal point increase becoming unstable for values higher than 2.

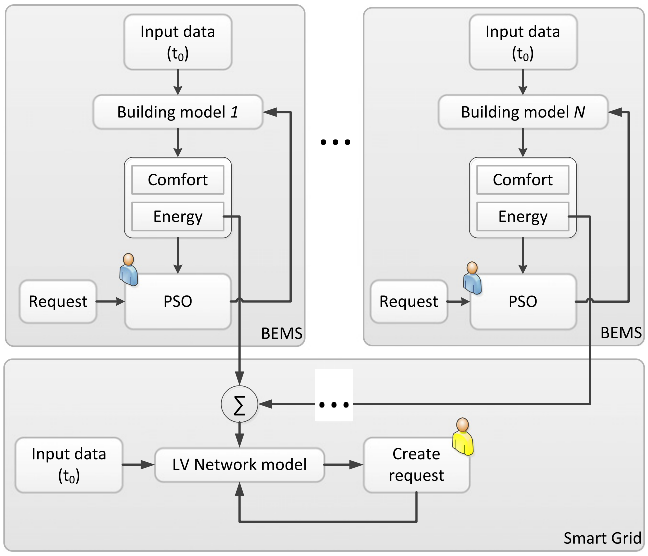

Fig. 3. Voltage support procedure flow chart.

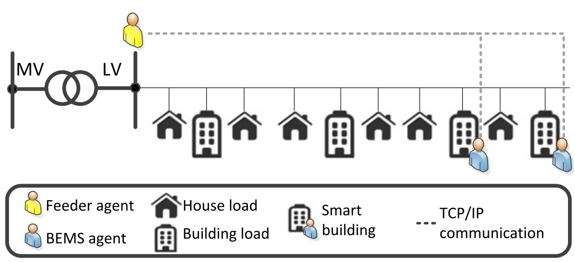

Fig. 4. LV test feeder diagram.

- BEMS agent: It has the highest level in BEMS and takes charge of solving the optimization problem while being the link to the distribution network. This agent is able to accept and prioritize requests made by agents and operators outside the building premises, e.g. the "feeder" agent. Based on the information received, it tunes up the PSO which defines the control variable values for the comfort systems.
- Zone agent: It is responsible for the floor operation and the rooms within the floor. The zone agent acts as an aggregator of the room information, monitoring the local zone and informing BEMS agent if the current status is within the parameters or not.
- Room agent: It is placed at local zone, i.e. room level, and take charge of the operation of the room within the building. It is responsible for gathering information to assess the comfort levels and determine the building flexibility.
- Comfort agent: It is located at the same level with the zone agent but aims for centralized systems, i.e. heat pump and HVAC. These systems are usually comfort systems designed to operate for larger parts of the building or even for the whole building,

The proposed dual agent-based platform tries to control the voltage variation in a feeder, by influencing the active power demand of the smart building. However, depending on the building comfort status, the MAS-BEMS has autonomy to choose whether it modifies its behavior or not. If so, this is done by changing the weight value, W, used in the PSO, see (16). The PSO and its parameters are then deployed by the BEMS agent based on the information gathered from the zone agents and the requests made from the feeder agent.

Although the agent structure is formed in a hierarchical way, each agent has the autonomy to operate the local environment. For instance, the zone agents in the MAS-BEMs platform have the autonomy to switch off local energy systems, e.g. lights, based on occupancy information. Furthermore, the comfort level is controlled by the comfort agent for the whole building but the zone agents have still the autonomy to correct deviation through the operation of heating and ventilation valves. The advantages of this hierarchical MAS system are about minimizing communication effort by sharing relevant information to interested agents and scalability of the structure.

5. Modeling and simulation

5.1. Modeling a test system

A test system has been developed including a distribution grid, household loads, building's offices loads, as well as agent-based control systems. Fig. 3 shows a general description of the voltage support methodology. At every time step, the comfort levels, energy demand, and voltage at the point of connection is measured at each smart building. Based on the measured voltage, the MAS-SG system creates a request in order to improve the voltage profile of the feeder. Simultaneously, each BEMS agent runs a PSO to obtain the optimal operation parameters of the comfort systems, i.e. $\dot{v}_s$, $\dot{v}_{s,h}$ and $\dot{v}_r$. This optimization step is based on the current building's comfort value and on the feeder agent's request. The resulting parameters give the optimal relation between energy demand and comfort for the next time step, in such a way that the voltage profile is improved at the building's point of connection. The following subsections describe in detail about each component model of the test system.

5.1.1. Modeling a distribution grid model

Modeling of the distribution grid and the building's offices is implemented in Matlab/Simulink. The LV distribution feeder is modeled by means of the SimPowerSystem toolbox. It represents a three-phase balanced system formed by a total of ten loads. These loads are equally distributed over the length of 1000 m, as shown in Fig. 4, with an X/R ratio of 0.0423. Among these ten loads, eight loads correspond to non-flexible loads and are implemented using the load profiles displayed in Fig. 5. Six of these eight loads are household loads. Their load profile is based on measured data at the beginning point of one feeder of a typical Dutch LV network with 74 customers and a length of about 300 m. The other two non-flexible loads correspond to a typical Dutch office, which is based on measured data at the point of connection of a typical 3-floor office building.

The remaining two loads represent two double-floor smart buildings, controlled by a MAS-BEMS. Using the Simscape toolbox, the physical modeling of the thermal behavior of the buildings is implemented by means of convection and conduction heat transfer mechanisms. This model provides the energy needs for comfort and energy demand, i.e. heat losses compensation. The HVAC, heat pump and electrical devices are implemented in Matlab/Simulink according to the formulations described in Sections 2.2.1 and 2.2.2. For each building, PSO is used to determine the optimal operation parameters, i.e. $\dot{v}_s$, $\dot{v}_r$, $\dot{v}_{s,h}$, of the comfort systems, as described in Section 3.1.

5.1.2. Modeling dual agent-based control system

The agent-based control system is implemented in JADE, a platform that provides a java environment for the behavior of agents. A TCP/IP communication is established between the two software platforms, with Matlab/Simulink as the server client. The system response is simulated in seconds, whereas the MAS based SG–BEMS and the optimization is done in 15 min intervals.[5] The

[5] This interval corresponds to the PTU, (Program Time Unit) period adopted by the Dutch transmission system operator TenneT, for scheduling and settlement of the electricity market participants. However, it can be extended to different time horizons.

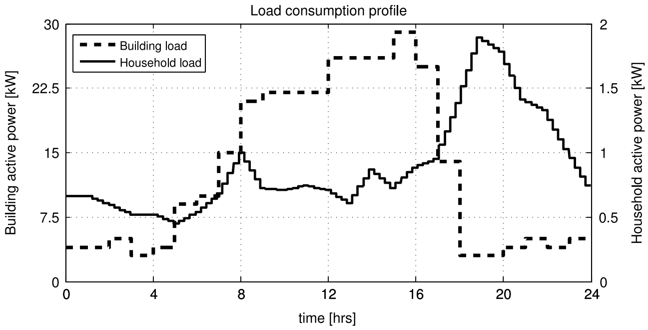

Fig. 5. Non-flexible load profiles.

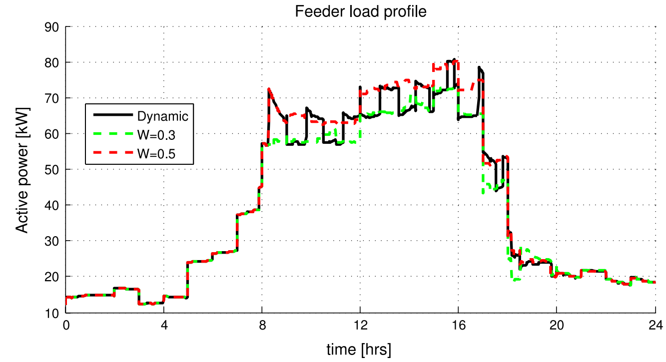

Fig. 6. Total load demand of the feeder.

environment parameters, i.e. temperature, relative humidity, CO_2 concentration, occupancy, power consumption, of each zone of the building; and the positive sequence voltage at three different locations[6] of the feeder are exchanged between the Matlab/Simulink model and the JADE agents.

Between the JADE agents, multiple ACL (Agent Communication Language) messages are exchanged. These messages contain the necessary information for the zone, BEMS, and feeder agents to take the adequate control decisions, and for the zone and comfort agents to control the environment. For this particular case of study, each building is formed by 5 different zones and 2 centralized comfort systems. In total there are 33 agents monitoring each smart building. This means that in total in the SG–BEMS platform, there are 67 agents interacting every 900 s.

5.1.3. Modeling occupancy level

As mentioned, a building's main function is comfort management with the main decision variable related to the occupancy. During off-work times, the room agents will shut down the electrical flexible loads if the occupancy level in that room is zero. Via the zone agent, information is forwarded to the BEMS agent to reduce the operation of the HVAC and heating systems, through communication with the comfort agents. As people are detected in any zone, the decision variables become the temperature, relative humidity, and CO_2 concentration levels, and the flexible loads are allowed to work.

Different occupancy profiles were used for each of the zones in the floor. Each zone has an average number of occupants with a random variation in time, as expressed in the following equation:

$$N = \begin{cases} 0 & \text{if } t_{out} \le t \le t_{in} \\ N_{av} + rand & \text{if } t_{in} < t < t_{out} \end{cases} \tag{20}$$

where, N is the number of people, N_{av} is the average number of occupants, *rand* represents a random variation in time, t_{in} the arrival time, randomly selected between 7 am and 9 am, and t_{out} the leaving time, also randomly selected between 4 pm and 7 pm.

Finally, the energy demand is also weather dependent. The models use measured weather data of a typical winter day in the Netherlands.

5.2. Simulation results

Simulations are run for a 24-h period with assessments for three different scenarios as follows:

- Bias scenario: Minimizing energy consumption has a higher priority in the building optimization problem, assuming "$W = 0.3$".
- Fair scenario: Comfort level and energy consumption are equally weighted in the building optimization, leading to "$W = 0.5$".
- Dynamic scenario: The building behavior is affected by the feeder agent's requests based on the voltage variations.

In the first two scenarios, the grid's requests are ignored and the MAS-BEMS platform operates only towards its own objectives. This aims to highlight the effects of the SG–BEMS inter-operation framework in the dynamic scenario. Furthermore, based on initial simulations, the acceptable voltage ranges are specified for the three voltage measuring points. For instance, at the first smart building's connection point the admissible range is 1 $p.u. \pm 2\%$, whereas at the second smart building connection point, the admissible range is 1 $p.u. \pm 3\%$.

Numerical results have been obtained from the simulation and will be discussed in each specific aspect as follows:

5.2.1. Energy consumption and comfort

Fig. 6 shows the total active power demand of the feeder for each scenario, including the non-flexible loads profile and the smart building power demand. The load profile in the dynamic scenario shows stepwise characteristics during the operating time of the buildings. This behavior is the result of the dynamic adjustment of the PSO weight, i.e. $\forall\, W \in [0.3\ 0.7]$, depending on the feeder agent requests. The fair scenario results in the highest energy consumption, while the bias one results in lowest energy demand but causing also lower comfort levels, as it will be discussed next.

Fig. 7 shows the load profile of the two smart buildings, while Fig. 8 shows the degree of comfort satisfaction in each building as described in (2). Different occupancy functions are used for each building, resulting in slightly different energy profiles obtained for the three scenarios defined. Relative comparison of three scenarios for building's energy consumptions is similar to the observation at the feeder level. Both buildings show similar demand and comfort profiles. While the fair scenario results in the highest comfort levels and the highest energy demand, the bias scenario results in the lowest comfort levels as well as the lowest energy demand. However, the dynamic scenario shows a fair comfort level, and energy demand bounded by the demand of the other two scenarios.

5.2.2. Impact on voltage levels

Fig. 9, Fig. 10, and Fig. 11 show the feeder's voltage profile over time for each scenario previously defined. As illustrated, during the time in which the buildings are empty the three profiles are quite similar. This is mainly because, while there are no occupants the PSO is giving energy a higher weight. However, during the operating time of the buildings, differences are appreciated between the three scenarios. Fig. 9 shows the operation of the building without offering grid support. It results in an optimal comfort profile as

6 These positions correspond to the beginning of the feeder and to each smart building connection point.

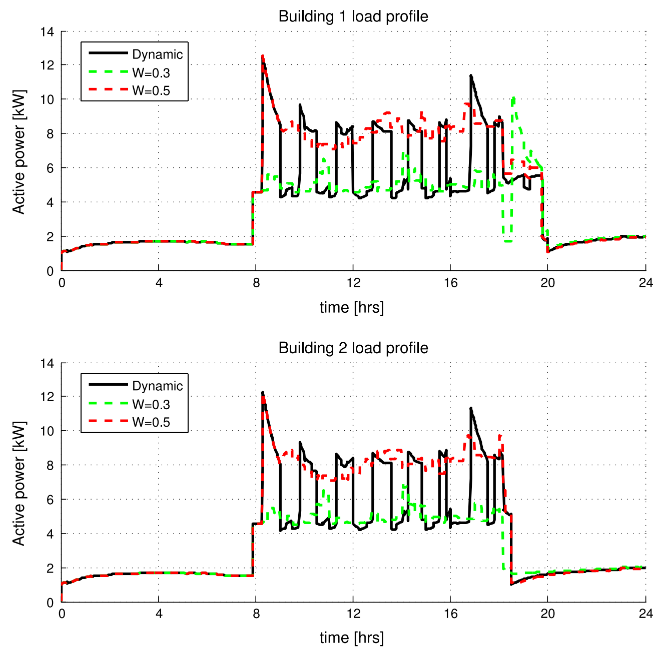

Fig. 7. Building energy demand.

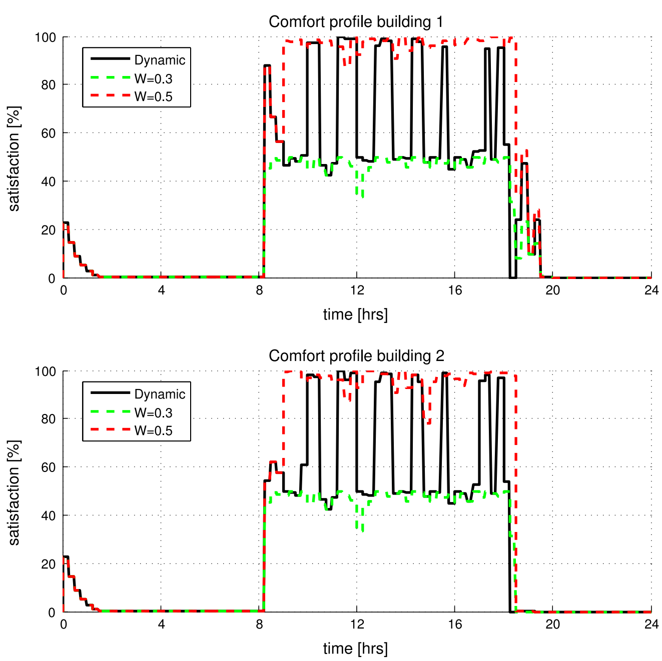

Fig. 8. Building comfort profiles.

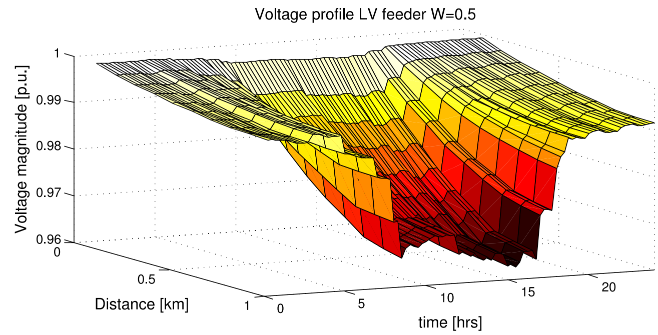

Fig. 9. LV feeder voltage profile for the fair scenario $W = 0.5$.

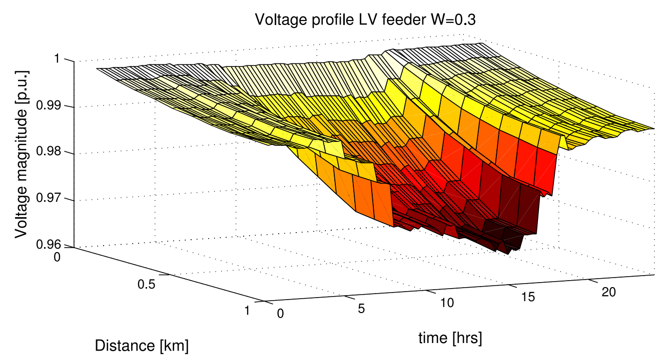

Fig. 10. LV feeder voltage profile for the bias scenario $W = 0.3$.

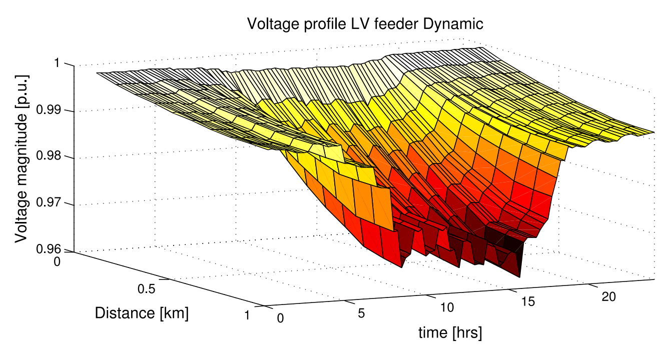

Fig. 11. LV feeder voltage profile with the SG–BEMS platform, i.e. dynamic scenario.

shown in Fig. 8. As comfort is not scarified, despite being efficient, it is the scenario with the higher energy consumption. This in turn means a lower voltage profile for the feeder. As expected, the bias scenario, Fig. 10, shows the highest voltage profile. However, Fig. 8 shows that this scenario also represents the worst comfort levels in the building, which makes it undesirable. Finally, Fig. 11, shows the operation of the SG–BEMS agent based system. This dynamic scenario shows a switching behavior in the voltage profile. Similar behavior is seen in Figs. 7 and 8. As the agent feeder detects the voltage going lower than specified it sends a request to the building. Depending on the comfort value, the building decides whether to accept the request or not. If so, the SG–BEMS changes the weight in the PSO block, resulting in a lower power demand. However, this also means a decrease in the satisfaction perception, as shown in Fig. 8. Despite the fact that this switching behavior might not be preferred over a steady voltage profile, in reality the switching will not happen all at the same moment in time, so the resulting voltage profile will be much smoother. Furthermore, in this case, the frequency of the variation is not sufficient to be considered a rapid voltage variation, and the change in magnitude is not big enough to be considered a slow voltage variation. Thus, not sufficient to create flicker problems, or problems in the operation of the consumer devices, and therefore admissible for network operation [30,31].

Fig. 12 shows a voltage swell scenario, during the time in which the building is no longer operating. As appreciated the voltage swell is decreased in a small amount by the action of a single building. Despite being a small improvement, this energy, through thermal or electrical storage, could be used to further enhance the building operation during the next day. As the control of more loads is combined into a single coordinated action, the support and flexibility offered to the distribution system could be significantly improved.

Finally, Fig. 13 shows the PSO results, i.e. $\dot{v}_s$, $\dot{v}_r$, $\dot{v}_{s,h}$, for the second building. As can be seen, the PSO adjusts the behavior of the comfort systems, by adjusting the required volumetric flow rates of the HVAC and heat pump. However, due to the stochastic nature of the PSO technique it cannot be ensured that the solution found

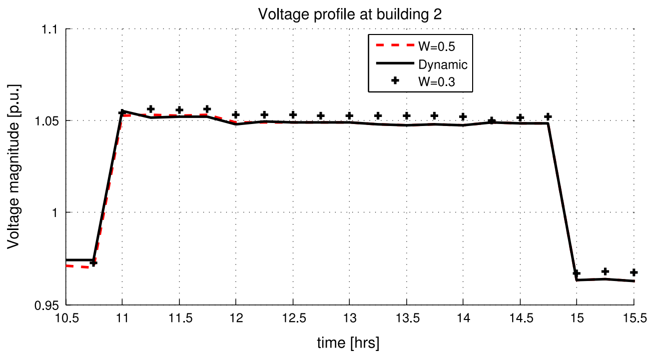

Fig. 12. Voltage magnitude at the end of the feeder during a voltage swell.

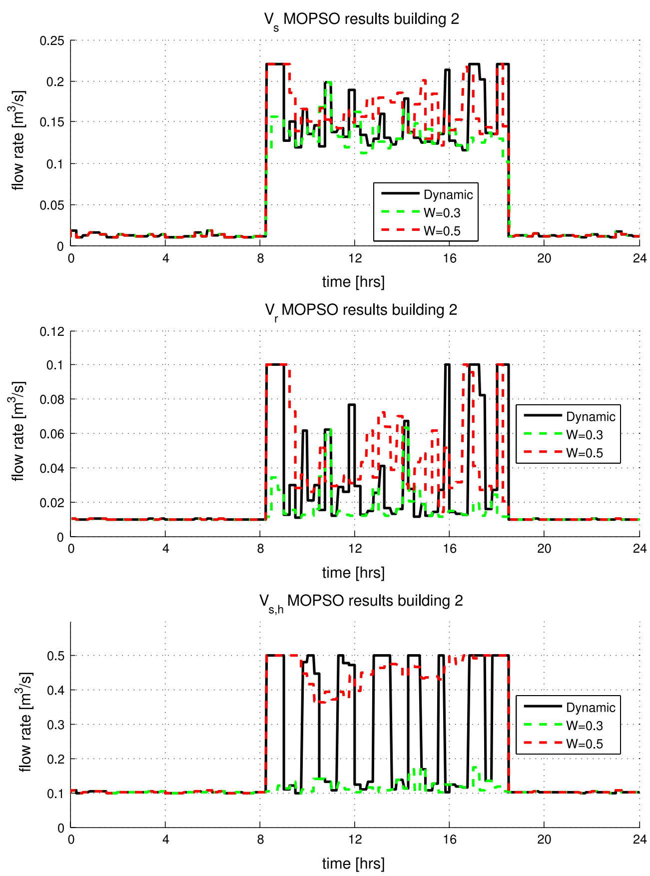

Fig. 13. Comfort system operation parameters.

each time is always a global optimum. Nonetheless, by having a sufficient number of iterations, and by monitoring the change in the movement of the particles, it can be ensured that the search domain has been well explored.

6. Conclusions

In this paper, a dual agent-based management system for the inter-operation of the smart grid and smart buildings is proposed. The abilities and benefits of this distributed control architecture are tested through virtual multi-zone buildings connected to a LV distribution feeder. It is shown that with the use of basic operation rules, the proposed system can effectively improve the voltage profile of the feeder, while ensuring acceptable comfort levels. Furthermore, the bottom-up architecture proposed guarantees that the information is treated in hierarchies reducing the flow of unnecessary information, which will become critical in larger systems.

Furthermore, an optimization strategy was presented for building energy management systems, which optimizes both energy and comfort in a zone. A dynamic weight PSO was compared against two constant weight scenarios, i.e. fair with "$W = 0.5$", and bias with "$W = 0.3$". From the results obtained, it can be concluded that the PSO algorithm offers great potential not only for energy savings and comfort optimization, but also for voltage grid support. In this work, the weight value in the dynamic scenario was changed based on the detection of occupancy as well as the voltage levels at the feeder. From the results it can be concluded that the combination of distributed intelligence with innovative optimization techniques offers not only benefits for both domains but also allows the inter-operation of them.

Finally, as the MAS based SG–BEMS platform is designed in the context of a balanced LV network, its functionalities need to be further developed in order to offer voltage support in an unbalanced system. In such systems, the power variation needs to be differentiated by phase in order to contribute to the voltage/current symmetry between the phases, i.e. voltage balance. This will require the aggregation and control of the single phase connected loads, and of single phase devices present within the building. However, large office buildings comfort systems, e.g. HVAC, are typically three phase loads, and their control will result in an equal demand variation over all the phases. This means that if the SG–BEMS platform is used to control only the three-phase loads, it will influence only the positive sequence voltage. This leads to very little change in the voltage unbalance level. Nonetheless, there is always some degree of unbalance in a network, but this is not a frequent issue, i.e. in some areas unbalance up to 3% is allowed, as indicated in the EN 50160 standard (the limit differs per country, e.g. 2% is the limit in the Netherlands).

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