Multi-level Optimal Control of a Microgrid-supplied Cooling System in a Building

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***Abstract*—Recent studies highlighted the model predictive control as a promising platform for complex systems management and energy efficiency improvement in a large number of applications, particularly prominent in building climate and smart grid control. Involvement of microgrids offered great possibilities of power consumption peak shaving, improved grid stability and decentralisation, by introducing buildings as active market participants. To this aim, the paper is focused on the development of a microgrid optimal control that acts as an intermediary method for integration of a building to the smart grid with dynamic pricing of electricity. A multilevel optimal control is applied on a building cooling system and energy flow optimization of a DC microgrid that consists of a photovoltaic array, batteries stack and fuel cells stack with electrolyser, and that is connected to the utility grid via a bidirectional power converter. Performance of the proposed approach is verified through 4-month simulations of a microgrid integrated with a building cooling system, in actual meteorological and electricity price data scenario. Microgrid energy storages and the proposed control method fully exploit possibilities of dynamic pricing and greatly reduce cooling system operation costs while ensuring the high level of user comfort.**

***Index Terms*—Multilevel optimal control, Building cooling system, Microgrid, Smart grid, Dynamic electricity pricing**

I. Introduction

With 40% of the world's total primary energy consumed by buildings operation, numerous policies and initiatives have emerged and are directing towards increase of buildings energy efficiency [1]. A nearly zero-energy building is a recently emerged term that indicates the goal of making buildings self-sustainable when it comes to energy demand. This topic is tightly followed by utilization of highly variable renewable energy production integrated through distributed energy storage by means of a microgrid concept [2], [3]. A microgrid acts as an energy buffer and energy costs reducer between dynamic profiles of the user energy consumption and variable electricity prices, and improves stability and decentralization of the utility grid through distributed storage.

In this paper we propose a multilevel optimal control of a microgrid-supplied cooling system in a building. Performance of the proposed approach is verified through 4-month simulations of a microgrid integrated with a building cooling system within Laboratory for Renewable Energy Systems (LARES), in actual meteorological and electricity price data scenario. The DC microgrid formed in LARES operates at 48 V [4] and consists of: (i) energy production systems – photovoltaic array (PV) and wind turbine emulator (WT), (ii) energy storage systems – ultracapacitor (UC), fuel cells stack (FC) with electrolyser (EL), and batteries stack (BAT), and of (iii) energy consumption systems, i.e., building cooling system (L). The microgrid is connected to the utility grid (UG) via a bidirectional power converter. The cooling system in the case study is based on a central chiller unit which operates over 23 controllable zones equipped with fan coil units.

The optimal decision when to buy/sell electricity from/to the utility grid and in which amount, i.e., when to charge and discharge energy storages, is a complex function of the predicted local energy production and consumption profiles, current storages state-of-charge (SoC), as well as of predicted electricity price profile [4]–[6]. This function is also subject to various techno-economic constraints like energy storages capacity, power converters power ratings, and even to utility grid possibly reduced availability. The described decision making process is formulated as a linear program (LP).

A building cooling system control problem is defined as a tracking problem with properly designed weighting matrices to ensure high level of comfort and minimal energy consumption at the same time. Considered approach has proved to outperform conventional zone controllers in terms of energy efficiency even in very strict comfort bounds of ± 0.2 °C around a temperature set-point [7]. The described temperature tracking problem is also formulated as an LP.

These two separate control problems are integrated together using a model predictive control (MPC) scheme with receding horizon philosophy, such that energy consumption plan obtained by solving the temperature tracking problem is passed to the energy flow optimization problem. In this way, energy storages within the microgrid, together with the proposed multilevel optimal control method, fully exploit possibilities of dynamic pricing and greatly reduce cooling system operation costs while ensuring a high level of user comfort.

This paper is organized as follows. Section II presents formulation of the energy flow optimization problem for the considered microgrid, while zone temperature optimization problem is given in Section III. Both microgrid and building cooling systems control schemes are integrated in an MPC scheme with receding horizon philosophy in Section IV. Section V discusses case study results on 4-month simulations based on actual meteorological and electricity price data.

II. Energy flow optimization

An electricity balance equation of the considered DC microgrid formed in LARES (see Fig. 1) is defined as follows:

$$\Big[E^{\text{PV}}+E^{\text{WT}}\Big]+\Big[E^{\text{UC}}+E^{\text{BAT}}+\big(E^{\text{FC}}-E^{\text{EL}}\big)\Big]+E^{\text{UG}}=E^{\text{L}}. \quad (1)$$

Note that fuel cells stack with electrolyser is also an energy storage system: (i) electrolyser produces hydrogen when there is excess power, while (ii) fuel cells use previously stored hydrogen to produce electricity when there is power shortage. For the sake of simplicity, fuel cells stack with electrolyser system is considered as a single controllable energy storage unit, denoted as E^{FC}. Since ultracapacitor has a very low energy storage capacity, we neglect this component in the subsequent energy flow optimization, as well as the wind turbine emulator. By convention, we assume that energy components are positive when supplying electricity to the DC link, e.g., energy components E^{BAT} and E^{FC} will be negative for charging, while the energy component E^{UG} will be negative for exporting (selling) energy to the utility grid. Load is assumed always to be unidirectional, i.e., the energy component E^{L} is always positive.

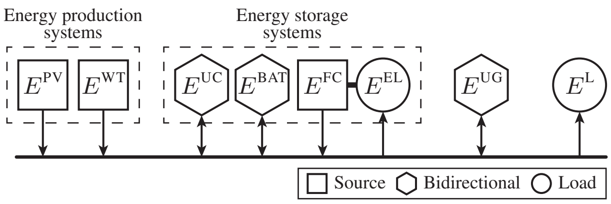

Fig. 1. Electricity balance diagram of the DC microgrid formed in LARES.

A. Discrete-time system model

Energy storage systems are modelled as discrete-time first-order difference equations with a 1 h sampling time [4]:

$$\begin{cases} x_{k+1}^{\text{BAT}} = x_k^{\text{BAT}} - \frac{1}{C^{\text{BAT}}}\Big(\frac{1}{\eta_{\text{dch}}^{\text{BAT}}}E_{\text{dch}}^{\text{BAT}} + \eta_{\text{ch}}^{\text{BAT}}E_{\text{ch}}^{\text{BAT}}\Big), \\ x_{k+1}^{\text{FC}} = x_k^{\text{FC}} - \frac{1}{C^{\text{FC}}}\Big(\frac{1}{\eta_{\text{dch}}^{\text{FC}}}E_{\text{dch}}^{\text{FC}} + \eta_{\text{ch}}^{\text{FC}}E_{\text{ch}}^{\text{FC}}\Big), \end{cases} \quad (2)$$

where k denotes discrete time instant, state x_k is a normalized SoC, C is an energy storage capacity, η is charging or discharging efficiency, while $E_{\text{dch}} \geq 0$ and $E_{\text{ch}} \leq 0$ represent discharge and charge energy components, respectively. Note that we divide energy components E^{BAT} and E^{FC} to discharge and charge components due to the different efficiencies η_{dch} and η_{ch}, in that way avoiding model formulation with propositional logic, which would lead to a mixed integer linear program (MILP), i.e., to a combinatorial optimization problem. Similarly, the utility grid energy component E^{UG} is divided to buying and selling components, $E_{\text{buy}}^{\text{UG}} \geq 0$ and $E_{\text{sell}}^{\text{UG}} \leq 0$, due to different electricity prices when buying and selling electricity.

The expression (2) can be written in a matrix form as:

$$x_{k+1} = Ax_k + Bu_k, \qquad A \in \mathbb{R}^{2\times 2},\, B \in \mathbb{R}^{2\times 6}, \quad (3)$$

where A is the identity matrix I_2, B is the system input matrix, the state vector is defined as $x_k = \big[\, x_k^{\text{BAT}},\, x_k^{\text{FC}} \,\big]^\top$, and the input vector is $u_k = \big[\, E_{\text{dch},k}^{\text{BAT}},\, E_{\text{dch},k}^{\text{FC}},\, E_{\text{buy},k}^{\text{UG}},\, E_{\text{ch},k}^{\text{BAT}},\, E_{\text{ch},k}^{\text{FC}},\, E_{\text{sell},k}^{\text{UG}} \,\big]^\top$.

B. Optimization problem

The energy flow optimization is formulated based on: (i) the current state of the microgrid storages x_0, (ii) the predicted local electricity production and consumption profiles in the microgrid, and (iii) the information obtained from the utility grid, i.e., predicted electricity price profile. As a result, the energy flow optimization gives the best values of discharging, charging, buying, and selling energy profiles throughout prediction horizon $0 \leq k \leq N-1$, where N is the length of the prediction horizon. For the sake of simplicity, in this paper we neglect electricity predictions uncertainty [4], [5], i.e., we consider a deterministic system variables description.

The following economic criterion J of the microgrid operation is considered:

$$J(\mathbf{u}, x_0, \mathbf{d}, \mathbf{c}) = \sum_{k=0}^{N-1} c_k E_{\text{buy},k}^{\text{UG}} + \big(0.9c_k\big)E_{\text{sell},k}^{\text{UG}}, \quad (4a)$$

$$\mathbf{u} = \big[u_0^\top, \quad u_1^\top, \quad \ldots, \quad u_{N-1}^\top\big]^\top, \quad (4b)$$

$$\mathbf{d} = \big[E_0^{\text{D}}, \quad E_1^{\text{D}}, \quad \ldots, \quad E_{N-1}^{\text{D}}\big]^\top, \quad (4c)$$

$$\mathbf{c} = \big[c_0, \quad c_1, \quad \ldots, \quad c_{N-1}\big]^\top, \quad (4d)$$

where $E_k^{\text{D}} = E_k^{\text{L}} - E_k^{\text{PV}}$ is the system disturbance at the discrete time instant k. Here we assume different electricity prices for buying and selling electricity, whereas the selling price is equal to 90% of the buying price.

The microgrid electricity balance equation (1) is implemented in a form of an equality constraint, as follows:

$$\mathbf{1}^\top u_k = E_k^{\text{D}}, \quad (5)$$

where $\mathbf{1} \in \mathbb{R}^6$ is a column vector with all elements equal to 1.

Minimization of the criterion (4a) is subject to various techno-economic constraints on microgrid variables over the future horizon. Energy storages state x_k must always be inside the corresponding storage capacity limits:

$$x_{\min} \leq x_k \leq x_{\max}, \qquad 0 \leq k \leq N, \quad (6)$$

where $x_{\min}$, $x_{\max} \in \mathbb{R}^2$. Energy components limits are defined by the corresponding power converter power rating, and by physical constraints (e.g., $E_{\text{dch}}^{\text{BAT}} \geq 0$ and $E_{\text{ch}}^{\text{BAT}} \leq 0$):

$$u_{\min} \leq u_k \leq u_{\max}, \qquad 0 \leq k \leq N-1, \quad (7)$$

where $u_{\min}$, $u_{\max} \in \mathbb{R}^6$. If information about the predicted utility grid availability is at disposal, one can include this information simply by modifying variables $u_{\min}$ and $u_{\max}$ for a specific time instant k.

Once objective function and constraints have been defined, one can write down the energy flow optimization problem in an LP form as follows:

$$\begin{aligned} \min_{\mathbf{u}} \quad & \mathbf{f}^\top \mathbf{u}, \\ \text{s.t.} \quad & \mathbf{I}_u \mathbf{u} \leq \mathbf{I}_x x_0 + \mathbf{g}, \\ & \mathbf{E}_u \mathbf{u} = \mathbf{E}_d \mathbf{d}, \end{aligned} \quad (8)$$

whereas vector $\mathbf{f}$, inequality constraints matrices $\mathbf{I}_u$, $\mathbf{I}_x$ and vector $\mathbf{g}$, and equality constraints matrices $\mathbf{E}_u$, $\mathbf{E}_d$, are straightforwardly calculated from (4)–(7).

III. Optimal control problem for building zones cooling

In this section an optimization problem used for the closed-loop optimal control of building cooling system is developed. Please note that here we use the same variables notation as in the previous section, e.g., A and B are system matrices, x and u are state and input vectors, J is criterion function etc. However, variables in this section are not related in any way to variables in the previous section.

A. Discrete-time system model

A mathematical model of the considered case-study thermal system is developed by using the resistor-capacitor (RC) network modelling framework [8]–[10]. It models 23 controllable zones spanned over cca. 700 m^2 area within the skyscraper building of University of Zagreb Faculty of Electrical Engineering and Computing. Due to a one-hour time resolution of meteorological variables prediction for the system location, the model built on RC principles is discretized with the one-hour sample time as follows:

$$x_{k+1} = Ax_k + B_u u_k + B_T T_{o,k} + B_T^+ T_{o,k+1} + B_d d_k, \quad \text{(9a)}$$

$$y_{k+1} = Cx_{k+1}, \quad \text{(9b)}$$

where $k \in \mathbb{Z}$ is the discrete time step, $x \in \mathbb{R}^n$ is the system state vector, $u \in \mathbb{R}^q$ is the system input vector, i.e., vector of thermal energy inputs to each of q controllable zones, $T_o \in \mathbb{R}$ is the outdoor temperature, $d \in \mathbb{R}^p$ is the vector of disturbances that act on the system (e.g., solar insolation, internal gains etc.), and $y \in \mathbb{R}^q$ is the system measurements vector, i.e., the vector of room temperatures. System matrices A, B_u, B_d^1, B_d^2, B_d^*, and C describe system dynamics and input-output relationships.

B. Optimization problem

The resulting performance of the MPC operated cooling system depends completely on the MPC problem formulation. In building zone temperature control the goal is to achieve the best possible user comfort with minimum energy consumption. Thus, the zone level optimization cost J is consisted of two parts, J_1 and J_2, as follows:

$$\min_{\mathbf{u},\boldsymbol{\sigma}_1,\boldsymbol{\sigma}_2} \quad J_1(\mathbf{u}, x_0, \mathbf{T}_o, \mathbf{d}) + J_2(\mathbf{u}, x_0, \mathbf{T}_o, \mathbf{d}, \boldsymbol{\sigma}_1, \boldsymbol{\sigma}_2, \eta), \quad \text{(10a)}$$

$$\text{s.t.} \quad \mathbf{y} = \mathbf{A}x_0 + \mathbf{B}_u\mathbf{u} + \mathbf{B}_T\mathbf{T}_o + \mathbf{B}_d\mathbf{d}, \quad \text{(10b)}$$

$$\mathbf{SP} - \boldsymbol{\Delta} - \boldsymbol{\sigma}_1 \leq \mathbf{y} \leq \mathbf{SP} + \boldsymbol{\Delta} + \boldsymbol{\sigma}_2, \quad \text{(10c)}$$

$$\mathbf{P}_{\text{min}} \leq \mathbf{u} \leq \mathbf{P}_{\text{max}}, \ \boldsymbol{\sigma}_1 \geq 0, \ \boldsymbol{\sigma}_2 \geq 0, \quad \text{(10d)}$$

where x_0 is the initial state of the system, $\mathbf{A}$, $\mathbf{B}_u$, $\mathbf{B}_T$, $\mathbf{B}_d$, $\mathbf{u}$, $\mathbf{T}_o$, $\mathbf{d}$, and $\mathbf{y}$ are augmented system matrices and vectors over the prediction horizon of length N, $\boldsymbol{\sigma}_1$ and $\boldsymbol{\sigma}_2$ are augmented vectors used to implement slack variables σ_1 and σ_2 needed for proper definition of the optimization problem, whereas $\mathbf{SP}$ and $\boldsymbol{\Delta}$ are augmented vectors of user-defined set points SP and allowed deviations around them Δ for each controllable zone q [7].

The term J_1, related to minimization of energy consumption, is defined as:

$$J_1(\mathbf{u}, x_0, \mathbf{T}_o, \mathbf{d}) = \sum_{k=0}^{N-1} \left| R_{t+k|t} u_{t+k|t} \right|_1, \quad \text{(11)}$$

where $R_{t+k|t} \in \mathbb{R}^{q \times q}$ is the weighting matrix. Temperature demands of end-users are forced by the term J_2:

$$\begin{aligned} J_2(\mathbf{u}, x_o, \mathbf{T}_o, \mathbf{d}, \boldsymbol{\sigma}_1, \boldsymbol{\sigma}_2, \eta) = \sum_{k=1}^{N} \left| G_{1\,t+k|t} \sigma_{1\,t+k|t} \right|_1 + \\ + \sum_{k=1}^{N} \left| G_{2\,t+k|t} \sigma_{2\,t+k|t} \right|_1 + \eta \sum_{k=1}^{N} \left| Q_{t+k|t} (y_{t+k|t} - \text{SP}_{t+k|t}) \right|_1, \end{aligned} \quad \text{(12)}$$

where $Q_{t+k|t} \in \mathbb{R}^{q \times q}$ is weighting matrix, and $\eta \geq 0$ is an arbitrary weighting coefficient. To tackle the opposing criteria of reference following and energy saving, weighting matrices $R_{t+k|t}$ and $Q_{t+k|t}$ have to be chosen in a way which enables smart switching between these two requirements based on predicted disturbance profiles. In order to be comparable, both parts of optimization cost have to expressed in the same units. Since J_1 is already defined in watts, weighting matrix $Q_{t+k|t}$ is utilized to convert temperature related cost part J_2 from degrees Celsius to watts. Sensitivity of the energy consumption to the zones temperature is defined as:

$$\frac{\partial \mathbf{u}}{\partial \mathbf{y}} = \frac{\partial (\mathbf{B}_u^{-1} (\mathbf{y} - \mathbf{A}x_0 - \mathbf{B}_T\mathbf{T}_o - \mathbf{B}_d\mathbf{d}))}{\partial \mathbf{y}} = \mathbf{B}_u^{-1}. \quad \text{(13)}$$

The matrix $\mathbf{B}_u^{-1}$ is lower bidiagonal matrix with all elements on the main diagonal equal to $(C \cdot B_u)^{-1}$ and to the $-(B_u^{-1} \cdot A \cdot C^{-1})$ on the secondary (-1) diagonal. By setting weighting matrices along the horizon to:

$$Q_{t+k|t} = \begin{bmatrix} (C \cdot B_u)^{-1} \\ -(B_u^{-1} \cdot A \cdot C^{-1}) \end{bmatrix}, \quad k = 1, \ldots, N-1, \quad \text{(14)}$$

and $Q_{t+N|t} = (C \cdot B_u)^{-1}$, J_2 is converted from degrees Celsius to watts. Thus, for $\eta = 1$ the same weight is put on both parts of the criteria, so the controller will decide what is the best regarding both energy consumption and comfort. By allowing the change of the weighting factor η, additional levels of freedom are introduced, so the user can adjust this factor according to its preferences [7].

IV. Closed-loop optimal control

In this section we formulate the model predictive control (MPC) scheme with receding horizon philosophy for closed-loop (i) energy management in the microgrid, and (ii) cooling system control. Solution to an MPC problem yields a trajectory of states and inputs (i.e., control signals) that satisfy the dynamics and constraints of the given system model while optimizing some given criteria.

A. The cooling system optimal control

Let the real cooling system dynamics in (9) be:

$$\begin{aligned} x(t+1) = Ax(t) + B_u u(t) + B_T T_o(t) + \\ + B_T^+ T_o(t+1) + B_d d(t), \quad t \in \mathbb{Z}, \end{aligned} \quad \text{(15)}$$

At each time instant t, the MPC scheme computes the optimal control sequence $\mathbf{u}^\star$ given an initial system state $x_0 = x(t)$, and disturbance sequences $\mathbf{T}_o = \left[\, T_o(t),\, ...,\, T_o(t{+}N{-}1),\, T_o(t{+}N) \,\right]^\top$ and $\mathbf{d} = \left[\, d^\top(t),\, ...,\, d^\top(t{+}N{-}1) \,\right]^\top$, as follows:

$$\begin{aligned} \mathbf{u}^\star = \arg\min_{\mathbf{u}} \quad & J(\mathbf{u}, x_0, \mathbf{T}_o, \mathbf{d}), \\ \text{s.t.} \quad & \text{(10b), (10c), (10d),} \end{aligned} \tag{16}$$

where $J(\cdot)$ is the criterion function defined in (10a). The optimal control sequence $\mathbf{u}^\star$ obtained in this way represents the best thermal energy profiles for each zone (room) throughout the prediction horizon, which will keep rooms temperature inside the specified range. To transform this thermal energy to electricity consumption profile needed for the energy management in the microgrid, the thermal energy profile is scaled with the coefficient of performance (COP) of the central chiller unit, which is a nonlinear function of air temperature and required thermal energy:

$$E^{\text{L}}(t) = \frac{\sum_{j=1}^{q} u_j^\star(t)}{\text{COP}(u^\star(t), d_1(t))}, \quad \forall t, \tag{17}$$

For the sake of simplicity here we use a constant $\text{COP} = 3.5$.

B. Energy management in the microgrid

Let the real microgrid system dynamics in (3) be:

$$x(t+1) = Ax(t) + Bu(t), \quad t \in \mathbb{Z}, \tag{18}$$

with electricity prices $c(t)$, and disturbances

$$d(t) = E^{\text{L}}(t) - E^{\text{PV}}(t), \tag{19}$$

where $E^{\text{L}}(t)$ is defined in (17), and $E^{\text{PV}}(t)$ is the electricity production by the PV array [11]. At each time instant t, the MPC scheme computes the optimal control sequence $\mathbf{u}^\star$ given an initial storages state $x_0 = x(t)$, electricity prices $\mathbf{c} = \left[\, c(t),\, c(t{+}1),\, ...,\, c(t{+}N{-}1) \,\right]^\top$, and disturbance sequence $\mathbf{d} = \left[\, d(t),\, d(t{+}1),\, ...,\, d(t{+}N{-}1) \,\right]^\top$, as follows:

$$\begin{aligned} \mathbf{u}^\star = \arg\min_{\mathbf{u}} \quad & J(\mathbf{u}, x_0, \mathbf{c}, \mathbf{d}), \\ \text{s.t.} \quad & \text{(5), (6), (7),} \end{aligned} \tag{20}$$

where $J(\cdot)$ is the criterion function defined in (4a). The optimal control sequence $\mathbf{u}^\star$ obtained in this way represents the best charging and discharging profiles of microgrid storages (batteries and fuel cell system), and optimal plan for electricity exchange with the utility grid.

C. Receding horizon philosophy

According to the receding horizon philosophy, only the first control vector $u_0^\star$ from an optimal control sequence $\mathbf{u}^\star$ is applied, i.e., $u(t) = u_0^\star$. Optimization problems in (16) and (20) are repeated again at the next time instant $t+1$, with new information on system measurements and outdoor conditions forecasts. By this approach, the new optimal control plan can potentially compensate for any disturbance that has meanwhile acted on the system. To solve optimization problems IBM ILOG CPLEX 12.6 is used together with YALMIP [12] for easier control problem implementation.

V. Simulation results

In this section performance of the proposed approach on the actual meteorological and electricity price data, during the 4-month period from 1 Jun 2014 to 30 Sep 2014 is verified. Historical meteorological data are provided by Meteorological and Hydrological Service, Croatia, whereas the electricity price data are freely available at the EPEX SPOT market web site [13]. Negative electricity prices that sometimes occur on the market, usually during holidays, are saturated to 0 € to preserve an LP formulation of the energy flow optimization problem. We consider closed-loop control scheme simulations with receding horizon philosophy as discussed in Section IV, whereas prediction horizon length is $N = 24$. Building operates in two working modes: (i) the daily mode (from 06:00 to 18:00) during which temperature requirements of end-users are set to 24 °C, and (ii) the nigh mode during which cooling is unavailable. Allowed temperature deviations from set-point are chosen to be $\{\pm 0.2, \pm 0.5, \pm 0.7\}$ °C which corresponds to limits of cyclic temperature variations of A, B and C classes of the thermal environment defined by ISO 7730 standard [14].

Revenue, i.e., economic gain, at the end of the 4-month period can be calculated as:

$$c_{\text{rev}} = \sum_{t=0}^{2927} c(t) E_{\text{buy}}^{\text{UG}}(t) + \big(0.9c(t)\big) E_{\text{sell}}^{\text{UG}}(t), \tag{21}$$

where $c(t)$ is the electricity price data, and 2928 is the total number of hours in the considered time period. In other words, revenue at time instant t is defined as a difference between electricity demand and actually imported electricity from the utility grid, multiplied by buying/selling electricity price. In order to be able to evaluate impact of energy storage systems on the revenue, we also calculate revenue for the case when there are no energy storage systems involved, defined as:

$$c_{\text{rev}}^{\text{D}} = \sum_{t=0}^{2927} c(t) \max\{0, E^{\text{D}}(t)\} + \big(0.9c(t)\big) \min\{E^{\text{D}}(t), 0\}, \tag{22}$$

where $E^{\text{D}}(t)$ is the difference between the cooling system electricity consumption and the PV array electricity production.

Figure 2 shows profiles of the microgrid simulation over 72 h exemplary period within the considered 4-month period, beginning on 6 Jul 2014 at 00:00, whereas the microgrid is driven by the MPC scheme with receding horizon philosophy with sampling time of 1 h. It can be seen that control algorithm uses FCs as little as possible compared to batteries stack, since overall efficiency of the FCs is below 30%, and the overall efficiency of the batteries is over 80%. In other words, FCs are used only when the difference between the maximum and minimum electricity prices along the prediction horizon is large enough, so that electricity loss is justified by economic gain. Similar logic is applied to batteries, i.e., they are charged during night-hours when electricity price is low, and are discharged during the daylight when electricity price is high. In this way, energy storage systems in the microgrid make it act as energy buffer and energy costs reducer between dynamic profiles of the cooling system electricity consumption

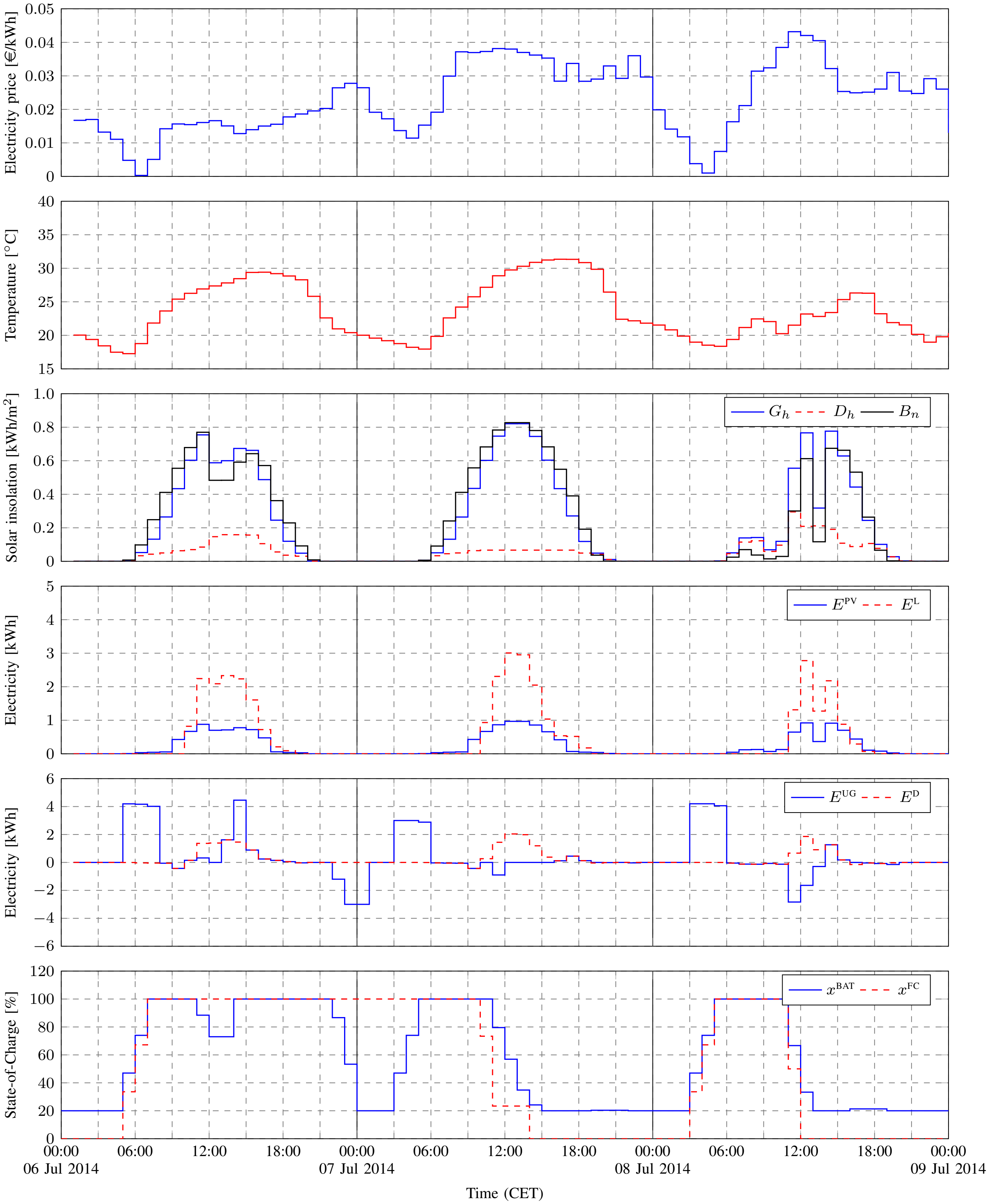

Fig. 2. Profiles for the closed-loop control simulation over 72 h exemplary period beginning on 6 Jul 2014 at 00:00, ordered from top to bottom as follows: (i) electricity price, (ii) air temperature, (iii) global horizontal G_h, diffuse horizontal D_h, and direct normal B_n solar insolation, (iv) electricity produced by the PV array E^{PV} and consumed by the cooling system E^{L} for $\Delta = 0.2$ °C and $\eta = 1$, (v) electricity exchanged with the utility grid E^{UG} and electricity balance for case when there are no energy storage systems E^{D}, and (vi) state-of-charge of the battery x^{BAT} and the fuel-cell system x^{FC}.

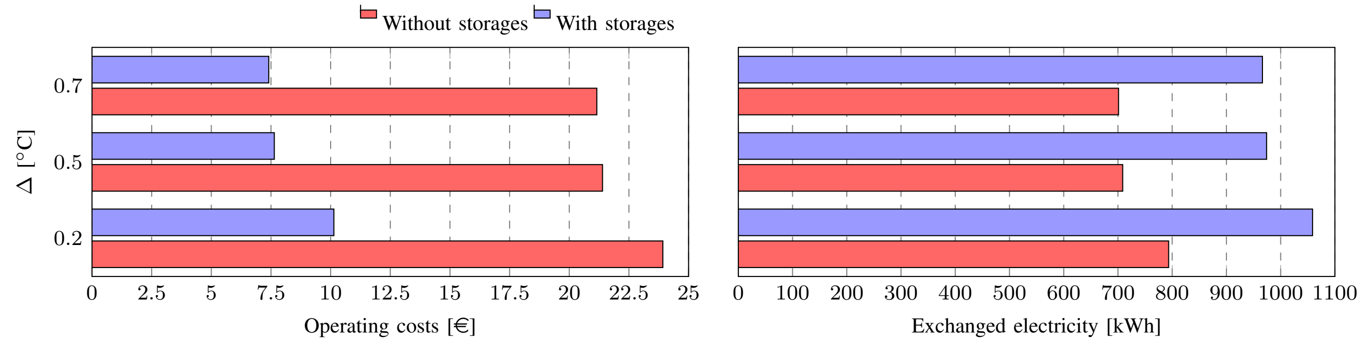

Fig. 3. Operating costs of the microgrid and the total electricity exchanged between the microgrid and the utility grid at the end of the cooling season, for three considered parameters Δ (0.2 °C, 0.5 °C, 0.7 °C with $\eta = 1$) and two control scenarios (balance without storages, and optimal control with storages). Positive costs denote charge imposed to the microgrid, while positive energy denotes imported electricity from the utility grid.

and variable electricity prices. This is especially important considering integration of renewable energy systems, since their electricity production is highly variable (intermittent) due to the strong dependence on atmospheric conditions.

Figure 3 shows operating costs of the microgrid and the electricity exchanged between the microgrid and the utility grid at the end of the considered 4-month period, for three considered parameters Δ (0.2 °C, 0.5 °C, 0.7 °C). It can be seen that operating costs of the microgrid are significantly less when using energy storage systems with the proposed multi-level control. However, total exchanged electricity is higher when energy storage systems are involved. This behaviour is logical since storages are used for electricity trading (buy when low, sell when high), and although economic gain is higher due to the optimal microgrid control, some electricity is lost on charging and discharging of storages.

VI. Conclusion

In this paper we proposed a multi-level optimal control of a microgrid-supplied cooling system in a building. The multi-level optimal control is based on (i) energy flow optimization in a microgrid, and (ii) optimization of building zones cooling in the presence of comfort constraints. Performance of the proposed approach was verified through 4-month simulations of a microgrid integrated with a building cooling system, in actual meteorological and electricity price data scenario. It was shown that a microgrid with integrated energy storage systems, together with the proposed multi-level optimal control, can significantly reduce operating costs of the building cooling system, by enabling electricity trading with the utility grid via simple principle "buy when low, sell when high". For the considered case-study, total savings of the microgrid operating costs are more than 50%.

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