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An MPC-based Energy Management System for Multiple Residential Microgrids

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Abstract— **In this study we present a Model Predictive Control (MPC) approach to Energy Management Systems (EMSs) for multiple residential microgrids. The EMS is responsible for optimally scheduling end-user smart appliances, heating systems and local generation devices at the residential level, based on end-user preferences, weather-dependent generation and demand forecasts, electric pricing, technical and operative constraints. The core of the proposed framework is a mixed integer linear programming (MILP) model aiming at minimizing the overall costs of each residential microgrid. At each time step, the computed optimal decision is adjusted according to the actual values of weather-dependent local generation and heating requirements; then, corrective actions and their corresponding costs are accounted for in order to cope with imbalances. At the next time step, the optimization problem is re-computed based on updated forecasts and initial conditions. The proposed method is evaluated in a virtual testing environment that integrates accurate simulators of the energy systems forming the residential microgrids, including electric and thermal generation units, energy storage devices and flexible loads. The testing environment also emulates real-word network medium conditions on standard network interfaces. Numerical results show the feasibility and the effectiveness of the proposed approach.**

I. INTRODUCTION

Within the smart grid scenario, microgrids are subsystems of the distribution grid, which comprise Distributed Energy Resources (DERs), storage devices, and interconnected loads, operating as a single controllable system either connected or isolated from the grid. The growing need of satisfying the increasing energy demand in a sustainable way makes the concept of microgrid indeed attractive. Distribution companies have to account for more complex load balancing scenarios so that the quality of electrical supply to consumers is maintained and the use of non-renewable generation is minimized. In this scenario, microgrids can efficiently manage and coordinate DERs and loads, as well as support high penetration of renewable energy sources [1].

In recent years, more and more utilities and governments offer programs that provide incentives for residential consumers to adopt on-site distributed generators and energy storage systems [2]. A home with local generation and storing capabilities forms a residential microgrid, which is capable of generating, storing, buying/selling and sharing energy in residential areas. However energy storage devices and renewables are not still common within homes, they are often included in energy management frameworks of future environmentally friendly homes [3]. In this paper, we focus on residential microgrids owning a shared DER and present an MPC approach to EMS for multiple residential microgrids, which comprise DERs, Electrical Energy Storage (EES) systems and both thermal and electrical loads (e.g., heating system, electrical appliances). The proposed system layout can represent either a residential district where several single-family houses with local generation capabilities owning a shared DER or a smart building where apartments with heating systems and storage devices share a common DER. However in the following we commonly refer to the single subsystems as "houses", we point out that then can also represent building apartments.

Our MPC-based EMS aims at reducing energy costs and improve consumers comfort levels. Smart appliances are basic components of an EMS: they can be switched on or off in response to price signals and are required if Demand Response (DR) policies are to be applied. DR policies are commonly defined as changes in electricity use by consumers in response to changes in the electricity price over time [4]. Effective energy management of microgrids with demand response policies can help flattening the aggregated demand curve and reducing the number of expensive generation plants used for peak load periods. DR policies can take advantage of the additional flexibility offered by storage devices, which are capable to store energy and release it when it is more convenient [5].

Thus microgrids present several challenges from the standpoint of control and modeling requirements. Optimal control and energy management of microgrids is an active field of research, further complicated by the inherent system uncertainty in the energy demand, renewable generation and energy prices, and by flexible loads, which account for consumers preferences [6], [7]. Model predictive control is the most common method for addressing forecast errors [3]. All the aforementioned aspects are included in this study. Both load curtailment and load shifting policies are accounted for and the energy demands are optimized while achieving a trade-off between demand peak reduction and user comfort. The overall problem is formulated using mixed-integer linear programming (MILP), which can be solved by using commercial solvers [8]. Microgrid operations are decided on the basis of predictions of future behavior of the system and renewable power generation and demand forecasts. We also account for user time preferences and the possibility to sell stored energy to the grid. The feedback mechanism introduced through the MPC receding horizon philosophy allows to compute current imbalances and corrective actions are taken such that power balance and user comfort are guaranteed. Further, we consider a scenario where several residential microgrids can share DERs so to distribute their costs and benefits and also participate to the

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day-ahead energy market through DR Aggregators (see, for instance, [9]).

The proposed frameworks is flexible and it can easily include other objectives or more complex technical features, such as generators minimum up and down times (see [10]). We would like to remark that our storage modeling rules out the possibility that the optimal solution contemplates simultaneous charging and discharging of the storage, a physically unrealizable policy.

A case study of a five residential microgrids sharing a micro-CHP device is implemented to assess the performance of the proposed EMS framework. The case study is built up in the Virtual MicroGrid Lab (VMGL), part of the EIT ICT Labs SES virtual smart grid laboratory activity, where partners from industry and academia have combined resources to develop a virtual laboratory for testing ICT infrastructures within the microgrid [11].

Literature review: Though there is already a vast literature on microgrids energy management system, there are still many research and development needs associated to microgrids, among these one of the most crucial elements is finding the best operational strategy under uncertainty. Several works can be found in the literature tackling the problem of energy management of residential microgrids [12], [13], [14], [15], [16], [17], [18], [19], [20]. The approaches described in the aforementioned are commonly based on mixed integer formulations, either linear or nonlinear, or fuzzy logic. They proposed scheduling frameworks typically consider a single microgrid scenario and do not account for uncertainty and user preferences; moreover modeling details of some of the components, such as smart appliances, are not included and the energy demand optimization is not included. Some studies consider only the scheduling of domestic loads using genetic algorithms, game theory, particle swarm [21], [22], [23]; other works deal with the scheduling of the energy demand (either electrical or thermal) considering either renewable energy source [24], [25], [26] or storage devices [27]. The effectiveness of MPC method for appliance scheduling in alleviating the effect of price uncertainty or in managing thermal loads with a thermal energy storage is illustrated respectively in [28] and [29].

The paper is further organized as follows: the multi-microgrids modeling approach is discussed in Section II; the MPC-based EMS is then described in Section III; in Section IV the virtual experimental setup is described and results are evaluated; finally, conclusions and future works are outlined in Section V.

II. MODELING

Here we briefly describe the modeling setup of the system architecture. The ultimate goal is to make the MPC problem formulation suitable for online computation.

A. Nomenclature

The forecasts, the parameters and the decision variables used in the proposed formulation are described respectively in

TABLE I

PARAMETERS

Parameters	Description
H	scheduling horizon
$N_{\mathrm{appliance,h}}$	number of home smart appliances for house h
N_{h}	number of houses
n_i	number of energy phases of appliance i
$E_{i,j}$	energy requirements for energy phase j of appliance i
$\underline{P}_{i,j}$, $\overline{P}_{i,j}$	bounds on energy phase power
$\underline{T}_{i,j}$, $\overline{T}_{i,j}$	bounds on number of time slots for energy phase j of appliance i
$\underline{D}_{i,j}$, $\overline{D}_{i,j}$	bounds on between-phase delays in the number of time slots
TP_i	user time preference interval for appliance i
c_{gas}	fuel (natural gas) cost for the micro-CHP
$\alpha_{\mathrm{s,h}}$	storage energy degradation for house h
$c_{\mathrm{s,h}}$	operating and maintenance cost of the power exchanged with the storage unit for house h
$\eta^{\mathrm{c}}_{\mathrm{s,h}}$, $\eta^{\mathrm{d}}_{\mathrm{s,h}}$	charging/discharging efficiencies of storage for house h
α_1,α_0,β_1,β_0	parameters of the micro-CHP model
$P^{\mathrm{peak,h}}$	"peak signal" for house h (i.e., total slot energy upper bound)
$\underline{P}^{\mathrm{heat}}_{\mathrm{chp}}$, $\overline{P}^{\mathrm{heat}}_{\mathrm{chp}}$	bounds on micro-CHP thermal power
$\underline{P}^{\mathrm{el}}_{\mathrm{chp}}$, $\overline{P}^{\mathrm{el}}_{\mathrm{chp}}$	bounds on micro-CHP electrical power
$\underline{P}_{\mathrm{gas}}$, $\overline{P}_{\mathrm{gas}}$	bounds on micro-CHP gas power
$\underline{P}^{\mathrm{heat}}_{\mathrm{hp,h}}$, $\overline{P}^{\mathrm{heat}}_{\mathrm{hp,h}}$	bounds on heat pump thermal power to house h
$\underline{P}^{\mathrm{el}}_{\mathrm{hp,h}}$, $\overline{P}^{\mathrm{el}}_{\mathrm{hp,h}}$	bounds on heat pump electrical power to house h
$\underline{P}_{\mathrm{s,h}}$, $\overline{P}_{\mathrm{s,h}}$	bounds on the power exchanged with the storage for house h
$\underline{E}_{\mathrm{s,h}}$, $\overline{E}_{\mathrm{s,h}}$	bounds on the storage energy level for house h

TABLE II

FORECASTS

Forecasts	Description
c_{tariff}	electricity tariff
$\underline{P}^{\mathrm{heat}}_{\mathrm{h}}$, $\overline{P}^{\mathrm{heat}}_{\mathrm{h}}$	bounds on thermal power demand for house h (corresponding to the thermal comfort range)
$COP_{\mathrm{hp,h}}$	Coefficient of Performance (COP) of the heat pump for house h)
$P_{\mathrm{res,h}}$	power generation from renewables for house h

TABLE III

DECISION AND LOGICAL VARIABLES

Variables	Description
δ_{chp}	off(0)/on(1) state of the micro-CHP
$\delta^{\mathrm{c}}_{\mathrm{s,h}}$,$\delta^{\mathrm{d}}_{\mathrm{s,h}}$	storage charging/discharging state for house h
$P_{i,j}$	power profile for each phase
$x_{i,j}$	indicator of whether a phase is on or off
$t_{i,j}$	indicator of whether a transition is happening
$s_{i,j}$	indicator of whether a phase has been off
$P^{\mathrm{grid}}_{\mathrm{h}}$	importing(positive)/exporting(negative) power from/to the grid for house h
P_{gas}	gas power input to the micro-CHP
$P^{\mathrm{heat}}_{\mathrm{chp,h}}$	micro-CHP thermal power to house h
$P^{\mathrm{el}}_{\mathrm{chp,h}}$	micro-CHP electrical power to house h
$P^{\mathrm{heat}}_{\mathrm{hp,h}}$	heat pump thermal power to house h
$P^{\mathrm{el}}_{\mathrm{hp,h}}$	heat pump electrical power to house h
$P^{\mathrm{heat}}_{\mathrm{h}}$	thermal power demand for house h
$P^{\mathrm{c}}_{\mathrm{s,h}}$,$P^{\mathrm{d}}_{\mathrm{s,h}}$	charging/discharging power exchanged with the storage for house h
$E_{\mathrm{s,h}}$	storage energy level for house h

Tables I, II and III. Power units are Watts. We point out that the time is discretized into time slots.

In this report a simple method is used for weather forecasts, namely the method of persistence forecasting. This means that yesterday's observations will serve as a forecast for today. As future extension of this work, more accurate forecasts can be easily included in the proposed framework.

B. Loads

We consider two types of loads:

- *thermal loads*, i.e. demand levels related to thermal indoor comfort;
- *electrical loads*, i.e. demand levels related to smart appliances.

Thermal loads.: Forecasts of the minimum and the maximum thermal energy required to keep the indoor temperature in the houses within a given comfort range is computed through a dynamic house model based on forecasts of the weather conditions. The house model runs on top of the Apros process simulation software [30]. The model includes the energy dynamics of building structure and indoor temperature and account for the outdoor temperature, the solar radiation and the internal gains from occupants and equipment.

Electrical loads.: An appliance operation process is made up of sub-processes called energy phases. An energy phase is considered uninterruptible, and it consumes a pre-specified amount of electric energy in order to finish the physical task. Several other technical and user specified constraints are to be included in the problem formulation: *i)* both the power assigned to the energy phase at any time slot and its duration have to take values within a certain range; *ii)* all energy phases associated with a single appliance must be run sequentially; *iii)* there can be delays between the energy phases, but the order must be observed; *iv)* for safety reason the total power assigned to all appliances at any moment cannot exceed a limit called peak signal; *v)* there might be user specified time preferences, requiring that certain appliances should be run within some particular time intervals; *vi)* there might be user specified preferences on appliances, e.g., a certain appliance cannot start before some other appliance finishes. Further details on appliance modeling and technical specifications are provided in [31].

C. EES system

For a storage unit of house h, we consider the following discrete time model [32]:

$$E_{\mathrm{s,h}}(k+1) = \alpha_{\mathrm{s,h}} E_{\mathrm{s,h}}(k) + \eta^{\mathrm{c}}_{\mathrm{s,h}} P^{\mathrm{c}}_{\mathrm{s,h}}(k)\Delta T - \eta^{\mathrm{d}}_{\mathrm{s,h}} P^{\mathrm{d}}_{\mathrm{s,h}}(k)\Delta T, \tag{1}$$

with $0 < \eta^c, \eta^d < 1$ accounting for the energy losses and $\Delta T = t_{k+1} - t_k$ being a constant sampling time. We introduce binary variables $\delta^{\mathrm{c}}_{\mathrm{s,h}}$,$\delta^{\mathrm{d}}_{\mathrm{s,h}}$ to model the following logical condition and the storage dynamics:

$$\begin{cases} P^{\mathrm{c}}_{\mathrm{s,h}}(k) > 0 & \Longleftrightarrow \delta^{\mathrm{c}}_{\mathrm{s,h}}(k) = 1 \\ P^{\mathrm{d}}_{\mathrm{s,h}}(k) > 0 & \Longleftrightarrow \delta^{\mathrm{d}}_{\mathrm{s,h}}(k) = 1. \end{cases} \tag{2}$$

Then we express the logical conditions above as the following mixed integer linear inequalities:

$$\begin{gathered} \underline{P}_{\mathrm{s,h}} \delta^{\mathrm{c}}_{\mathrm{s,h}}(k) < P^{\mathrm{c}}_{\mathrm{s,h}}(k) < \overline{P}_{\mathrm{s,h}} \delta^{\mathrm{c}}_{\mathrm{s,h}}(k) \\ \underline{P}_{\mathrm{s,h}} \delta^{\mathrm{d}}_{\mathrm{s,h}}(k) < P^{\mathrm{d}}_{\mathrm{s,h}}(k) < \overline{P}_{\mathrm{s,h}} \delta^{\mathrm{d}}_{\mathrm{s,h}}(k) \\ \delta^{\mathrm{c}}_{\mathrm{s,h}}(k) + \delta^{\mathrm{d}}_{\mathrm{s,h}}(k) \leq 1. \end{gathered} \tag{3}$$

The last inequality rule out the possibility to have charging and discharging during the same sampling period.

D. Heat pump

Heat pumps are devices able to transfer thermal energy by absorbing heat from a cold medium (heat source) and release it to a warmer one (heat sink). In this study we consider an electrically operated heat pump, since they are by far the most frequently used. The thermal efficiency of heat pump systems depends strongly on the temperature difference between heat source and sink as well as the overall operating temperature level. The main performance measure of heat pumps is the coefficient of performance (COP), which is a function of temperature level and temperature difference between source and sink. A black box model is created that calculates the COP as a function of source and sink temperature, based on heat pump type specific mean values for two different sink temperature levels. Further, the air heat pump is assumed to be controlled locally such that: *i)* the power consumption is independent of the source temperature; *ii)* the sink temperature is kept constant at 35°C, so that the COP does only rely on the source temperature. This control strategy is reasonable assuming an existing thermal buffer storage and low temperature heating and is implemented by some manufacturers of heat pumps (e.g. [33]). For further details on the heat pump modeling and on its control strategy, we refer the interested reader to the technical report [11].

Thus, at each time slot, forecasts of the COP based on temperature predictions are integrated in the proposed control framework in order to predict the future heat generation from each heat pump.

E. Micro-CHP

The component represents a typical micro combined heat and power (micro-CHP) unit. the component model was developed by CREATE-NET and refers to the installation located in the town of Roncegno (Trento)[34]. The development of the component followed a data-driven approach, where data from a real-world deployment were used, in combination with machine learning and big data techniques.

The micro-CHP model is:

$$\begin{aligned} P^{\mathrm{el}}_{\mathrm{chp}} =& \alpha_1 \cdot P_{\mathrm{gas}} + \alpha_0 \\ P^{\mathrm{heat}}_{\mathrm{chp}} =& \beta_1 \cdot P_{\mathrm{gas}} + \beta_0. \end{aligned} \tag{4}$$

For further details we refer the interested reader to the technical report [11].

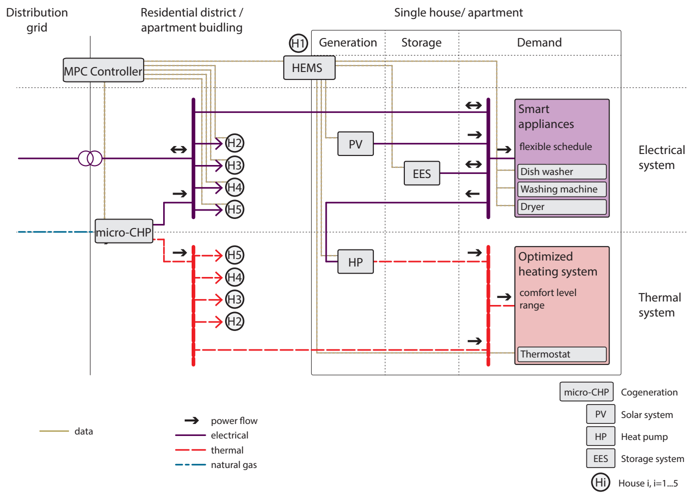

Fig. 1. System architecture

F. Photovoltaic system

Currently, photovoltaic (PV) systems are the only renewable electrical energy sources deployed in the residential sector with a considerable share. The model integrated in the proposed framework calculates efficiency changes due to the given weather data in more detail while further losses are taken into account as lump values. The system parameters influencing the output the most are the peak power under Standard Test Conditions (STC) [1], the STC efficiency and the efficiency of the inverter. An integrated control loop, the maximum power point (MPP) tracker, keeps the PV system running with maximum power.

For specific data and further details on the PV model we refer the interested reader to the technical report [11].

III. MPC-based EMS for microgrids

This section details the proposed stochastic MPC controller for microgrids.

The system under study is a residential multi-microgrid system with a shared energy source. We recall that each single microgrid can represent either a single-family house or an apartment in a building.

As depicted in Figure 1, each house is equipped with a Home Energy Management System (HEMS), which is responsible for operating the end-user smart appliances, the local generation devices and the interaction with the grid at the residential level according the setpoints computed by the control system. The MPC controller is responsible for energy management and energy sources coordination. The core of the proposed MPC-based control system is an optimization problem, which consists in taking decisions on how to optimally schedule production by generators, storage, as well as controllable loads, to cover the system demand and minimize the generation costs and the cost of imported electricity from the distribution grid in the next hours or day.

[1]Standard Test Conditions: air mass 1.5, irradiance 1000 W/m2, temperature of PV panels 25°C

Supply and demand of electrical and thermal energy are both modeled and handled. The thermal energy is required to provide the needed thermal comfort to the house occupants, while the electrical energy is needed to run the smart appliances and the heat pump (when required). The natural gas is instead required to run the shared micro-CHP.

At every time step, the MPC problem is solved and optimal decision on unit commitment, energy dispatch, storage schedule and DR policies is computed, based on weather forecasts and the current system conditions. The computed optimal decision is then adjusted according to the actual values of the photovoltaic generation and of the heating requirements from the house; hence, corrective actions and the corresponding costs are taken in order to cope with potential imbalances. At the next time step, the MPC problem is solved again based on updated forecasts and system condition.

By using the modeling approach of Section II, the MPC problem can be formulated as a MILP optimization problem. We next define the cost function and the constraints of the MILP.

1) Cost function: The aim is to minimize the cost of satisfying both the thermal and electrical loads, hence the objective function is

$$\min \sum_{k=1}^{H}\sum_{h=1}^{N_{\mathrm{h}}}\Big[\big(c_{\mathrm{tariff}}(k)\cdot P^{\mathrm{grid}}_{\mathrm{h}}(k)+c_{\mathrm{s,h}}\cdot(P^{\mathrm{c}}_{\mathrm{s,h}}+P^{\mathrm{d}}_{\mathrm{s,h}})\big) \\ + c_{\mathrm{gas}}\cdot P_{\mathrm{gas}}(k)\Big]\Delta T. \tag{5}$$

2) Electrical and thermal power balance: The electrical and thermal power balances at each house need to be satisfied. At the current point in time, k, if an appliance is running, the power assigned to the current energy phase by the optimization problem solved at the previous time slot must be considered as a critical load for the current time slot, which cannot be rescheduled and has to be satisfied, since an energy phase is uninterruptible. We denote this amount of power for the house h as $P_{\mathrm{assigned,h}}(k)$.

The balance between electrical energy production and consumption to be met at each time k for house h, $\forall h,k$ is:

$$\sum_{i=1}^{N_{\mathrm{appliance,h}}}\sum_{j=1}^{n_i}P_{i,j}(k)+P_{\mathrm{assigned,h}}(k)+P^{\mathrm{c}}_{\mathrm{s,h}}-P^{\mathrm{d}}_{\mathrm{s,h}} \\ +P^{\mathrm{el}}_{\mathrm{hp,h}}+P^{\mathrm{el}}_{\mathrm{chp,h}}-P_{\mathrm{res,h}}=P^{\mathrm{grid}}_{\mathrm{h}}. \tag{6}$$

Regarding the thermal energy balance, three energy sources have to be taken into account to fulfill the thermal requirements: the heat pump, the micro-CHP and the waste heat generated by running appliances. Studies suggest that 70% of regular household electric use contributes to the household's heat demand [35].

The balance between thermal energy production and use to be met at each time k for house h, $\forall h,k$ is:

$$\underline{P}^{\mathrm{heat}}_{\mathrm{h}}\le 0.7P_{\mathrm{assigned,h}}(k)+P^{\mathrm{heat}}_{\mathrm{hp,h}}+P^{\mathrm{heat}}_{\mathrm{chp,h}}\le\overline{P}^{\mathrm{heat}}_{\mathrm{h}}. \tag{7}$$

We remark that the thermal energy demand is optimized through (7) such that the indoor temperature in each house is within a given comfort range.

3) Appliance model: The appliance model is based on [31], so the interested reader is referred to those studies for further details. Here we outline the constraints included in the MILP problem. Notice that, at each time slot, the schedulable energy phases and corresponding operational times and delays are appropriately updated according to the running appliance and energy phase.

An energy phase being uninterruptible and sequential processing of the energy phases can be modeled by using the auxiliary decision variables s_{ij}^k and imposing additional constraints; the interested reader is referred to [31].

To make sure that the energy phases fulfill their energy requirements, the bounds on power assignment and time limits, the following constraints are imposed, $\forall i, j, k$:

$$\begin{aligned} \sum_{k=0}^{H-1} P_{i,j}(k) &= E_{i,j} \\ \underline{P}_{i,j}\, x_{i,j}(k) \le P_{i,j}(k) &\le \overline{P}_{i,j}\, x_{i,j}(k) \\ \underline{T}_{i,j} \le \sum_{k=1}^{H} x_{i,j}(k) &\le \overline{T}_{i,j} \\ \underline{D}_{i,j} \le \sum_{k=1}^{H} t_{i,j}(k) &\le \overline{D}_{i,j} \\ t_{i,j}(k) = s_{i,(j-1)}(k) &- \big(x_{i,j}(k) + s_{i,j}(k)\big). \end{aligned} \tag{8}$$

The household user can set up the time preference constraints, specifying the time interval a particular appliance must be finished within. The corresponding constraints are written as

$$x_{ij}^k \le \mathrm{TP}_i^k, \quad \forall\, i, j, k \tag{9}$$

Notice that $\mathrm{TP}_i^k = 0$ if and only if none of the energy phases of appliance i can be processed during time slot k.

4) EES model: The EES for each house h is modeled through equations and inequalities (1) and (3).

To consider the bounds on the storage capacity, we include the following constraint

$$\underline{E}_{\mathrm{s,h}} \le E_{\mathrm{s,h}}(k) \le \overline{E}_{\mathrm{s,h}} \tag{10}$$

5) Micro-CHP model: The micro-CHP is driven by natural gas and generates both electric and thermal power.

The following set of constraints model the behavior of the micro-CHP at each time slot k

$$\begin{aligned} \underline{P}_{\mathrm{chp}}^{\mathrm{el}} \cdot \delta_{\mathrm{chp}}(k) \le P_{\mathrm{chp}}^{\mathrm{el}}(k) &\le \overline{P}_{\mathrm{chp}}^{\mathrm{el}} \cdot \delta_{\mathrm{chp}}(k) \\ \underline{P}_{\mathrm{chp}}^{\mathrm{heat}} \cdot \delta_{\mathrm{chp}}(k) \le P_{\mathrm{chp}}^{\mathrm{heat}}(k) &\le \overline{P}_{\mathrm{chp}}^{\mathrm{heat}} \cdot \delta_{\mathrm{chp}}(k) \\ \underline{P}_{\mathrm{gas}} \cdot \delta_{\mathrm{chp}}(k) \le P_{\mathrm{gas}}(k) &\le \overline{P}_{\mathrm{gas}} \cdot \delta_{\mathrm{chp}}(k) \\ \sum_{h=1}^{N_{\mathrm{h}}} P_{\mathrm{chp,h}}^{\mathrm{el}}(k) &= P_{\mathrm{chp}}^{\mathrm{el}}(k) \\ \sum_{h=1}^{N_{\mathrm{h}}} P_{\mathrm{chp,h}}^{\mathrm{heat}}(k) &= P_{\mathrm{chp}}^{\mathrm{heat}}(k) \\ P_{\mathrm{chp,h}}^{\mathrm{heat}}(k) &\ge 0 \\ P_{\mathrm{chp,h}}^{\mathrm{heat}}(k) &\ge 0, \end{aligned} \tag{11}$$

where $P_{\mathrm{chp}}^{\mathrm{el}}$ and $P_{\mathrm{chp}}^{\mathrm{heat}}$ are defined according (II-E). The constraints above guarantee that the thermal and the electrical power outputs of the micro-CHP are properly shared among the houses and the bounds on the power generation and on the gas power are not exceeded.

6) Heat pump model: The following set of constraints model the behavior of the heat pump at each time slot k and for each house h

$$\begin{aligned} P_{\mathrm{hp,h}}^{\mathrm{heat}}(k) &= COP_{\mathrm{hp,h}}(k) \cdot P_{\mathrm{hp,h}}^{\mathrm{el}}(k) \\ \underline{P}_{\mathrm{hp,h}}^{\mathrm{heat}} \le P_{\mathrm{hp,h}}^{\mathrm{el}}(k) &\le \overline{P}_{\mathrm{hp,h}}^{\mathrm{heat}} \\ P_{\mathrm{hp,h}}^{\mathrm{el}}(k) &\ge 0, \end{aligned} \tag{12}$$

where $COP_{\mathrm{hp,h}}(k)$ is the forecasted COP of the heat pump at time slots k based on weather forecasts.

7) Interaction with the grid: The following constraint models the interaction with the distribution grid

$$-P^{\mathrm{peak,h}} <= P_{\mathrm{h}}^{\mathrm{grid}} <= P^{\mathrm{peak,h}}. \tag{13}$$

The peak signal is provided by the external power grid operator, which can be a demand response signal. The houses have the possibility to sell power to the grid (negative $P_{\mathrm{h}}^{\mathrm{grid}}$).

A. MPC problem formulation

In this section we formulate the MPC optimization problem. At the current point in time, an optimal plan is formulated based on forecasts in Table II and the current EES storage level. Only the first sample of the input sequence is implemented, and subsequently the horizon is shifted. At the next sampling time, a new optimization problem is solved using updated information on forecasts and system initial condition. By this receding horizon approach, a feedback policy is designed and the new optimal plan can potentially compensate for any disturbance that has meanwhile acted on the system.

At each time step $\hat{k}$, given an initial storage state $\hat{E}_{\mathrm{s,h}}(\hat{k})$ for each house h, the MPC scheme computes the optimal energy dispatch and unit commitment plan and setpoints to the energy sources by solving the following optimization problem, $\forall\, i, j, k, h$:

$$
\begin{aligned}
J(\hat{E}_{\mathrm{s,h}}(\hat{k})) = \min \sum_{k=0}^{H-1} \sum_{h=1}^{N_\mathrm{h}} \Big[\big(c_{\mathrm{tariff}}(k) \cdot P_{\mathrm{h}}^{\mathrm{grid}}(k) \\
+ c_{\mathrm{s,h}} \cdot (P_{\mathrm{s,h}}^{\mathrm{c}} P_{\mathrm{s,h}}^{\mathrm{d}})\big) + c_{\mathrm{gas}} \cdot P_{\mathrm{gas}}(k)\Big] \Delta T
\end{aligned}
$$

$$
\begin{aligned}
&\text{subject to} \qquad (14)\\
&(6) - (13)\\
&E_{\mathrm{s,h}}(0) = \hat{E}_{\mathrm{s,h}}(\hat{k}).
\end{aligned}
$$

IV. Virtual experimental evaluation

In this section we outline the virtual testing setup and discuss virtual experimental results.

A. Virtual experimental setup

The VMGL is built by interconnecting emulators of the microgrid components available in each partner laboratory using secure connections on top of the public Internet. The connections are formed using a software package called LABgw developed by the Technical Research Centre of Finland (VTT). In addition to the basic connectivity, the laboratory links can also emulate real-world network medium conditions on standard network interfaces (e.g., 3G, LTE, or Wi-Fi) [36].

A case study of five residential microgrids is implemented and simulated in the virtual laboratory. Each house is connected to the distribution grid and equipped with a heat pump, a 1 kWh/kWp PV plant [37] and an EES. Three appliances in each house are to be scheduled: a washing machine, a dryer and a dishwasher. Time preferences are considered and washing machines are always required to be finished before starting dryers.

The implemented heat pumps have a rated electrical power of 2000 W and a minimum electrical power of 500 W. The EESs have 1.0 kWh capacity and 0.85 as charging/discharging efficiencies. The implemented micro-CHP for the residential district/building has 20 kW of maximum electrical power output and 25kW of maximum thermal power output.

The heating requirements in order to guarantee the indoor thermal comfort, i.e., indoor temperature within 20 and $26°C$, are computed based on weather conditions and occupancy in the houses. All data (weather, electricity prices, photovoltaic generation) refers to November 2014. The weather conditions are actual data from a weather station located in Östermalm, Stockholm area (SE3). The electricity prices used in this study are taken from the Nordic market Nordpool using the Stockholm area (SE3). The price of natural gas for the micro-CHP is the price from Eurostat (2013, online data code: nrg-pc-202).

The prediction horizon of the MPC problem is 24 hours (144 time slots) and the sampling time is 10 minutes. A longer prediction horizon will not usually provide an improvement because the forecasts degrade as time increases, but the computational burden can be affordable. The computation of MILP solution at each iteration took at most 55.6 seconds, a time shorter than the sampling time of 10 minutes.

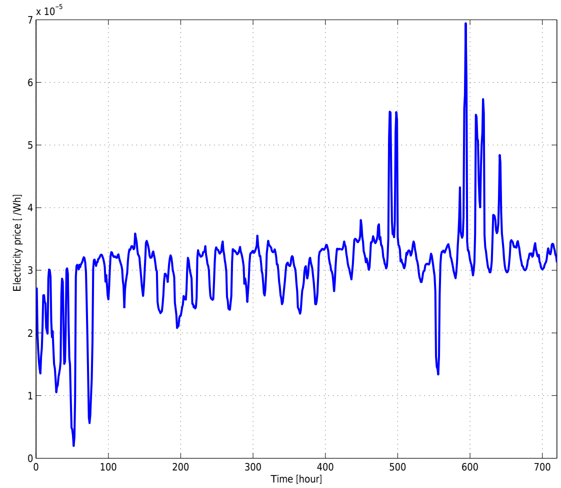

Fig. 2. Electricity price profile over November 2014

The MILP formulation presented in this study is implemented using Matlab. ILOG's CPLEX 12.0 [38] (an efficient solver based on the branch-and-bound algorithm) is used to solve the MILP optimizations [39]. The main advantage of the branch and bound method is that, if a solution is reached, the solution is known to be globally optimal. All computations are done on an Intel Core 2 Duo CPU, 2 GHz.

B. Virtual experimental results

Here we discuss and evaluate the results of three virtual experiments performed on the VMGL. In the first experiment we assume that no EES system is available, while in the second experiment an ESS is connected to each house. Finally, we ran a third experiment to understand how much cost saving the proposed energy management framework can achieve. Thus, the MPC problem (14) is turned into a worst case problem by changing the cost function from minimization to maximization.

Each experiment was run for November 2014. Figure 2 depicts the electricity prices in the simulated month.

To understand the benefits in using storage devices, we focus on the house 4. The appliance time intervals set by users for house 4 contain a number of price peaks significantly larger than the time intervals for the other houses; hence, house 4 shows the most significant differences when the EES is used. Figure 3 shows the interaction between the fourth residential microgrid and the distribution grid: notice that the EES allows to have a more flattened profile of the power exchanged with the grid. Specifically, with respect to the experiment without EES, a peak shaving occurs during the first week, then quite a few peak reductions occur. The stored energy profile is depicted in Figure 5: as commonly seen, EES is charged when prices are low and discharged when prices are high. Notice that PV electrical power can be also used for running the heat pump when prices are high and for charging the EES; when there is not PV generation, the grid and the EES are instead employed to satisfy the heat

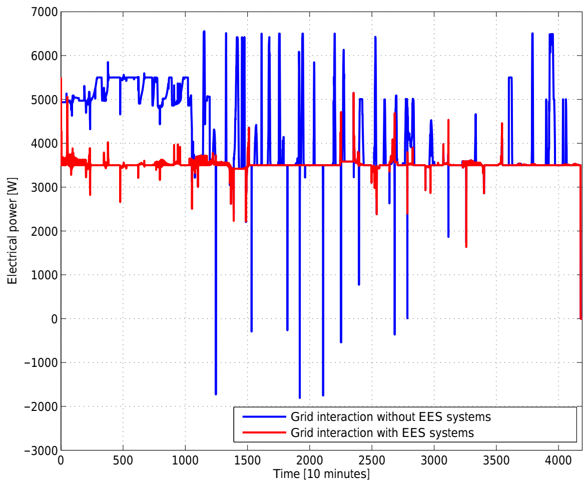

Fig. 3. Power exchanged with the grid over November 2014 for the house 4

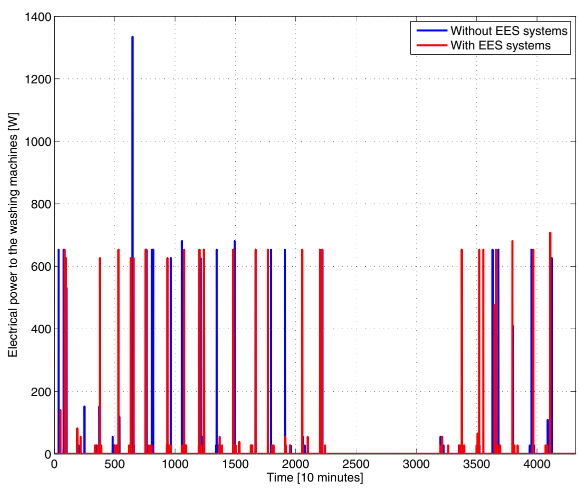

Fig. 4. Total electrical power profile of washing machines over November 2014 for the 5 houses

requirements. Further, when EES is deployed, more constant electrical power is required from the micro-CHP, which can be more convenient than the grid (see Figure 6).

The advantages of using storage devices can also be seen from Figure 4, where peaks correspond to the electrical power assigned to the washing machine energy phases for all five houses. Commonly, appliances are run when prices are low, compatibly with user preferences. However, EES systems allow to reduce peak (see, for instance, the peak during the evening of the fourth day): the running time of the appliances is less sensitive to the price profile and it can be convenient to use the EES and process the appliances also when prices are higher. This likely produces a benefic effect on the pricing and on the aggregated demand profile (e.g., see Figure 3).

We remind that at each time slot, actual thermal and electrical

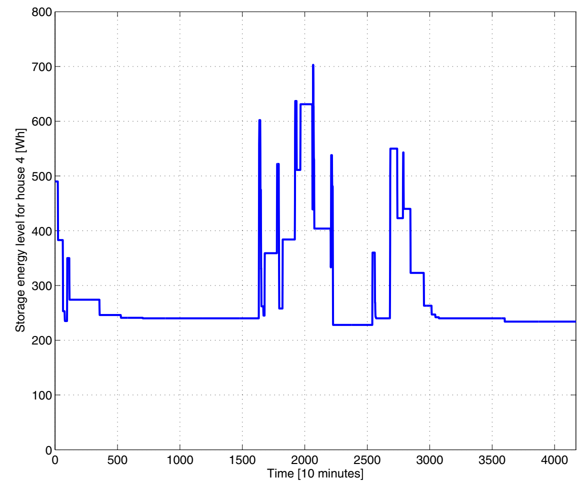

Fig. 5. Storage energy profile over November 2014 for house 4

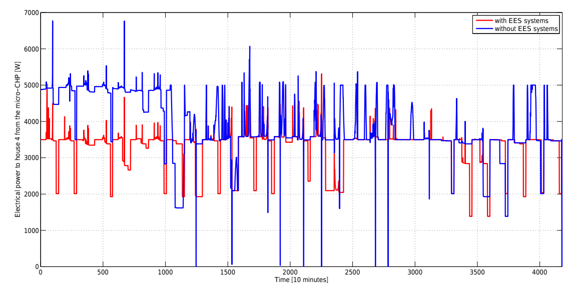

Fig. 6. Electrical power profile of the micro-CHP over November 2014 for house 4

power imbalances are computed based on the actual outputs from the available energy resources; hence, the total costs include also the cost of corrective actions compensating for actual power imbalances, needed to meet power balance and thermal comfort criteria.

The total cost for the case without EES systems is 81.2783€, for the case with EES systems is 73.57€. Then storage devices allow a 10.47% of cost saving. The worst case virtual experiment yields a total cost of 178.48€; thus, the proposed control framework can achieve up to 58.8% of cost saving.

V. Conclusion and Future Studies

In the paper we propose a novel MPC-based EMS for residential microgrids to optimally manage and coordinate energy supply and demand in multiple houses, taking user preferences and user comfort into account. The control system computes an optimal energy plan based on forecasts of weather conditions, renewable generation and thermal demand: imbalances can be compensated through the feedback mechanism integrated in our framework. The single subsystems can represent either single-family houses with local generation capabilities or apartments in an apartment building equipped with DERs and storage devices. The proposed formulation can handle an arbitrary number of houses/apartments, equipped with several appliances and local generators. DR policies have been also integrated in the proposed control framework. A virtual experimental testbed has been built for evaluating experimental results, which show the effectiveness of the proposed approach and the benefits of using storage devices in achieving relevant cost saving. We are currently working on extending the proposed framework to include lighting. Future work will also focus on analyzing the scalability of the proposed control framework and investigating distributed approaches.

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References

[1] "Strategic deployment document for europe electricity networks of the future," 2008, http://www.smartgrids.eu/.

[2] L. Bird, A. Reger, and J. Heeter, "Distributed solar incentive programs: Recent experience and best practices for design and implementations," NREL/TP-6A20-56308, National Renewable Energy Laboratory, Tech. Rep., December 2012.

[3] M. Beaudin and H. Zareipour, "Home energy management systems: A review of modelling and complexity," *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 318 – 335, 2015.

[4] S. Singh and J. Ostergaard, "Use of demand response in electricity markets: An overview and key issues," in *Energy Market (EEM), 2010 7th International Conference on the European*, 2010, pp. 1–6.

[5] A. A. Khan, S. Razzaq, A. Khan, F. Khursheed, and Owais, "{HEMSs} and enabled demand response in electricity market: An overview," *Renewable and Sustainable Energy Reviews*, vol. 42, pp. 773 – 785, 2015.

[6] J. Ilic, M. Prica, S. Rabiei, J. Goellner, D. Wilson, C. Shih, and R. Egidi, "Technical and economic analysis of various power generation resources coupled with caes systems," National Energy Technology Laboratory, DOE/NETL-2011/1472, Tech. Rep., June 2011.

[7] W. Su and J. Wang, "Energy management systems in microgrid operations," *The Electricity Journal*, October 2012.

[8] J. Maciejowski, *Predictive Control with Constraints*. Harlow, UK: Prentice Hall, 2002.

[9] http://pge-adr.com/act/pge-dr-programs/.

[10] A. Parisio, E. Rikos, and L. Glielmo, "A model predictive control approach to microgrid operation optimization," *Control Systems Technology, IEEE Transactions on*, vol. PP, no. 99, pp. 1–15, 2014.

[11] http://www.eitictlabs.eu/evsgl/areas-of-application/supporting-sub-projects/virtual-micro-grid-lab/.

[12] D. Zhang, N. Shah, and L. G. Papageorgiou, "Efficient energy consumption and operation management in a smart building with microgrid," *Energy Conversion and Management*, vol. 74, pp. 209 – 222, 2013.

[13] A. Anvari-Moghaddam, H. Monsef, and A. Rahimi-Kian, "Cost-effective and comfort-aware residential energy management under different pricing schemes and weather conditions," *Energy and Buildings*, vol. 86, pp. 782 – 793, 2015.

[14] G. Comodi, A. Giantomassi, M. Severini, S. Squartini, F. Ferracuti, A. Fonti, D. N. Cesarini, M. Morodo, and F. Polonara, "Multi-apartment residential microgrid with electrical and thermal storage devices: Experimental analysis and simulation of energy management strategies," *Applied Energy*, vol. 137, pp. 854 – 866, 2015.

[15] F. Brahman, M. Honarmand, and S. Jadid, "Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system," *Energy and Buildings*, vol. 90, pp. 65 – 75, 2015.

[16] F. De Angelis, M. Boaro, D. Fuselli, S. Squartini, F. Piazza, and Q. Wei, "Optimal home energy management under dynamic electrical and thermal constraints," *Industrial Informatics, IEEE Transactions on*, vol. 9, no. 3, pp. 1518–1527, Aug 2013.

[17] Y. Guo, M. Pan, Y. Fang, and P. Khargonekar, "Decentralized coordination of energy utilization for residential households in the smart grid," *Smart Grid, IEEE Transactions on*, vol. 4, no. 3, pp. 1341–1350, Sept 2013.

[18] A. Anvari-Moghaddam, H. Monsef, and A. Rahimi-Kian, "Optimal smart home energy management considering energy saving and a comfortable lifestyle," *Smart Grid, IEEE Transactions on*, vol. 6, no. 1, pp. 324–332, Jan 2015.

[19] J. Aghaei and M.-I. Alizadeh, "Multi-objective self-scheduling of {CHP} (combined heat and power)-based microgrids considering demand response programs and {ESSs} (energy storage systems)," *Energy*, vol. 55, pp. 1044 – 1054, 2013.

[20] G. M. Kopanos, M. C. Georgiadis, and E. N. Pistikopoulos, "Energy production planning of a network of micro combined heat and power generators," *Applied Energy*, vol. 102, pp. 1522 – 1534, 2013, special Issue on Advances in sustainable biofuel production and use - {XIX} International Symposium on Alcohol Fuels - {ISAF}.

[21] A. Soares, C. H. Antunes, C. Oliveira, and A. Gomes, "A multi-objective genetic approach to domestic load scheduling in an energy management system," *Energy*, vol. 77, pp. 144 – 152, 2014.

[22] A. Barbato, A. Capone, L. Chen, F. Martignon, and S. Paris, "A distributed demand-side management framework for the smart grid," *Computer Communications*, vol. 57, pp. 13 – 24, 2015.

[23] S. Li, D. Zhang, A. Roget, and Z. O'Neill, "Integrating home energy simulation and dynamic electricity price for demand response study," *Smart Grid, IEEE Transactions on*, vol. 5, no. 2, pp. 779–788, March 2014.

[24] C. Wang, Y. Zhou, B. Jiao, Y. Wang, W. Liu, and D. Wang, "Robust optimization for load scheduling of a smart home with photovoltaic system," *Energy Conversion and Management*, pp. –, 2015.

[25] H. Scherer, M. Pasamontes, J. Guzman, J. Alvarez, E. Camponogara, and J. Normey-Rico, "Efficient building energy management using distributed model predictive control," *Journal of Process Control*, vol. 24, no. 6, pp. 740 – 749, 2014, energy Efficient Buildings Special Issue.

[26] Y. Wu, V. Lau, D. Tsang, L. P. Qian, and L. Meng, "Optimal energy scheduling for residential smart grid with centralized renewable energy source," *Systems Journal, IEEE*, vol. 8, no. 2, pp. 562–576, June 2014.

[27] T. Jiang, Y. Cao, L. Yu, and Z. Wang, "Load shaping strategy based on energy storage and dynamic pricing in smart grid," *Smart Grid, IEEE Transactions on*, vol. 5, no. 6, pp. 2868–2876, Nov 2014.

[28] C. Chen, J. Wang, Y. Heo, and S. Kishore, "Mpc-based appliance scheduling for residential building energy management controller," *Smart Grid, IEEE Transactions on*, vol. 4, no. 3, pp. 1401–1410, Sept 2013.

[29] D. I. Mendoza-Serrano and D. J. Chmielewski, "Smart grid coordination in building {HVAC} systems: {EMPC} and the impact of forecasting," *Journal of Process Control*, vol. 24, no. 8, pp. 1301 – 1310, 2014, economic nonlinear model predictive control.

[30] http://www.apros.fi/en/.

[31] K. C. Sou, J. Weimer, H. Sandberg, and K. Johansson, "Scheduling smart home appliances using mixed integer linear programming," in *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on*, 2011, pp. 5144–5149.

[32] A. Parisio, C. Del Vecchio, and A. Vaccaro, "A robust optimization approach to energy hub management," in *International Journal of Electrical Power & Energy Systems*, 2012.

[33] www.dimplex.de/.

[34] http://www.trentinosviluppo.com/Contenuti-istituzionali/News/News/2012/Crisalide-a-Roncegno-nasce-l-isola-cogenerativa.

[35] P. Levin, "Brukarindata för energiberäkningar i bostäder," SVEBY, Tech. Rep., 2009.

[36] http://www.linuxfoundation.org/collaborate/workgroups/networking/netem.

[37] http://files.pvsyst.com/help/inverter_euroeff.htm.

[38] ILOG, *CPLEX 12.0 Users Manual*, 2010.

[39] C. Floudas, *Nonlinear and Mixed-Integer Programming-Fundamentals and Applications*. Oxford, UK: Oxford University Press, 1995.