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A Supervisory Approach to Microgrid Demand Response and Climate Control

Christos D. Korkas, Simone Baldi, Iakovos Michailidis, Yiannis Boutalis and Elias B. Kosmatopoulos

Abstract— **Microgrids equipped with small-scale renewable-energy generation systems and energy storage units offer challenging opportunity from a control point of view. In fact, in order to improve resilience and enable islanded mode, microgrid energy management systems must dynamically manage controllable loads by considering not only matching energy generation and consumption, but also thermal comfort of the occupants. Thermal comfort, which is often neglected or oversimplified, plays a major role in dynamic demand response, especially in front of intermittent behavior of the renewable energy sources. This paper presents a novel control algorithm for joint demand response management and thermal comfort optimization in a microgrid composed of a block of buildings, a photovoltaic array, a wind turbine, and an energy storage unit. In order to address the large-scale nature of the problem, the proposed control strategy adopt a two-level supervisory strategy: at the lower level, each building employs a local controller that processes only local measurements; at the upper level, a centralized unit supervises and updates the three controllers with the aim of minimizing the aggregate energy cost and thermal discomfort of the microgrid. Comparisons with alternative strategies reveal that the proposed supervisory strategy efficiently manages the demand response so as to sensibly improve independence of the microgrid with respect to the main grid, and guarantees at the same time thermal comfort of the occupants.**

I. Introduction

Increasing energy demand and stricter environmental regulations have enabled the transition from traditional electric grids, in which centralized power plants transmit energy to the users directly, to smart electrical microgrids where the existing power grid is enhanced by distributed, small-scale renewable-energy generation systems such as photovoltaic (PV) panels, wind turbines, and energy storage units. Microgrids can be seen as miniature versions of the larger utility grid except that, when necessary, they can disconnect from the main grid and can continue to operate in 'islanded mode' [1]. Despite their potential advantages, the use of renewable sources inserts uncertainty into the system, due to their output profile which strongly depends on local weather conditions: in some cases the lack of monitoring and control of these energy sources might contribute to the instability of the electric grid [2], [3]. For these reasons, one of the main challenges in the development of microgrids is to deploy a control system to manage controllable loads and guarantee grid stability with minimum the energy cost.

However, energy cost is not the only variable to be considered: a critical factor in determining the energy consumption optimization in a microgrid is the end-user (building occupant) thermal comfort which, according to EN15251 standard [4] should not be violated except for small intervals during the building operation. In the current state-of-the-art, most microgrid control systems consider only matching energy generation and consumption, while thermal comfort of the occupants is often neglected. Thermal comfort constraints should be satisfied by all acceptable control strategies. While dry-bulb temperature tracking has been used as a comfort-maintaining criterion [5], neglecting humidity and radiant temperatures can lead to insufficient estimation of actual thermal comfort. The Fanger index [6] or adaptive thermal comfort models [7] can yield a realistic estimate of thermal comfort.

This paper presents a novel control algorithm for joint demand response management and thermal comfort optimization in microgrids composed of a block of buildings, a photovoltaic array, a wind turbine, and an energy storage unit. The proposed control uses a simulation-based optimization procedure, with a model built using EnergyPlus [8]. Differently from other simulation-based control strategy for energy-efficient control of microgrids [9], [10], [11], the proposed one aims at solving iteratively the optimal control problem defined by the Hamilton-Jacobi-Bellman equation. In contrast with Model Predictive Control (MPC) strategies [12], [13], the resulting solution is a closed-loop solution, which is shown, via extensive simulations, to be robust to different weather conditions. Comparisons with alternative strategies reveal that the proposed supervisory strategy efficiently sensibly improve independence of the microgrid with respect to the main grid, and guarantees at the same time thermal comfort of the occupants.

The paper is organized as follows: Section II describes the problem setting, the control objectives along with the performance index, the microgrid and its attributes. Section III presents the proposed supervisory control strategy and Section IV presents the simulation results.

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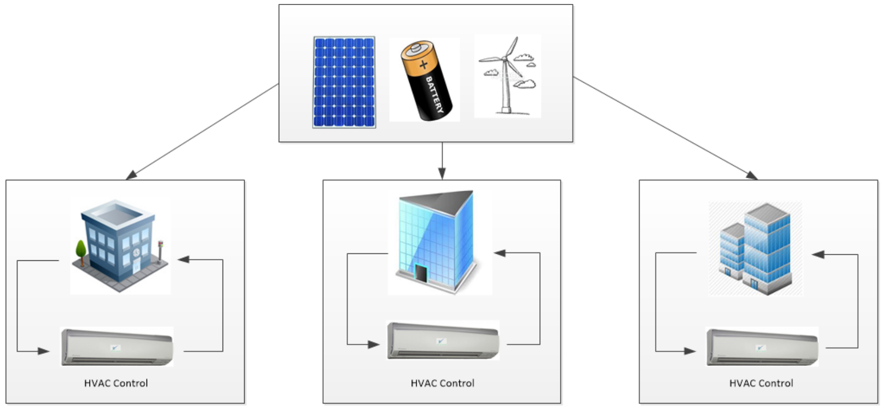


Fig. 1: Microgrid setting

II. Problem Description

In this section we present the setting of the joint demand response and thermal comfort control problem. A grid-connected microgrid, shown in Fig. 1, is composed of N buildings and equipped with renewable energy sources (photovoltaic panels and wind turbine) and an energy storage unit for electricity (battery). For simulation purposes we will consider three buildings, even if the proposed methodology can be generalized to N buildings.

The emphasis of the work is thus on the development of a control strategy for joint optimization of energy cost and thermal comfort. The solution to the problem must take into account the fact that renewable energy is available depending on weather conditions.

Given the two control objectives, the performance index to be optimized takes into account two terms: the energy cost and the thermal comfort of the occupants. At time t the aggregate performance index of a microgrid with N buildings is defined as

$$TC(t) = \sum_{i=1}^{N} (k * ES_i(t) + (1-k) * CS_i(t)) \tag{1}$$

where ES_i is the energy score and CS_i the thermal comfort score of building #i. The energy and the comfort score are typically scaled, so as to be of the same order of magnitude and contribute fairly to the total score. According to the importance that the designer wants to give to one term with respect to the other the summation can be weighted using the scaling factor $0 < k < 1$.

A. Microgrid Attributes

An EnergyPlus model [8] simulates the complex energetic and thermal behavior of each building composing the microgrid. The focus is on controlling the HVAC during summer, in order to cool-climate the rooms in an energy-efficient manner to a user comfort satisfying level. In the EnergyPlus model each one of the three buildings is composed of ten thermal zones, and each thermal zone is equipped with an HVAC unit. We consider the scenario where each building has different size and thus different energetic needs: every HVAC is opportunely dimensioned according to the size of the thermal zone. The operation of the each HVAC unit has one manipulable input that is the temperature set point (in ^oC) with which each unit is operating. In our specific case, the daily energy consumption of the aggregate microgrid is of the order of 80-130 kWh, while the PPD is a percentage from 0 to 100%. Due to the similar order of magnitude, the weight factor k in (1) is chosen equal to 0.5, so that energy cost and thermal comfort contribute equally in the total cost. In the following, more details of the EnergyPlus model are given.

In order to make the joint demand response and thermal comfort optimization tasks more realistic, the three buildings are assumed to have different occupancy schedules, which are shown in Table I: this heterogeneous occupancy schedule might arise for example from the different use of each building.

B. Renewable Energy Sources

The EnergyPlus simulator adopts historical weather data from summer 2009. The data have been taken from the EnergyPlus website [14] and refer the city of Athens. The 4th of July was selected, as a typical Greek summer day. The EnergyPlus data provide us with all the necessary weather information as solar radiation and wind speed in order to calculate renewable energy. The amount of PV generation P_s can be calculated by:

$$P_s = \eta S I_a (1 - 0.005(T_{amb} - 25)) \quad [kWh] \tag{2}$$

where, η is the conversion efficiency of PV array (%), S is the array area (m^2), I_a is the solar radiation (kW/m^2), T_{amb} is the outside air temperature (^oC). In this paper, it is assumed that sum of total insulation are falling on the PV array, and the angle of incidence is not considered. Conversion efficiency η is equal with 20% which is a typical value and the array area S is equal with 200 m^2.

The wind turbine produces energy P_M based on the following equation:

$$P_M = 1/2 \rho \pi R^2 V^3 C_P(\lambda, \beta) \quad [kWh] \tag{3}$$

where V is wind speed in $[m/s]$, ρ is the air density in $[Kg/m^3]$, R is the blades radius in $[m]$ and C_P the power

TABLE I: Occupancy Schedule

	No. of Thermal Zones	Occupancy Schedule
Building 1	10 thermal zones	7am - 6 pm
Building 2	10 thermal zones	6am - 2 pm and 5pm - 10pm
Building 3	10 thermal zones	0am - 8am and 2pm - 5pm and 9pm - 12pm

coefficient. We assume $\rho = 1.1839 Kg/m^3$, which is the common value of air density at sea level and $25^o C$, $R = 20m$, and a constant $C_P = 0.4$.

Finally, the battery is charged when there is excess of energy coming from the renewable resources and discharged when the energy coming from the renewable resources is not enough to satisfy the energy demand of the microgrid. The capacity of the battery unit is set to 150 kWh. The above equations and parameters were adopted from [15], [16], [17], [18].

III. Control Strategy

A. PCAO Algorithm

The problem consists in finding an optimal strategy for the HVAC set points such that the combined performance index defined in (1) is minimized. The problem is thus formulated as an optimal control problem aiming at minimizing the index

$$\begin{aligned} J &= \int_0^{T_f} \Pi(x(t))dt && (4) \\ s.t. & \\ \dot{x} &= f(x) + Bu, \quad B = [0 \; I]' && (5) \end{aligned}$$

where $\Pi(\cdot)$ is the analytical expression of the performance index (1), where x is an augmented, with state and control variables, vector of the transformed system dynamics while u is the time derivative of the actual control signals, as demonstrated in 5. The function $f(x)$ represents the micro-grid dynamics, which are implemented inside the EnergyPlus model, but that are unknown for our purposes. Finally T_f is a control horizon over which we have reliable weather forecasts (typically 2-3 days). Using dynamic programming arguments, we know that the optimal strategy u^* satisfies the Hamilton-Jacobi-Bellman (HJB) equation

$$\min_u \left\{ \frac{\partial V^*}{\partial x} \left(f(x) + Bu \right) + \Pi(x) \right\} \qquad (6)$$

The difficulty in solving the HJB equation in large-scale systems (like our microgrid) was known to Bellman itself, which coined the term 'curse-of-dimensionality' [19]: in order to overcome such difficulties, the PCAO (Parametrized Cognitive Adaptive Optimization) algorithm parametrizes the solution of the HJB equation (6) as $V^*(x) = z'(x)Pz(x)$ and the optimal control strategy via $u^* = -\frac{1}{2}B' \frac{\partial V^*}{\partial x}$, P is a positive definite matrix. More details for the function $z(\cdot)$ can be found in [20], [21]: in our specific microgrid case we found that a linear transformation $z(x) = x$ is sufficient to achieve important improvements (as demonstrated in Section V). With such parametrization, the problem of solving the HJB equation is recast as the problem of finding the matrix P (and thus the strategy u) that better approaches the solution of the HJB equation. The PCAO algorithm defines the close-to-optimality index (mutated for the principle of optimality [19])

$$\varepsilon(x, P) = V(x(k+1)) - V(x(k)) + \int_k^{k+1} \Pi(x(t))dt \qquad (7)$$

The solution of the HJB equation (6) brings (7) to zero: the PCAO algorithm, whose steps are presented in [22], [20], [23] updates at every time step the strategy parametrized by $\hat{P}$ in an attempt to minimize the close-to-optimality index $\varepsilon(\hat{P})$ and to make $\hat{P}$ converge as close as possible to the solution of the HJB equation.

B. Feedback vector

Each local P-CAO algorithm employs a controller based on a local feedback vectors. The structure of each local feedback vector is the following:

- 3 measurable external weather conditions: outside temperature, outside humidity and solar radiation.
- 6 forecasts for the mean outside temperature in the next 6 hours.
- 6 forecasts for the mean solar radiation over the next 6 hours.
- The n temperatures of the thermal zones (n is the number of thermal zones).
- The n humidities of the thermal zones.
- A constant term (since the equilibrium of the system is not in the origin).
- The n set points of the HVAC devices in the thermal zones.
- The n detectors of occupancy in the thermal zones.

Hereafter we explain with more details the choice of the feedback vector: the zone temperature and humidities are a natural choice for the thermal state of the building; outdoor weather conditions both in the present and the future help to achieve a pro-active control strategy. Finally, the information about the occupancy of a thermal zone is provided as a feedback component to the control strategy.

C. Simulation based Optimization

Using the PCAO algorithm, as presented above, a double feedback loop procedure runs in each building (cf. Fig. 2a). The primary feedback loop runs in real-time, with actions applied to the actual building and measurements collected. In parallel with the primary loop, a secondary simulation-based loop interacts with the EnergyPlus model of the building, in order to find better strategies at the next time step. With the term 'simulation-based' design we refer to a method where the optimization of the cost function involves an iterative process of system simulation/controller redesign. At this point is crucial to introduce and explain two time metrics. The control horizon and the simulation horizon. By control horizon we refer to the time interval of HVAC management. For example in our test case, the HVAC set points are changed by the algorithm every 10 minutes. On the other hand, as a simulation horizon we refer to the whole duration of the experiment. Usually, as a simulation horizon we refer to one day or more. This two-loop design is implemented in each building separately. The secondary loop, which is implemented based on the EnergyPlus model, operates in order to find a better controller for the real system. Simultaneously, the primary loop/system, uses the best so-far controller to manage the HVAC. The above two-loop procedure can be investigated better in Figure 2a.

Remark 1: The proposed control strategy differs from the classical rolling (or receding) horizon philosophy. In particular, the objective is to update at every time step a feedback controller, rather then solving at every time step an open loop control problem. After convergence, it was verified via simulations that the proposed feedback solution provides robustness to the resulting HVAC controller, also in the presence of different weather conditions than the one used for the design (cf. the results in Table II). As a result, simulation results reveal that one can realistically assume keep the same control strategy over long horizons (indicatively, one week) without the need of redesign the control and without sensible loss of performance.

D. Supervisory Logic

The purpose of this work is to provide a control architecture that that be scalable to an arbitrary number N of buildings: for this reason, a centralized control architecture was discarded and the following bi-level supervisory strategy was implemented for the control and manipulation of each building/HVAC unit of the microgrid. The two levels can be identified as: a *local* building level and an *aggregate* microgrid level. As compared to a fully centralized strategy, the computational and communication requirements of the proposed control architecture are reduced. In Figure 2b the logic behind the supervisory strategy that we adopt is presented. In each building one local controller and one local optimization (PCAO Algorithm) is operated. The goal of each optimization algorithm is to optimize the performance of the building by taking into account only local information such as the thermal state of the building, occupancy information, and weather conditions. Each local controller communicates with the central node and offer information about the cost that the proposed control strategy is achieving and achieved in the past. The central node concentrates this information from each different building, calculates the total cost and decides if the 'team' of controllers achieved the best aggregate performance. The central node, informs the local levels with a binary signal, if the the best performance was achieved. Based on the Figure 2a the supervisory logic interacts only in the red circle (memorization of the best strategy). This simple strategy has been shown to be effective in achieving a good global performance: in particular, section V will show that, when a centralized architecture can be implemented, the performance of the centralized and of the proposed supervisory architecture (denoted as Supervisory PCAO) are comparable.

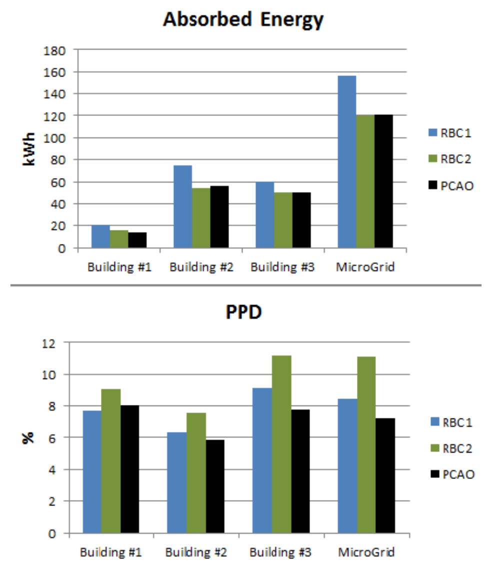


Fig. 4: Energy absorbed from the main grid and Mean PPD

IV. Simulation Results

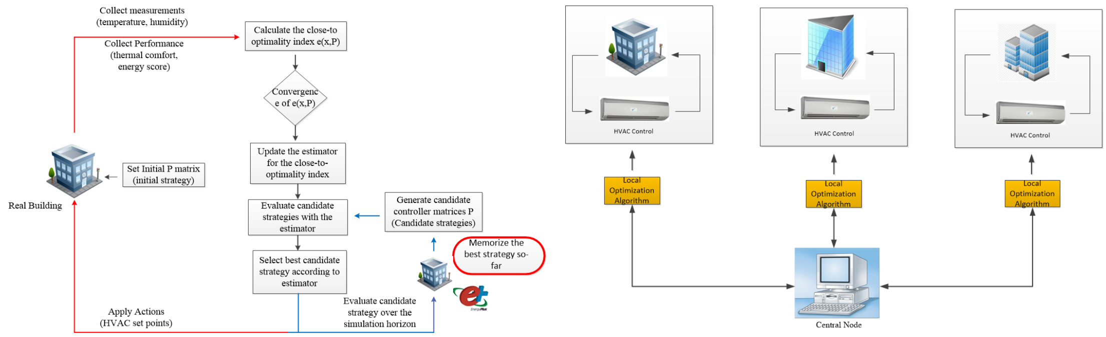
This section describes the simulation results for the presented microgrid test case. The results of the optimization of the demand response and of the thermal comfort achieved via the Supervisory PCAO algorithm will be exhibited as compared with 2 rule-based control strategies: RBC_1 and RBC_2.

A. Rule-based demand response programs

For comparison reasons, two Rule Based Controllers (RBC) implementing simple but common demand response programs are adopted. The RBCs employ a simple control strategy, which consists of keeping the HVAC set points of each thermal zone constant to 24^oC (RBC_1) or to 25^oC (RBC_2) during occupancy hours. Such control strategies, yet simple, provide acceptable (but far from optimal) performances in terms of the total score. In order to achieve some energy savings (especially during night), the HVAC set point manipulation of RBC_1 and RBC_2 is combined with control of windows. Every time that HVAC units operate, windows are closed. When the HVAC unit are switched off, the window control is as follows:

$$\begin{cases} \text{open window} & \text{if } T_{amb} < T_z \text{ and } T_z > 20 \\ \text{close window} & \text{otherwise} \end{cases} \tag{8}$$

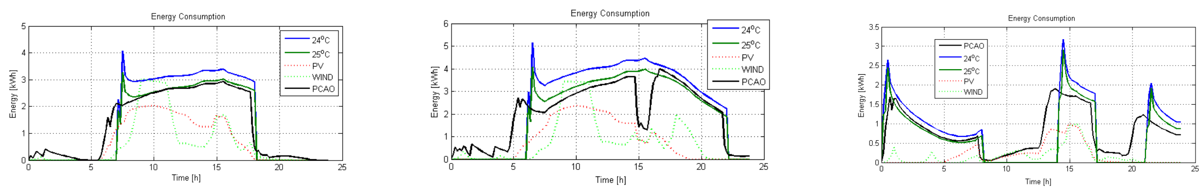
where T_{amb} is the outside temperature and T_z the temperature of the thermal zone. Taking into account that we want to cool-climate the buildings, rule (8) is meant to exploit the natural ventilation effect occurring typically at night. The



(a) Local simulation-based optimization

(b) Supervisory control strategy

Fig. 2: Simulation based Optimization Procedure and Supervisory Control Logic



(a) Building 1

(b) Building 2

(c) Building 3

Fig. 3: (a)-(b)-(c): Energy Consumption during the day, for the three buildings of the microgrid test case

upper bound of 20^oC is set in order to guarantee thermal comfort.

B. Comparison results

Figure 3 shows the energy consumption and PPD under three control strategies (RBC_1, RBC_2 and Supervisory-PCAO). The distribution of solar and wind energy under the Supervisory-PCAO control strategy is also shown (the distribution of renewable energy under RBC_1 and RBC_2 is not shown for better readability of the plots). As mentioned, the renewable energy is distributed proportionally to the energy of each building. It can be noted how the Supervisory-PCAO algorithm is actively and dynamically managing the demand response side via HVAC regulation. In particular, note that in the third building the RBCs do not switch off the HVAC between 2 pm - 5 pm: this action has been implemented on purpose, and it emulates the fact that people usually do not switch off HVAC if they leave the building for short periods of time. The Supervisory-PCAO algorithm, on the other side, realizes that by (almost) switching the HVAC off, the energy consumption of the microgrid can be reduced without sacrificing the PPD index. Finally, Figure 4 demonstrates the ability of Supervisory-PCAO to request 25% less energy absorbed from the main grid as compared scenarios RBC_1, while achieving at the same time time a better PPD (more than 20% improvement). On the other hand, if Supervisory-PCAO requests similar levels of energy absorbed from the main grid as scenarios RBC_2, the PPD is improved by more than 35%.

Figure 5 examines the exploitation of the renewable energy resources and the charging/discharging of the battery. One can notice that both RBC_2 and Supervisory-PCAO algorithm

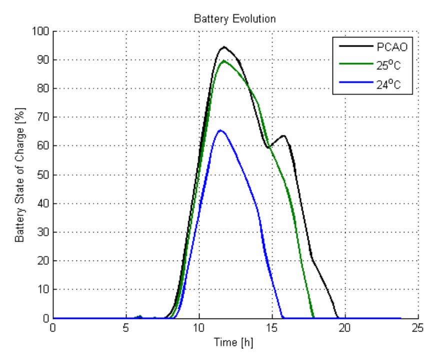


Fig. 5: Battery evolution during the day

perform better than RBC_1. In fact, RBC_2 and Supervisory-PCAO manage to charge the battery to a greater extent, so as to exploit this energy in the evening when no PV energy is available. In this respect, Supervisory-PCAO outperforms RBC_2, as it achieves a higher charging peak and uses the battery for a longer time (notice in particular the charging phase at around 3pm). As a result, Supervisory-PCAO exploits better the renewable energy resources and with reduced energy consumption.

To evaluate the robustness of the proposed solution in front of different weather conditions, 7 different sets of 3 summer days are used for validation, with different environmental conditions (external temperature, humidity, solar radiation, and wind) than July 4th. The controller obtained for July 4th was used for all scenarios and Table II shows the improvement of such controller with respect to the 2 rule-based controllers. In each case, the Supervisory-PCAO

TABLE II: PCAO Improvement (Total Cost) with respect to RBC_1 and RBC_2 (results validated over 7 different sets of 3 days)

Case	Improvement wrt RBC_1	Improvement wrt RBC_2
Building 1	20-25%	15-20%
Building 2	23-27 %	18-21%
Building 3	27-32 %	22-25%
Microgrid	21-25 %	18-22%

strategy attain relevant improvements, from which we derive the consistency and robustness of the proposed results.

C. *Comparisons against a centralized architecture*

As a final comparison, the proposed supervisory strategy is compared with a PCAO centralized strategy, proposed in [22], using information stemming from the entire microgrid.

TABLE III: Comparison (Total Cost) between supervisory and centralized PCAO strategy with respect to RBC_2 (results validated over 7 different sets of 3 days)

PCAO-Strategy	Improvement wrt RBC_2	Iterations
Supervisory	18-22 %	≈ 250
Centralized	22-26 %	≈ 550

In Table III the comparison between the two strategies is presented. The Centralized-PCAO strategy offers better performance than Supervisory-PCAO, but at the expense of slower convergence. It is to be expected that, with data stemming from the entire microgrid, the Centralized-PCAO is not scalable to microgrids with an increasing number of buildings.

V. Conclusions and future work

This paper presented a novel control algorithm for joint demand response management and thermal comfort optimization in a microgrid composed of a block of buildings, a photovoltaic array, a wind turbine, and an energy storage unit. In fact, thermal comfort plays a major role in dynamic demand response, especially in front of intermittent behavior of the renewable energy sources. Comparisons with alternative strategies revealed that the proposed supervisory strategy efficiently manages the demand response so as to sensibly improve independence of the microgrid with respect to the main grid, and guarantees (and improves) at the same time thermal comfort of the occupants.

Future work will include comparison with more advanced demand response programs (e.g. obtained via global optimization algorithms), and inclusion of plug-in electrical vehicles acting as an additional load and additional storage.

References

[1] Hassan Farhangi. The path of the smart grid. *Power and Energy Magazine, IEEE*, 8(1):18–28, 2010.

[2] O Alsayegh, S Alhajraf, and H Albusairi. Grid-connected renewable energy source systems: challenges and proposed management schemes. *Energy Conversion and Management*, 51(8):1690–1693, 2010.

[3] Ali Bidram and Ali Davoudi. Hierarchical structure of microgrids control system. *Smart Grid, IEEE Transactions on*, 3(4):1963–1976, 2012.

[4] EU Commission et al. Renewable energy road map-renewable energies in the 21st century: building a more sustainable future. *COM (2006)*, 848, 2007.

[5] Xiaohong Guan, Zhanbo Xu, and Qing-Shan Jia. Energy-efficient buildings facilitated by microgrid. *Smart Grid, IEEE Transactions on*, 1(3):243–252, 2010.

[6] ASHRAE. ANSI/ASHRAE standard 55-2004: thermal environmental conditions for human occupancy. *American Society of Heating, Refrigerating and air-Conditioning Engineers.*, 2004.

[7] NZ Azer and S Hsu. The prediction of thermal sensation from a simple model of human physiological regulatory response. *ASHRAE Trans*, 83(Pt 1), 1977.

[8] Drury B Crawley, Jon W Hand, Michaël Kummert, and Brent T Griffith. Contrasting the capabilities of building energy performance simulation programs. *Building and environment*, 43(4):661–673, 2008.

[9] Zhen Yu and Arthur Dexter. Simulation based predictive control of lowenergy building systems using two-stage optimization. *Proc. IBPSA09*, pages 1562–1568, 2009.

[10] Carina Sagerschnig, Dimitrios Gyalistras, Axel Seerig, Samuel Prívara, Jiří Cigler, and Zdenek Vana. Co-simulation for building controller development: The case study of a modern office building. In *Proc. CISBAT*, pages 14–16, 2011.

[11] Mousa Marzband, Majid Ghadimi, Andreas Sumper, and José Luis Domínguez-García. Experimental validation of a real-time energy management system using multi-period gravitational search algorithm for microgrids in islanded mode. *Applied Energy*, 128:164–174, 2014.

[12] Roberto Z Freire, Gustavo HC Oliveira, and Nathan Mendes. Predictive controllers for thermal comfort optimization and energy savings. *Energy and buildings*, 40(7):1353–1365, 2008.

[13] D Kolokotsa, A Pouliezos, G Stavrakakis, and C Lazos. Predictive control techniques for energy and indoor environmental quality management in buildings. *Building and Environment*, 44(9):1850–1863, 2009.

[14] U. S Department of Energy. Energyplus energy simulation software. `http://apps1.eere.energy.gov/buildings/energyplus/`, 2008.

[15] Yang Peihong, Liu Wenying, and Wei Yili. A survey on problems in smart grid with large capacity wind farm interconnected. *Energy Procedia*, 17:776–782, 2012.

[16] Kenichi Tanaka, Akihiro Yoza, Kazuki Ogimi, Atsushi Yona, Tomonobu Senjyu, Toshihisa Funabashi, and Chul-Hwan Kim. Optimal operation of dc smart house system by controllable loads based on smart grid topology. *Renewable Energy*, 39(1):132–139, 2012.

[17] Changsun Ahn, Chiao-Ting Li, and Huei Peng. Optimal decentralized charging control algorithm for electrified vehicles connected to smart grid. *Journal of Power Sources*, 196(23):10369–10379, 2011.

[18] Francesco Borrelli, Carmen Del Vecchio, and Alessandra Parisio. Robust invariant sets for constrained storage systems. *Automatica*, 45(12):2930–2936, 2009.

[19] Richard Bellman and Robert E Kalaba. *Dynamic programming and modern control theory*. Academic Press New York, 1965.

[20] Simone Baldi, Iakovos Michailidis, Hossein Jula, Elias B Kosmatopoulos, and Petros A Ioannou. A plug-n-play computationally efficient approach for control design of large-scale nonlinear systems using co-simulation. In *Decision and Control (CDC), 2013 IEEE 52nd Annual Conference on*, pages 436–441. IEEE, 2013.

[21] S. Baldi, I. Michailidis, E. B. Kosmatopoulos, and P. A. Ioannou. A plug and play computationally efficient approach for control design of large-scale nonlinear systems using cosimulation. *IEEE Control Systems Magazine*, 34:56–71, 2014.

[22] Christos D Korkas, Simone Baldi, Iakovos Michailidis, and Elias B Kosmatopoulos. Intelligent energy and thermal comfort management in grid-connected microgrids with heterogeneous occupancy schedule. *Applied Energy*, 149:194–203, 2015.

[23] Christos D Korkas, Simone Baldi, Iakovos Michailidis, and Elias B Kosmatopoulos. Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage. *Applied Energy*, 163:93–104, 2016.