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Nonlinear hierarchical building zone and microgrid control based on sensitivity analysis

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***Abstract*—Model predictive control has proven to be a promising platform for complex systems management and energy efficiency improvement in a large number of applications, particulary prominent in building climate or smart grids control. Interoperation of those systems often turns out to be of a nonlinear nature. The paper proposes a modular coordination mechanism between building zones comfort control and building microgrid energy flows control based on nonlinear model predictive control. The modularity of coordination implies technology separation with interaction through consumption profiles and equivalent prices, where nonlinearity occurs in electricity-heat energy conversion. A method based on sensitivity analysis is exploited and put to parametric formulation to tackle the problem of high computational complexity. The nonlinearity is addressed by choosing the convergence of the local optimum towards the microgrid global optimum in the direction of the lowest cost function values. Iterative approach between zone and microgrid level nonlinear problem finally results in the cost-optimal zone level operation. Results show the ability of the proposed approach to cope with system nonlinearities and illustrate how introduction of a central chiller unit characteristic rises the overall cost benefit of the system.**

***Index Terms*—Buildings energy management, Chiller characteristic, Sensitivity analysis, Nonlinear hierarchical MPC.**

I. INTRODUCTION

Buildings and microgrids are complex systems consisted of many subsystems responsible for maintaining safe and steady operation, which are also different in dynamics, energy levels, protocols, maintenance services etc. Rather than having one large control structure to handle all the tasks, it is more natural to segregate it into subunits in a hierarchical or distributed way [1], [2], [3]. In addition, many of those subsystems can be entrusted to optimization methods, and many of them already have such algorithms implemented. If more subsystems operate in an optimal way and are coordinated, the larger is the mutual gain together with overall economic balance of the whole system. Retaining the subsystem independency and modularity is also crucial from the implementation perspective with the aim of minimal on-site modifications and interconnection of different technologies by scarce communication signals. This finally reflects to significant cost reduction since the equipment integration and required expert staff knowledge is identified as the most pronounced contributor of implementation expenses [4].

Model predictive control (MPC) is recognized as a promising platform for energy management in buildings and smart grids with an ability of comprehending more and more subsystems together. Interoperation of the systems is often a very complex problem and issues such as nonlinearities or integer variables occur frequently. Examples of recent contributors in general control theory and distributed control are in topological approach of robust hierarchical control [1] and solvers efficiency increase with decentralized active-set method [5] for systems with communication delays or in distributed alternating direction method of multipliers [6]. In [7], problem partitioning topics are examined where subsystems interoperation is equivalently included in the problem optimisation cost.

In building zone and microgrid control the energy-optimal and the cost-optimal operation is expected to be in reasonable proximity for the case of building consumption control with coordinated grid power profile optimisation [8], [9]. Among the nonlinear problem handling algorithms, sensitivity analysis is utilized here as a suitable approach. Fundamentals of distributed control and sensitivity analysis were introduced already in the 1970s [10] and the approach is further elaborated in [11]. Some recent examples in the sensitivity analysis algorithm application to nonlinear systems can be found in [12] and [13], applied to biological processes.

This paper utilizes the existing sensitivity analysis theory from [11] and places it in the parametric optimisation form where shifting towards the price optimum within a critical region (CR) is trivial in complexity and time requirements. With the main goal of major mutual cost saving opportunities, we apply the proposed method for system interoperation through predicted energy consumption and corresponding prices of the building with integrated microgrid. The two subsystems are coupled through nonlinear characteristics of energy efficiency ratio (EER) of a central chiller unit as a cooling efficiency measure that states how much electrical power is needed for supplying the required thermal power. Building zone control acts as a lower hierarchy level (LHL) where its control variable is introduced as a parametric disturbance in the microgrid control that acts as a higher hierarchy level (HHL) problem. Transformation of the zone energy-optimal control to microgrid cost-optimal control is performed via parametric problem value function.

The paper is organized as follows. Problem definition is set in Section II with LHL and HHL optimal problem formulation and chiller nonlinearity. Section III presents the sensitivity analysis applied through parametric MPC for shifting the locally optimal LHL solution to globally optimal HHL solution.

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Section IV presents a simulation scenario and provides results. Conclusions are given in Section V.

II. Problem definition

A. Linear problem

In the following, superscripts l and h denote LHL and HHL variables, respectively. Bold notation is used to denote variables stacked over the prediction horizon of N. Considered LHL and HHL problems are defined as:

$$J^{l*}(x_0^l) := \min_{\mathbf{u}^l} \mathbf{h}^{l\top}\mathbf{u}^l + \mathbf{f}^l + J^{l'}(\mathbf{u}_l, x_0^l), \\ \text{s.t.} \begin{cases} \mathbf{x}^l = \mathbf{A}^l x_0^l + \mathbf{B}^l\mathbf{u}^l + \mathbf{D}^l\mathbf{d}^l \\ \mathbf{G}^l\mathbf{u}^l \leq \mathbf{w}^l \end{cases}, \tag{1}$$

and

$$J^{h*}(x_0^h, \boldsymbol{\theta}^h) := \min_{\mathbf{u}^h} \mathbf{h}^{h\top}\mathbf{u}^h + \mathbf{f}^{h\top}\boldsymbol{\theta}^h \\ \text{s.t.} \begin{cases} \mathbf{x}^h = \mathbf{A}^h x_0^h + \mathbf{B}^h\mathbf{u}^h \\ \mathbf{G}^h\mathbf{u}^h \leq \mathbf{w}^h + \mathbf{E}^h\boldsymbol{\theta}^h \end{cases}, \tag{2}$$

where $\mathbf{x}^l = \mathbf{A}^l x_0^l + \mathbf{B}^l\mathbf{u}^l + \mathbf{D}^l\mathbf{d}^l$ describes building thermodynamic behavior, with zones temperature information incorporated within vector $x^l \in \mathbb{R}^{n_{xl}}$, uncontrollable disturbances affecting the building (outdoor temperature, solar irradiance, etc.) denoted with $d^l \in \mathbb{R}^{n_d}$ and thermal energy inputs into each of n_{ul} controllable zones denoted with $u^l \in \mathbb{R}^{n_{ul}}$. Matrices $\mathbf{A}^l$, $\mathbf{B}^l$ and $\mathbf{D}^l$ are of appropriate dimensions. Microgrid dynamic is defined with the equation $\mathbf{x}^h = \mathbf{A}^h x_0^h + \mathbf{B}^h\mathbf{u}^h$ where $x^h \in \mathbb{R}^{n_{xh}}$ is a storages state of charge (SoC) vector, $u^h \in \mathbb{R}^{n_{uh}}$ is a vector of energies exchanged between the microgrid and the storage systems, and A^h and B^h are corresponding model matrices. Vectors $h^l \in \mathbb{R}^{n^{xl}}$, $h^h \in \mathbb{R}^{n^{xh}}$, $f^l \in \mathbb{R}^1$ and $f^h \in \mathbb{R}^{n^\theta}$ are appropriately chosen vectors to impel the desired building and microgrid behavior while respecting the constraints defined with $G^l \in \mathbb{R}^{n^{cl}\times n^{ul}}$, $G^h \in \mathbb{R}^{n^{ch}\times n^{uh}}$, $w^l \in \mathbb{R}^{n^{cl}}$, $w^h \in \mathbb{R}^{n^{ch}}$ and $E^h \in \mathbb{R}^{n^{ch}\times n^\theta}$. Symbols $n^x \in \mathbb{N}$, $n^u \in \mathbb{N}$, $n^c \in \mathbb{N}$, $n^\theta \in \mathbb{N}$ denote the number of states, inputs, constraints and parameters, respectively. The $J^{l'}$ part in LHL cost function is given to emphasize the setpoint tracking part of the cost [14]. Higher level (2) is formed as parametric problem with parameter $\theta_k^h \in \mathbb{R}^{n^\theta}$ chosen as the sum of all optimal u_k^{l*} vector elements j for a certain discrete time step k:

$$q_k^l = \sum_{j=1}^{n^{ul}} u_{j,k}^{l*} = 1_\theta u_k^{l*}, \tag{3a}$$

$$\boldsymbol{\theta}^h := \frac{1}{\text{EER}}\mathbf{q}^l, \tag{3b}$$

with block diagonal matrix $1_\theta \in \mathbb{R}^{1\times n^{ul}}$.

Problem from (1) corresponds to building zone energy-optimal control elaborated in [14]. Problem from (2) corresponds to building microgrid energy flows optimisation elaborated in [15] and further extended here to interoperate with LHL via parametric formulation. The hierarchical coordination of the two problems is elaborated in details in [16] by using a constant EER.

Original algorithm for multiparametric MPC was proposed in [17] and we utilize it here for hierarchical coordination with a distinction that only a single region is determined at one step and no additional partitioning of the parameter space is performed. For convenience, some of the main points of the corresponding results are concisely given in the sequel. The parametric formulation implies finding CRs in which operations on parameter-space sets are trivial.

Definition 1 Critical region is a subset of all the parameters θ for which a certain basis is optimal for problem (2), i.e., the same set A of constraints is active. We denote K as a polyhedral set $K \subseteq \mathbb{R}^s$ of parameters $K \triangleq \{\theta^h \in \mathbb{R}^s | \mathrm{G}_{\mathrm{CR}}^h\theta^h \leq \mathrm{w}_{\mathrm{CR}}^h\}$ and $K^* \subseteq K$ as region of parameters $\theta^h \in K$ such that (2) yields J^{h*}. Critical region for (2) formed with θ_0^h is then defined as:

$$\mathrm{CR}_{\mathrm{A}} \triangleq \{\theta^h \in K | \mathrm{A}(\theta^h) = \mathrm{A}(\theta_0^h)\}. \tag{4}$$

Contrary to set A, nonactive constraints belong to disjoint set NA, and $\mathrm{A} \cup \mathrm{NA} = C$ holds, where $C \triangleq \{1, \ldots, m\}$ is set of constraint indices. Constraints are therefore parted as:

$$\mathbf{G}_{\mathrm{A}}^h\mathbf{u}^{h*}(\theta) = \mathbf{w}_{\mathrm{A}}^h + \mathbf{E}_{\mathrm{A}}^h\boldsymbol{\theta}^h, \tag{5}$$

$$\mathbf{G}_{\mathrm{NA}}^h\mathbf{u}^{h*}(\theta) < \mathbf{w}_{\mathrm{NA}}^h + \mathbf{E}_{\mathrm{NA}}^h\boldsymbol{\theta}^h, \tag{6}$$

By using the local optimum $\mathbf{u}^{l*}$ of the LHL problem and correlating with HHL by (3), a HHL problem solution yields the critical region $\mathrm{CR}(\boldsymbol{\theta}^h)$ and corresponding affine descriptions $\mathbf{u}^{h*}(\boldsymbol{\theta}^h)$ and $J^{h*}(\boldsymbol{\theta}^h)$:

$$\mathbf{u}^{h*}(\boldsymbol{\theta}^h) = \underbrace{(\mathbf{G}^{\mathrm{A}})^{-1}\mathbf{E}^{\mathrm{A}}}_{\mathbf{D}}\boldsymbol{\theta}^h + \underbrace{(\mathbf{G}^{\mathrm{A}})^{-1}\mathbf{w}^{\mathrm{A}}}_{\mathbf{g}}, \quad \boldsymbol{\theta}^h \in \mathrm{CR}. \tag{7}$$

$$J^{h*}(\boldsymbol{\theta}^h) = \underbrace{\left(\mathbf{h}^h\mathbf{D}^\top + \mathbf{f}^h\right)}_{\mathbf{r}^h}\boldsymbol{\theta}^h + \mathbf{h}^{h\top}\mathbf{g}. \tag{8}$$

The active critical region $\mathrm{CR}(\boldsymbol{\theta}^h)$ is defined with:

$$\mathbf{G}_{\mathrm{CR}}^h\boldsymbol{\theta}^h \leq \mathbf{w}_{\mathrm{CR}}^h, \tag{9}$$

where

$$\mathbf{G}_{\mathrm{CR}}^h = \mathbf{G}_{\mathrm{NA}}^h\mathbf{D} - \mathbf{E}_{\mathrm{NA}}^h, \\ \mathbf{w}_{\mathrm{CR}}^h = \mathbf{w}_{\mathrm{NA}}^h - \mathbf{G}_{\mathrm{NA}}^h\mathbf{g}.$$

For imposing a coordination between the two levels, weighting vector $\mathbf{h}^l$ is simply chosen as $\mathbf{h}^l = \frac{1}{\mathrm{EER}}\mathbf{r}^h$ in (1), and the problem (1) is augmented by an additional set of constraints from (9), transformed to the LHL by (3) [16].

B. Nonlinear problem

In the particular case of application in buildings, required thermal and electric power are related by EER in the cooling season and its equivalent, the so-called coefficient of performance (COP), in the heating season. Both are dependent on the operating point (the electrical equivalent θ^h of the required thermal energy q^l) and outside air temperature T_0, as shown in Fig. 1 for a specific chiller used in our case study.

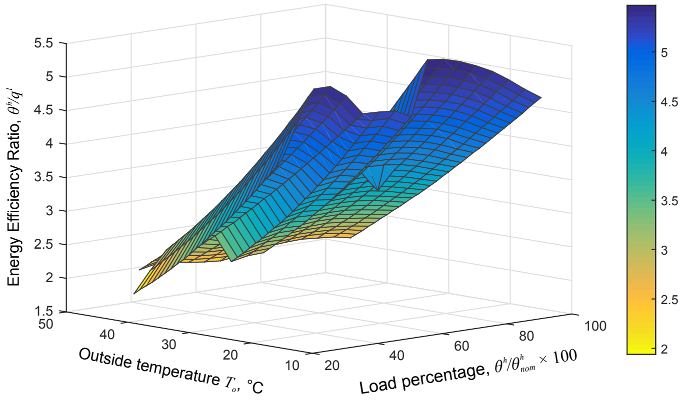

Fig. 1. Chiller EER characteristic with respect to outside temperature T_o and partial electrical load θ^h/θ^h_{nom} for chiller TRANE RTAC HE.

Figure 1 also shows highly nonlinear characteristic of the $\mathrm{EER}(T_o, \theta^h)$, which is expressed as a look-up table from the manufacturers data sheet. When observing a chiller with a sampling time large enough to disregard its dynamics, the look-up table from Fig. 1 is justified to be tied with thermal partial load $\mathrm{EER}(T_o, q^l) \approx \mathrm{EER}(T_o, \theta^h)$. The two levels, HHL and LHL, are now related by $\mathrm{EER}(T_o, q^l)$, which leads to nonlinear problem formulation of the higher level:

$$J^h = \mathbf{h}^{h\top}\mathbf{u}^h + \mathbf{f}^{h\top}\boldsymbol{\theta}^h(\mathbf{q}^l),$$

$$\text{s.t.} \begin{cases} \boldsymbol{\theta}^h(\mathbf{q}^l) = \frac{1}{\mathrm{EER}(\mathbf{T}_o,\mathbf{q}^l)}\mathbf{1}_\theta \mathbf{q}^l \\ \mathbf{x}^h = \mathbf{A}^h x_0^h + \mathbf{B}^h\mathbf{u}^h \\ \mathbf{G}^h\mathbf{u}^h \leq \mathbf{w}^h + \mathbf{E}^h\boldsymbol{\theta}^h \end{cases}, \tag{10}$$

and lower level:

$$J^l = \mathbf{h}^{l\top}(\boldsymbol{\theta}^h)\mathbf{u}^l + \mathbf{f}^{l\top} + J^{l'}(\mathbf{u}^l, x_0^l),$$
$$\text{s.t.} \begin{cases} \mathbf{x}^l = \mathbf{A}^l x_0^l + \mathbf{B}^l\mathbf{u}^l + \mathbf{D}^l\mathbf{d}^l \\ \mathbf{G}^l\mathbf{u}^l \leq \mathbf{w}^l \\ \boldsymbol{\theta}^h(\mathbf{q}^l) \in \mathrm{CR}_\varepsilon \end{cases}. \tag{11}$$

The problem from (11) is harder to handle and minimization of a value function over the critical region CR_ε, i.e., the linearized space, is not straightforward as in (8). Furthermore, the $\mathrm{EER}(T_o, q^l)$ is presented as a look-up table and is not possible to be explicitly used in the problem formulation. In the sequel, we present a method based on sensitivity analysis of the value function that iteratively improves the local LHL optimum $\mathbf{u}^{l*}$ towards the global optimum $\mathbf{u}^{l**}$ and corresponding $\mathbf{u}^{h**}$ defined with the minimum of the HHL cost function.

III. Hierarchical coordination

A. *Linear parametric coordination*

When considering linear problems (e.g. constant or only temperature-dependent EER), the coordination between the two levels is performed by choosing the $\boldsymbol{\theta}^h = \frac{1}{\mathrm{EER}(\mathbf{T}_o)}\mathbf{q}^{l*}$ and $\mathbf{h}^l(\boldsymbol{\theta}^h) = \frac{1}{\mathrm{EER}(\mathbf{T}_o)}\mathbf{r}^h$ that act as an interface between the two levels. The $\boldsymbol{\theta}^h$ holds an information of LHL consumption profiles and feedback is provided by $\mathbf{h}^l$ as a consumption price profile. If the LHL problem is solved with obtained $\mathbf{h}^l$, and then the HHL is solved with this new information, the local optima $(\mathbf{u}^{l*}, \mathbf{u}^{h*})$ are shifted towards the global optima $(\mathbf{u}^{l**}, \mathbf{u}^{h**})$. This is trivial for affine control law and value function within the active CR. To ensure this, the LHL is augmented to include the active CR boundaries from (9) as additional set of constraints. If the LHL solution is on the activated CR boundary, the solution is to be found in the adjacent CR and the procedure is iteratively repeated until the LHL constraints are triggered or an adjacent CR is non-existent. The procedure is presented in Fig. 2. The global optima $\left(\mathbf{u}^{l**}_{(M)}, \mathbf{u}^{h**}_{(M)}\right)$ are obtained in M iterations. For a one-year simulation with hourly sampling time on this particular application, the solution was obtained in $M = 1$ iteration for 92% of cases as shown in [16] (together with more details about the approach). In a receding horizon approach, the global optimum $\mathbf{u}^{l**}_{0,(M)}$ is further passed as a set of references to the lower level controllers (e.g., fan coil controllers) [18], and $\mathbf{u}^{h**}_{0,(M)}$ to storage power converter controllers [19]. The lower level controllers operate in real-time closed loops with much slower sampling times.

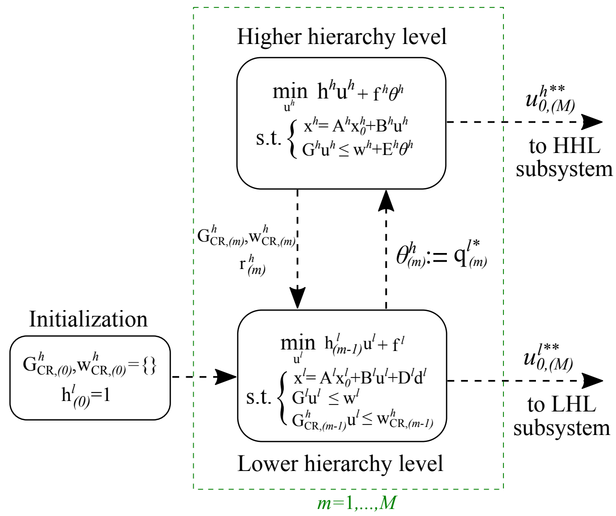

Fig. 2. Iterative hierarchical coordination for linear system.

B. *Coordination based on sensitivity analysis*

With a nonlinear parametric problem, it is not possible to obtain critical regions and explicit affine laws for J^{h*} and u^{h*}, and approach with minimization of a value function is not applicable. In general representation, sensitivity function represents the sensitivity of state or cost function to (small) variations in model parameter. The partial derivative of the cost function J^{h*} with respect to the parameter vector elements q^{l+} in the given point q^{l*}, so-called the sensitivity vector, is defined by:

$$\boldsymbol{\sigma}_{(m)} = \left.\frac{\partial J^{h*}_{(m)}}{\partial \mathbf{q}^{l+}_{(m)}}\right|_{\mathbf{q}^{l*}_{(m-1)}}, \tag{12}$$

with dimensions of $\sigma_{(m)} \in \mathbb{R}^N$ where m is the iteration index.

Different approaches are possible for determining the sensitivity functions. Here we opt for iterative approach with scattering large number of points around the initial solution and choosing the one with the smallest value of cost function. The points are chosen by a small deviation of ε around the initial solution $\mathbf{q}_0^l$:

$$q_{j_\varepsilon,k}^{l+} = q_{0,k}^l \pm \varepsilon \quad \forall j_\varepsilon, \forall k, \tag{13}$$

where j_ε is the index of scattered points and k is the prediction time instant. For the particular case of building optimization, i are microgrid storages, $j_\varepsilon = 1, 2$, and $k = 0, \ldots, N-1$.

The sensitivity analysis starts with solving (11) to obtain $u_{j_\varepsilon}^{l*}$ and then scattering the points to obtain $\mathbf{q}^{l+}$. The optimization problem from (10) is further solved with $q_{j_\varepsilon,k}^{l+}$ for each j_ε and k, yielding $j_\varepsilon N$ different HHL optimum costs $\mathbf{J}^{h+*}$. A hyperplane is now constructed through obtained $(\mathbf{q}^{l+}, \mathbf{J}^{h+*})$ points, together with the starting point $(\mathbf{q}^l, J^{h*})$. Since there are more points then needed ($2N+1$ total) to uniquely define a hyperplane, the least squares approach is used in order to obtain the best fit as weighted combination of all the points:

$$\begin{bmatrix} a^+ \\ b^+ \end{bmatrix} = \left(\boldsymbol{\phi}^\top \boldsymbol{\phi}\right)^{-1} \boldsymbol{\phi}^\top \mathbf{J}^{h+*}, \tag{14}$$

where $\boldsymbol{\phi} = [\mathbf{1} \;\; \mathbf{q}^{l+}]$ and $\boldsymbol{\sigma}_i = a^+$.

The LHL cost from (10) is rewritten to include the so-called linearised partial goal-interaction operator according to [11]:

$$\begin{aligned} \min_{\mathbf{q}^l} J^{l+} &= \min_{\mathbf{q}^l} a^{+\top}\mathbf{q}^l + J^l(\mathbf{u}^l, x_0^l), \\ \text{s.t.} &\left\{ \begin{array}{l} \mathbf{G}^l\mathbf{u}^l \leq \mathbf{w}^l \\ \mathbf{q}^l - \mathbf{q}_0^l \leq \varepsilon \end{array} \right. , \end{aligned} \tag{15}$$

where J^l is used from (11) as an initial value function cost before sensitivity analysis and $\mathbf{q}_0^l = \mathbf{q}_{(m-1)}^{l*}$ as a previous iteration optimal solution.

When the constraints $\mathbf{G}^l\mathbf{u}^l \leq \mathbf{w}^l$ are hit, the solution is obtained. Otherwise, the solution is passed to the HHL and problems are iteratively solved. The approach is based on the premises that globally-optimal solution is near the local one and the optimal solution is reached within small number of iterations. When the premise is compromised, the approach results in large number of iterations and time requirements.

Once the globally optimal solution is found in M iterations, microgrid power converter price optimal control signals are $\mathbf{u}^{h**} = \mathbf{u}_{(M)}^{h**}$ and fan coil price optimal control signals $\mathbf{u}^{l**} = \mathbf{u}_{(M)}^{l**}$. The method for sensitivity analysis is geometrically represented in Fig. 3 and the whole coordination algorithm is given in Algorithm 1. Figure 3 shows algorithm steps in 2-dimensional space. The method iteratively scatters points, chooses the one with the minimum cost and evolves along the hyperplane value function until the zone level constraints are reached.

IV. Simulation Results

Simulations are performed on a case study of one building floor at the University of Zagreb Faculty of Electrical Engineering and Computing consisting of 23 zones equipped

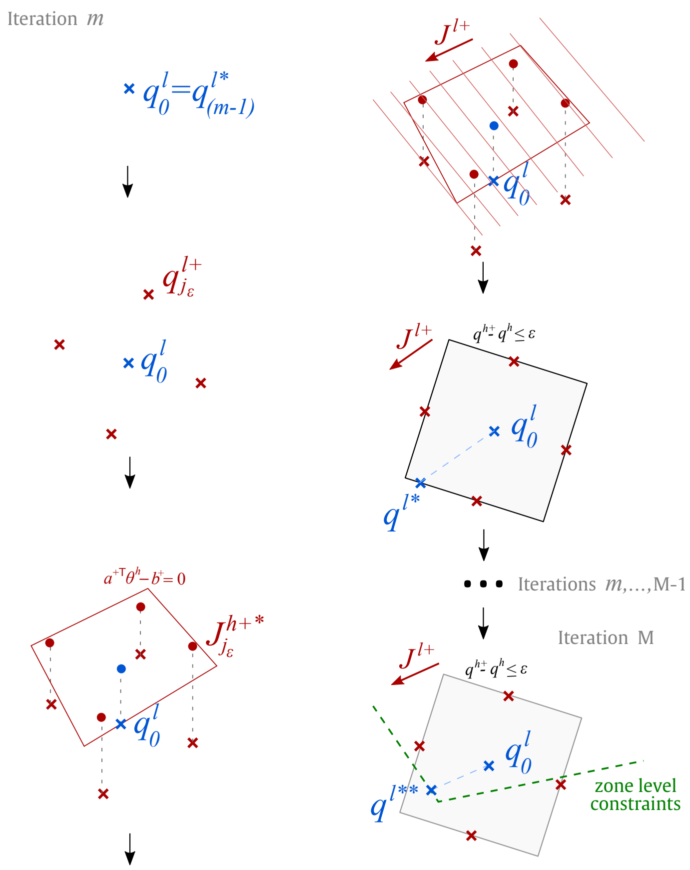

Fig. 3. Geometric representation of sensitivity analysis steps minimization of the value function.

Algorithm 1 Nonlinear parametric coordination with sensitivity analysis

1. Obtain the $\mathbf{u}^{l*}$ as the lower level locally-optimal solution from (11) and calculate $\mathbf{q}_0^l$ from (3);
2. Select points in the vicinity of solution $\mathbf{q}_0^l$: obtain $\mathbf{q}^{l+}$ from (13);
3. Obtain $\boldsymbol{\theta}^{h+}(\mathbf{q}^{l+})$ from (10);
4. Solve $j_\varepsilon N$ number of HHL problems from (10) for each given vector $\boldsymbol{\theta}^{h+}(\mathbf{q}^{l+})$ and obtain value function optimums J^{h+*};
5. Construct a hyperplane over $2N+1$ points of J^{h+*} by using (14);
6. Shift the solution towards the global optimum by solving the (15) to obtain $\mathbf{q}_{0,(m+1)}^l := \mathbf{q}^{l*}$;
7. Repeat from Step 2 until LHL constraints $\mathbf{G}^l\mathbf{u}^l \leq \mathbf{w}^l$ from (15) are activated;
8. Solve (10) with $\mathbf{q}_{(M)}^{l*}$ to obtain $\mathbf{u}_{(M)}^{h*}$
9. Pass obtained global optimum $\mathbf{u}_{(M)}^{l**} = \mathbf{u}_{(M)}^{l*}$ and $\mathbf{u}_M^{h**} = \mathbf{u}_{(M)}^{h*}$ to inner control loops and proceed to the next time instant k.

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with fan coils. The zone level problem is formed as a trade-off between temperature setpoint tracking and a cost for energy consumption with 23 control inputs and building model consisted of 391 states. More details can be found in [14] or [16]. Microgrid level consists of 1.5 kW photovoltaic array, 2 kW wind turbine, lead-acid batteries of 10 kWh capacity and fuel-cell hydrogen storage of 2.5 kWh capacity. The zone level is included in the microgrid as a controllable load and nonlinear hierarchical optimisation is imposed to obtain the price-optimal solution. The two levels are connected with TRANE RTAC HE chiller characteristics from Fig. 1. Simulations are performed and compared for the case of linear problems for both levels with constant EER and nonlinear problems with load-dependent EER, both with imposed hierarchical coordination between the levels. An exemplary one day of cooling period (June 1, 2014) is chosen with semi-clouded weather and real volatile market prices obtained from European Power Exchange portal. Sampling time of 1 h is chosen to meet the availability of weather forecast.

For linear problems scenario, a constant EER $= 4.17$ is chosen as a mean value of the variable EER and nonlinear scenario. Figure 5 shows comparison of zone temperatures for a selected 8^{th} individual zone (office) with presented linear and nonlinear parametric hierarchical MPC approaches. Since the EER is dependent on the weather conditions, nonlinear case results in higher zone temperature dynamics over time due to different efficiencies and corresponding costs. The setpoint of 24°C is chosen with allowed deviation of ±0.5°C outside which a high penalty is applied. The temperature setpoint tracking is imposed during working hours, from 7:00 to 18:00, as a tradeoff between desired comfort level and energy savings with equal weights inside the 24 ± 0.5 °C interval.

Figure 4 irradiance on the chosen room, which is located on the south side of the building, together with the outside temperature and energy market prices. Energy efficiency ratio is also shown for linear and nonlinear case, dependent on the outside conditions and current load. For EER calculation, the rated power is scaled by factor of 12 to adjust the curve for a single building floor.

Figure 5 shows comparison of presented nonlinear and linear hierarchical approaches. It may be observed how chiller characteristics are exploited for costs-saving opportunity that outweigh the trajectory tracking part of the criterion for the nonlinear scenario case. Thermal energy with negative sign depicts cooling regime. The figure also shows how the time period 13:00-14:00 is exploited to meet the lowest price of electricity, a bit lower outside temperature and, most important, to avoid the low value of EER.

Comparison of energy exchanged with the grid is shown in Fig. 6 and exploitation of variable EER is evident here as well. Additional cost savings of about 6% are obtained for the one-day simulation and are expected to rise with the longer period of simulations. Costs are calculated by multiplying the electricity price and energy exchanged with the grid during one hour period. In [16], we showed that coordinated zone and microgrid levels may contribute up to about 123% in cost savings (23% of revenue) with a constant EER and linear problem. Here, additional 6% is added for a simple one-day observed case.

Evolution of HHL cost function, i.e., the global criterion, is presented in Fig. 7 with chosen $\varepsilon = 10$ W of electrical power.

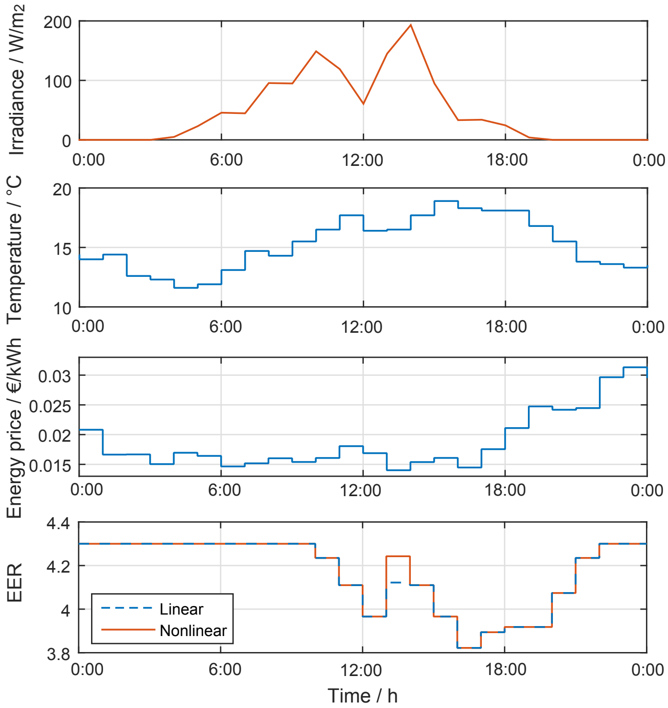

Fig. 4. Outside weather and market conditions.

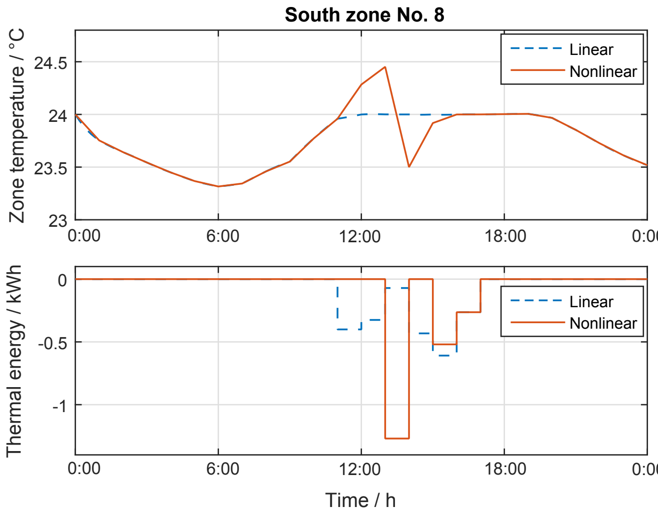

Fig. 5. Zone temperature comparison for linear approach and nonlinear with sensitivity analysis.

V. Conclusion

The paper presented a method for coordination between coupled hierarchy levels with included nonlinearity via parametric formulation of the optimization problem and applied

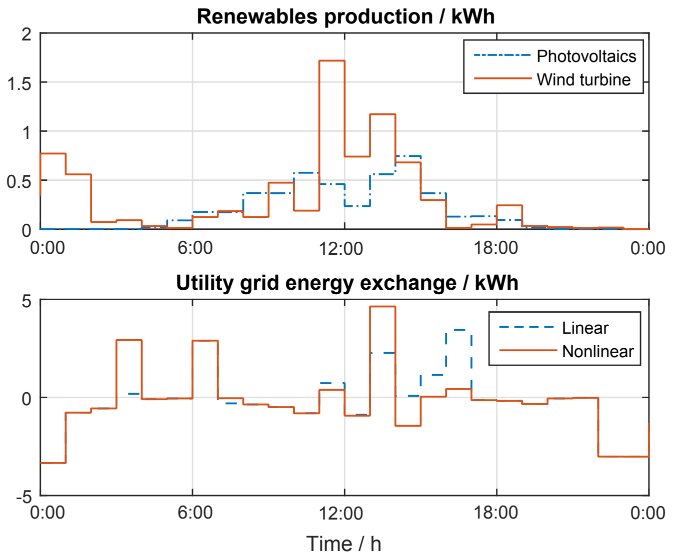

Fig. 6. Grid power comparison for linear approach and nonlinear with sensitivity analysis.

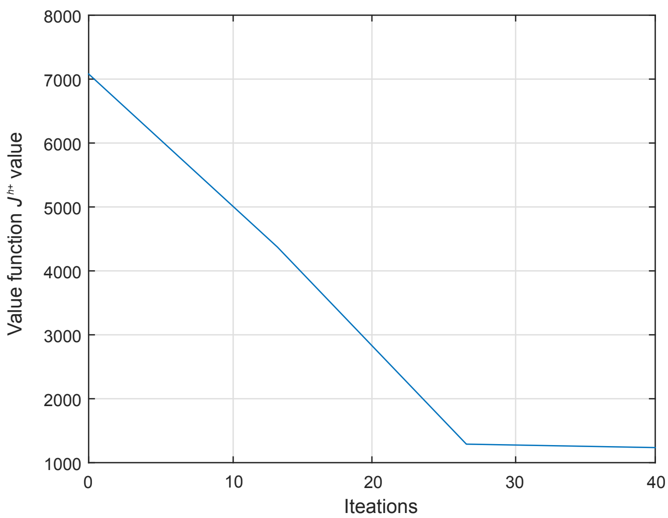

Fig. 7. Evolution of higher hierarchy level cost function over iterations introduced by sensitivity analysis.

sensitivity analysis. An iterative approach is exploited for shifting between local optimum of the hierarchy levels to the global system optimum. A mathematical basis is set for what we expect to become a contributive way for joining different hierarchical levels with nonlinear characteristics for this particular application. Results show that the introduction of chiller efficiency improved the overall cost benefit of the system. Future work will be directed to method validation realistic scenarios and configurations of the Faculty building with 23 offices and integrated 48 V microgrid. Future work will also be focused on introducing the central chiller and medium transport dynamics as an additional level of the hierarchical problem.

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