# Cooperative MPC-Based Energy Management for Networked Microgrids

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***Abstract*—Microgrids are subsystems of the distribution grid operating as a single controllable system either connected or isolated from the grid. In this paper, a novel cooperative model predictive control (MPC) framework is proposed for urban districts comprising multiple microgrids sharing certain distributed energy resources (DERs). The operation of the microgrids, along with the shared DER, are coordinated such that the available flexibility sources are optimised and a common goal is achieved, e.g., minimizing energy exchanged with the distribution grid and the overall energy costs. Each microgrid is equipped with an MPC-based energy management system, responsible for optimally controlling flexible loads, heating systems, and local generation devices based on end-user preferences, weather-dependent generation and demand forecasts, energy prices, and technical and operational constraints. The proposed coordination algorithm is distributed and guarantees constraints satisfaction, cooperation among microgrids and fairness in the use of the shared resources, while addressing the issue of scalability of energy management in an urban district. Furthermore, the proposed framework guarantees an agreed cost saving to each microgrid. The described method is implemented and evaluated in a virtual testing environment that integrates accurate simulators of the microgrids. Numerical experiments show the feasibility, the computational benefits, and the effectiveness of the proposed approach.**

***Index Terms*—Model predictive control, flexibility services, energy management systems, demand response, distributed optimization, mixed integer linear programming.**

## I. INTRODUCTION

DECARBONISATION of the electricity generation and increased penetration of Renewable Energy Resources (RES), such as wind power and photovoltaics (PV), in the energy grids are under way in several countries [1]. Demand for new sources of flexibility and growing recognition of the multi-energy nature of districts are increasing interest in the interaction between energy sectors, like electricity, heating/cooling and gas and in the significant amount of flexibility available from heating [2], [3]. This interaction, in combination with demand response services and energy storage technologies, has been proven to offer numerous benefits, e.g., providing flexibility to counteract the intermittency of RES [4], [5]. By fostering consumer's participation in different types of energy market, control systems considering smart appliances and heating systems are expected to be relevant drivers [4], [6]. At the same time, technological development, in monitoring, communication and actuation technology are increasing the viability of flexibility provision by Distributed Energy Resources (DER), like energy storages, available within districts and many markets are now becoming more accommodating to demand side resources [7], [8]. Distribution System Operators (DSOs) can have the opportunity to use flexibility services from DER and demand in order to optimise network availability or to manage network conditions in the most economic manner. Residential consumers can be contracted by a third party aggregator for its flexibility, in addition to its contract with the supplier. Aggregators may then have a contract with the DSO for providing it with peak shifting or demand adjustment services [9]. DSO will act as a neutral market facilitator between aggregators and suppliers participating in the balancing and ancillary services markets, providing the communication, relevant grid-related data management and settlement services [10].

The main focus of this work is to design an energy management system for urban districts comprising multiple microgrids, which have the opportunity to offer flexibility services to the DSO through an aggregator and be paid for it. Several types of flexibility and technologies available in urban districts will be considered (e.g., storage, demand side management, heat pumps, combined heat and power), as well as the interaction between electricity, heating and gas energy vectors. In addition, by adopting a Model Predictive Control (MPC) technique, the proposed energy management system can take advantage of the opportunity for re-optimization based on real-time measurements and/or state estimation and compensate more effectively for uncertainty (e.g., in RES power output). Lastly, the proposed framework

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is scalable and can coordinate an arbitrary number of microgrids.

### A. Literature Review

Though there is already a vast literature on energy management systems, there are many research and development needs associated to it, especially to control and management of multiple energy systems and optimal exploitation of their flexibility resources. Both centralized [11], [12] and decentralized optimization schemes have been proposed [13]–[16]. Several methods have been utilized, such as Lagrangian relaxation-based mechanisms [14], consensus-algorithms [16], neural networks-based multi-agent schemes [15], cooperative game theory [17], alternating directions method of multipliers algorithm [18], primal decomposition methods [19]. Distributed algorithms have been proposed in the literature to solve the economic dispatch problem, as in [20], considering typically a network of power generating units or a smart grid with renewable and energy storage integration.

Recently, Model Predictive Control (MPC) has drawn the attention of the power system community because of its capability to handle the future behaviour of the system, demand and renewable energy generation forecasts, systems constraints, as well as the feedback mechanism it provides, making the controlled system more robust against uncertainty [21], [22]. The potential of centralized and distributed MPC methods for use in future power networks has been illustrated for voltage control [23], for thermal loads [24], for managing the Heating, Ventilation and Air Conditioning units (HVAC) [25], and as a framework for controlling networked microgrids or multiple units with flexible power consumption [26], [27].

The results of the aforementioned studies demonstrate that the cooperation among microgrids has significant advantages and benefits with respect to single microgrid operations.

### B. Statement of Contributions

The aforementioned studies do not consider storage and/or building thermal dynamics, or inter-temporal constraints, multi-step optimization and user preferences; moreover modeling details of some of thermal and electrical components, such as smart appliances or controllable generators, are not included. Smart energy systems like microgrids have many heterogeneous components and energy carriers (e.g., electrical, heat) which need to be integrated seamlessly. Thus, there is a strong need for an energy management framework that is generalizable, scalable and able to handle inherent complexity and differences in energy performance between various systems.

We aim to address the aforementioned challenges by designing an MPC-based cooperative energy management system that adopts a holistic approach and optimises, via aggregators, the flexibility capacity offered by energy users (e.g., renewables, storage systems and controllable loads). We focus on local energy systems at distribution network level, which can represent, for instance, urban districts or university campuses. Through an incentivisation/penalization mechanism embedded in the proposed framework, the microgrids comprised in the local energy system shape their electrical and thermal energy profile to cooperate and achieve a common goal. The common control objective is to minimize the running costs of the entire local energy system, thus reducing as much as possible energy exchange with the distribution grid, while keeping an acceptable level of comfort. A fair allocation of profits and benefits of the available shared resource is guaranteed; in addition, microgrids adopting the proposed energy management scheme are ensured to achieve a minimum cost saving. By doing so, each microgrid will optimally manage its flexibility resources not only for reducing its energy costs, but also for supporting the overall energy system and being rewarded for that. The overall energy management problem is solved in a distributed fashion, based on the use of MPC in combination with a Mixed Integer Linear Program (MILP) [28]. The feedback mechanism introduced through the MPC scheme will partially compensate for the uncertainty associated with RES power outputs, time-varying load and energy prices.

The reduction of the energy exchange with the utility grid through a more efficient energy management and coordination of microgrids and their flexibility sources has been proved to relieve power distribution line congestions and potentially improve the reliability of the main grid [29]. This aspect is under study.

We highlight that the proposed framework is flexible, i.e., different components and shared resources can be incorporated and different performance criteria can be optimised (e.g., shape the local demand profiles such that the aggregated profile meets specific DSO requirements).

This paper extends the preliminary studies presented in [30] and [31] by designing an MPC-based distributed algorithm aiming at coordinating an arbitrary number of microgrids, which can provide flexibility services through an aggregator.

## II. System Description and Modeling

In this section we will outline models of the components included in the system under consideration. We model building thermal dynamics, storage dynamics, shiftable loads and user preferences; further, we represent generator technical and physical features by using a number of constraints and variables.

### A. System Description

Figure 1 illustrates the local energy system under consideration and the information exchange among $N$ microgrids and an aggregator. The system is divided into $N$ interacting dynamical energy subsystems, i.e., microgrids, which can include shiftable loads, distributed generators, RES's, and storage systems, and it can comprise shared distributed energy resources, e.g., a cogeneration plant or an electrical storage system. A hierarchical architecture is proposed: each microgrid is equipped with a local MPC-based energy management system (MG-EMS in Figure 1), which computes setpoints to the local controllers of the distributed energy resources and controllable loads available in that energy subsystem. The shared resource is equipped with a local controller to track

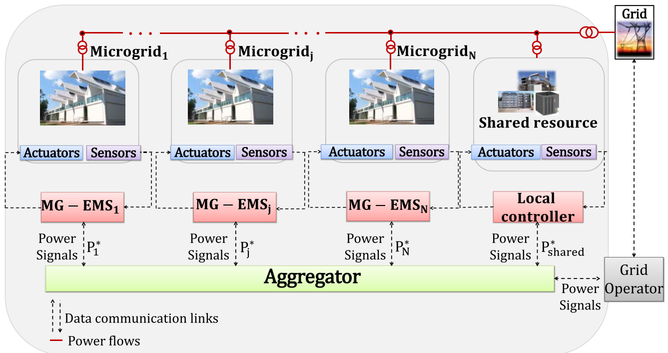


Fig. 1. Network of cooperative microgrids.

the power setpoint decided by the proposed framework. The $N$ interconnected microgrids cooperate through the aggregator, which manages also the shared resource. Without loss of generality, we consider a cogenerator plant as shared resource, since we aim at showing how to manage both thermal and electrical power. We assume that local management systems are synchronous and communication delays can be neglected. The information exchange is based only on the power profiles computed by the local decision systems. Thus, detailed information at microgrid level, e.g., user preferences, number of appliances, local generation capabilities, can be kept private. Furthermore, by including bounds on distribution lines' capacity, the steady-state power quality is preserved, i.e., our approach does not violate the voltage limits according to the grid and does not cause line congestion.

### B. Modeling

Here we outline the modeling of the main components considered in the framework.

Due to space constraints, the interested reader is referred to [30], [32], and [33] for detailed models of DERs, including the energy storage systems, and to [31] and [34] for detailed models of shiftable loads.

We remark that the focus of this work is not on the modeling of the single components of an energy subsystem, but on the design of a distributed algorithm to optimise the flexibility sources available in an urban district. We aim to show how aggregation among microgrids can be promoted by information exchange so that coupling constraints are satisfied and global criteria are optimized.

Without loss of generality, in this study we focus on flexible loads and consider heat pumps and combined heat and power plants (micro-CHPs) as controllable generators. We point out that any type of controllable generator with its specific technical and operational constraints and inflexible loads with their forecasts can be incorporated by employing the modeling illustrated in [32].

*1) Flexible Loads:* We consider two types of flexible loads:

- *thermal loads*, i.e., demand levels related to thermal indoor comfort. Limits on thermal power required to keep the internal temperature within a given comfort range for each microgrid are computed through a dynamic house model based on forecasts of the weather conditions and forecasted occupancy patterns. The building model runs on top of the Apros process simulation software [35]. Further details can be found in [30].
- *electrical loads*, i.e., demand levels related to smart appliances. A load operation process is made up of sub-processes called energy phases, which require a pre-specified amount of electric energy. Several other technical and user specified constraints are included in the problem formulation, e.g., user specified time preferences. Further details on shiftable loads modeling and technical specifications are provided in [34] and references therein.

*2) Storage:* An energy storage system (ESS) is modeled as a first-order discrete time model, accounting for the energy losses in the charging and discharging process. We also include bounds on the storage capacity and on the power exchanged with it, as well as limits on the total number of daily charging and discharging cycles in order to take the state of health of the storage device into account. Details on the comprehensive storage modeling are provided in [31] and [34].

*3) Heat Pump:* The behaviour of a heat pump at each time $k$ and for each microgrid $i$ is represented as $P_{k,i}^{\mathrm{HP,heat}} = \mathrm{COP_{k,i}} \cdot \mathrm{P_{k,i}^{HP,el}}$, where $\mathrm{COP_{k,i}}$ is the forecasted Coefficient of Performance (COP) of the heat pump at time $k$ based on weather forecasts over the prediction horizon. At each time step, COP forecasts are integrated in the proposed control framework in order to predict the future heat generation from each heat pump.

*4) Micro-CHP:* The component represents a typical micro combined heat and power (micro-CHP) unit. The micro-CHP model is described by the following equation: $P_k^{\mathrm{CHP,el}} = \alpha_1 \cdot P_k^{\mathrm{gas}} + \alpha_0$ and $P_k^{\mathrm{CHP,heat}} = \beta_1 \cdot P_k^{\mathrm{gas}} + \beta_0$. The modeling of the component adopts a data-driven approach, and model parameters, $\alpha$'s and $\beta$'s are estimated by employing machine learning technique with data from a real-world deployment. For further details we refer the interested reader to [33].

### C. Nomenclature

Table I reports all the other parameters and variables defined in the algorithm. Power variables represent the average power over a given sampling period. In this study, storage systems and buildings are modeled as discrete-time dynamical systems with a $\Delta k$ sampling time. For simplicity we omit the subscript denoting the time $k$ in Table I.

## III. Cooperative MPC-Based Energy Management System

In this section, the proposed energy management framework based on model predictive control is described.

### A. Description of MPC Framework

At each point in time $\kappa$, $\kappa = 1, \ldots, H$, an MPC problem is solved in a distributed manner through the coordination algorithm described below. The solution of the MPC problem is an optimal energy plan to be applied at any time $k = \kappa, \ldots, \kappa + T - 1$. Only the first control actions are applied,

TABLE I
PARAMETERS AND VARIABLES INVOLVED IN THE ALGORITHM

| | |
|---|---|
| $H$ | planning horizon |
| $T$ | prediction horizon |
| $N$ | number of microgrids |
| $c^{\text{gas}}$ | fuel (natural gas) cost for the micro-CHP |
| $c^{\text{grid}}$ | electrical power buying/selling cost |
| $P^{\text{gas}}$ | gas power input to the micro-CHP |
| $P^{\text{grid}}$ | power exchanged with the electrical network |
| $P^{\text{CHP,el}}$ | micro-CHP electrical power as shared resource |
| $P^{\text{CHP,heat}}$ | micro-CHP thermal power as shared resource |
| $P_i^{\text{HP,el}}$ | micro-CHP electrical power to microgrid $i$ |
| $P_i^{\text{HP,heat}}$ | HP thermal power to microgrid $i$ |
| $P_i^{\text{ESS,c}}$ | charging power for microgrid $i$ |
| $P_i^{\text{ESS,d}}$ | discharging power for microgrid $i$ |
| $P_i^{\text{app}}$ | total power required by shiftable loads in microgrid $i$ |
| $E_i^{\text{app}}$ | total energy required by shiftable loads in microgrid $i$ |
| $P_i^{\text{RES}}$ | total power from RESs in microgrid $i$ |
| $P_i^{\text{el}}$ | total electrical power exchanged with microgrid $i$ |
| $P_i^{\text{max}}$ | maximum power capacity for microgrid $i$ |
| $P^{\text{gas,max}}$ | limit on gas power input to the micro-CHP |
| $P^{\text{grid,max}}$ | limit on power exchanged with the electrical network |
| $P_i^{\text{heat,max}}$ | maximum thermal power needed by microgrid $i$ |
| $P_i^{\text{heat,min}}$ | minimum thermal power needed by microgrid $i$ |
| $\beta_i$ | agreed cost saving to microgrid $i$ at the end of the planning horizon |
| $\alpha_i$ | deviation from the power required by the aggregator in microgrid $i$ |
| $\eta_i^{\text{max}}$ | maximum cost affordable by microgrid $i$ for deviating from the power profile required by the aggregator |
| $\Delta_i^{\text{el}}$ | change of power level required for microgrid $i$ |
| $\mathcal{X}^{\text{CHP}}$ | set defined by the mixed integer linear modeling of the micro-CHP |
| $\mathcal{X}_{\text{i}}^{\text{app}}, \mathcal{X}_{\text{i}}^{\text{HP}}, \mathcal{X}_{\text{i}}^{\text{ESS}}$ | sets defined by the mixed integer linear modeling of the shiftable loads, of the heat pump and of the storage system in microgrid $i$ respectively |

and then the MPC problem is solved for a shifted prediction horizon, based on updated forecasts (prices, weather forecasts, heating requirements) and initial conditions (local power measurements of distributed generators, shiftable loads and storage systems, and local measurements of internal temperatures). At each point in time, the computed optimal decisions are 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.

The control objective is to minimise the overall operational costs and the energy exchanged with the distribution grid. We assume the same price for purchasing and selling electrical energy from and to the distribution network or the upstream energy market, respectively. However, by following the procedure illustrated in [32] for modeling the interaction with the grid, different prices can be easily integrated into the proposed framework.

The proposed framework requires the computation of mixed-integer linear programs (MILP). As MILP problems are known to be NP complete, we can take advantage of computational advances in MILP solving algorithms and commercial solvers, such as CPLEX. The branch-and-bound techniques are mostly applied to MILP problems [28]. The main advantage of the branch and bound method is that if a solution is reached, the solution is known to be globally optimal. Incidentally, we also notice that approaches commonly used in distributed optimization and distributed MPC, e.g., fast gradient techniques, dual decomposition, alternating direction method of multipliers, are not applicable to MILP problems.

In the following we describe the MPC problem and the developed algorithm that solves it and computes a feasible energy plan at any time step.

### *B. Description of the Distributed Coordination Algorithm*

The proposed algorithm consists of three phases: *i)* an initialization phase, where local optimization problems are solved for each subsystem in parallel; *ii)* a power distribution phase, where first an optimization problem is solved to coordinate the microgrids and then solutions of the local problems at microgrid level are computed in parallel based on the energy management plan obtained by the aggregator; *iii)* a power redistribution phase, where problems at microgrid level are sequentially solved in order to redistribute, whereas feasible, power deviations from the power profile computed at aggregator level.

We next describe the three phases of the algorithm.

*1) Initialization Phase:* In the initialization phase each local energy management system solves, in parallel, an optimal energy plan for the corresponding microgrid based on local measurements, forecasts and constraints.

*Problem 1:* Initialization problem for microgrid $i$

$$
\begin{aligned}
\min \quad & \sum_{k=1}^{T} c_k^{\text{grid}} P_{k,i}^{\text{el}} \\
\text{s.t.} \quad & P_{k,i}^{\text{HP,el}}, P_{k,i}^{\text{HP,heat}} \in \mathcal{X}_{\text{i}}^{\text{HP}} \\
& P_{k,i}^{\text{ESS,c}}, P_{k,i}^{\text{ESS,d}} \in \mathcal{X}_{\text{i}}^{\text{ESS}} \\
& P_{k,i}^{\text{app}}, E_{k,i}^{\text{app}} \in \mathcal{X}_{\text{i}}^{\text{app}} \\
& P_{k,i}^{\text{el}} = P_{k,i}^{\text{HP,el}} + P_{k,i}^{\text{app}} + P_{k,i}^{\text{ESS,c}} - P_{k,i}^{\text{ESS,d}} - P_{k,i}^{\text{PV}} \\
& - P_{k,i}^{\text{max,IN}} \le P_{k,i}^{\text{el}} \le P_{k,i}^{\text{max,IN}} \\
& P_{k,i}^{\text{heat,min}} \le P_{k,i}^{\text{HP,heat}} \le P_{k,i}^{\text{heat,max}},
\end{aligned}
$$

with $i = 1, \ldots, N$. We assume that $P_{k,i}^{\text{max,IN}} = \frac{P_k^{\text{grid,max}}}{N} \le P_{k,i}^{\text{max}}$ in order to guarantee feasibility of the power capacity constraint in the power distribution phase.

Problem 1 can easily include cooling by allowing for a negative $P_{k,i}^{\text{HP,heat}}$ and forecasts of the energy efficiency ratio $\text{EER} = 1 - \text{COP}$. When also cooling is accounted for, a binary variable, $\delta_{k,i}^{\text{HP}}$, is to be introduced to model the heating ($\delta_{k,i}^{\text{HP}} = 1$)/cooling ($\delta_{k,i}^{\text{HP}} = 0$) mode of the heat pump. In the cooling case, the micro-CHP heat power output can be stored or utilized for hot water. For the sake of simplicity, in this study we discuss only the heating scenario.

We denote by $\bar{P}_{k,i}^{\text{el}} = P_{k,i}^{\text{el}}$ the optimal power profile computed in the initialization phase for each microgrid $i$.

*2) Power Distribution Phase:* Based on the optimal plan obtained in the initialization phase, the following Problem 2 is formulated for globally coordinating the energy subsystems.

*Problem 2:* Coordination problem for the aggregator

$$\begin{aligned}
\min \quad & \sum_{k=1}^{T}\Big(c_k^{\text{grid}}P_k^{\text{grid}} + c_k^{\text{gas}}P_k^{\text{gas}}\Big)\\
\text{s.t.} \quad & P_k^{\text{CHP,el}}, P_k^{\text{CHP,heat}} \in \mathcal{X}^{\text{CHP}}\\
& -P_k^{\text{grid,max}} \le P_k^{\text{grid}} \le P_k^{\text{grid,max}}\\
& -P_k^{\text{gas,max}} \le P_k^{\text{gas}} \le P_k^{\text{gas,max}}\\
& P_k^{\text{grid}} = \sum_{i=1}^{N}\Big(\bar{P}_{k,i}^{\text{el}} + \Delta_{k,i}^{\text{el}}\Big) - P_k^{\text{CHP,el}}\\
& -\Delta_{k,i}^{\max} \le \Delta_{k,i}^{\text{el}} \le \Delta_{k,i}^{\max}\\
& 0 \le \frac{P_k^{\text{CHP,heat}}}{N} \le P_{k,i}^{\text{heat,max}}\\
& \sum_{k=1}^{T} c_k^{\text{grid}}\left(\Delta_{k,i}^{\text{el}} - \frac{P_k^{\text{CHP,el}}}{N}\right) + \frac{c_k^{\text{gas}}P_k^{\text{gas}}}{N} + \beta_i^{\kappa} \le 0
\end{aligned}$$

where $\Delta_{k,i}^{\text{el}}$ represents the change of power level required for microgrid $i$ at time $k$, and $\Delta_{k,i}^{\max}$ introduces additional flexibility and represents the local remaining power capacity not utilized in the initialization step. We remind that $P^{\text{CHP,el}}$ and $P^{\text{CHP,heat}}$ refer to the micro-CHP electrical power acting as shared resource (see Figure 1). The parameter $\beta_i$ represents a cost saving assigned to the microgrid $i$ adopting the proposed energy management scheme, which is to be agreed between the local energy management system and the aggregator. Both $\Delta_{k,i}^{\max}$ and $\beta_i$ are to be carefully estimated based on the specific key features of the microgrid $i$. To account for the iterative nature of the MPC scheme, the remaining cost saving to the end of the planning horizon $H$ is updated at each time step and is denoted by $\beta_i^{\kappa}$. If the remaining time to the end of the planning horizon, $T^{\kappa}$, is less than the prediction horizon $T$, the last constraint is replaced with $\sum_{k=1}^{T^{\kappa}} c_k^{\text{grid}}(\Delta_{k,i}^{\text{el}} - \frac{P_k^{\text{CHP,el}}}{N}) + \frac{c_k^{\text{gas}}P_k^{\text{gas}}}{N} + \beta_i^{\kappa} \le 0$. The last constraint of Problem 2 guarantees that the local optimal costs of each energy subsystem in this phase are lower than the local optimal costs obtained at the initialization phase, as proved in the following proposition.

*Proposition 1:* Assume an equal allocation of thermal and electrical micro-CHP power outputs, as well as of the corresponding cost savings. Constraint $\sum_{k=1}^{T} c_k^{\text{grid}}(\Delta_{k,i}^{\text{el}} - \frac{P_k^{\text{CHP,el}}}{N}) + \frac{c_k^{\text{gas}}P_k^{\text{gas}}}{N} + \beta_i^{\kappa} \le 0$ guarantees that the local energy costs to each microgrid in the power distribution phase decrease at least by $\beta_i^{\kappa}$, with respect to costs obtained at the initialization phase.

*Proof:* Denote by $J_i^{\text{IN}} = \sum_{k=1}^{T} c_k^{\text{grid}}\bar{P}_{k,i}^{\text{el}}$ the optimal values computed at the initialization phase for each microgrid $i$. The optimal value of Problem 2, $J^{\text{AGG}}$, is to account for the electrical micro-CHP power output and the power changes: this optimal value is given by $J^{\text{AGG}} = \sum_{k=1}^{T}(c_k^{\text{grid}}P_k^{\text{grid}} + c_k^{\text{gas}}P_k^{\text{gas}}) = \sum_{i=1}^{N} J_i^{\text{IN}} + \sum_{k=1}^{T}[c_k^{\text{grid}}(\sum_{i=1}^{N}\Delta_{k,i}^{\text{el}} - P_k^{\text{CHP,el}}) + c_k^{\text{gas}}P_k^{\text{gas}}] \le \sum_{i=1}^{N} J_i^{\text{IN}}$. Thus the coordination problem yields a decrease in the total energy costs of the overall system. However this does not imply that individual costs decrease at microgrid level. Since we assume an equal allocation of thermal and electrical micro-CHP power outputs, as well as of the corresponding cost savings, the total costs for a microgrid $i$ is $J_i^{\text{PD}} = J_i^{\text{IN}} + \sum_{k=1}^{T}(c_k^{\text{grid}}\Delta_{k,i}^{\text{el}} - \frac{c_k^{\text{grid}}P_k^{\text{CHP,el}}}{N} + \frac{c_k^{\text{gas}}P_k^{\text{gas}}}{N})$. In order to achieve a cost decrease of $\beta_i^{\kappa}$, $J_i^{\text{PD}} \le J_i^{\text{IN}} - \beta_i^{\kappa}$; this implies that $\sum_{k=1}^{T} c_k^{\text{grid}}(\Delta_{k,i}^{\text{el}} - \frac{P_k^{\text{CHP,el}}}{N}) + \frac{c_k^{\text{gas}}P_k^{\text{gas}}}{N} + \beta_i^{\kappa} \le 0$, which is the last constraint of Problem 2. ■

The following problem is solved, in parallel, by each microgrid $i$, $i = 1, \dots, N$, aiming at tracking the new power profile required by the aggregator, $\bar{P}_{k,i}^{\text{el,PD}} = \bar{P}_{k,i}^{\text{el}} + \Delta_{k,i}^{\text{el}}$. Define $\bar{P}_k^{\text{CHP,el}} = P_k^{\text{CHP,el}}$ and $\bar{P}_k^{\text{CHP,heat}} = P_k^{\text{CHP,heat}}$.

*Problem 3:* Problem for microgrid $i$

$$\begin{aligned}
\min \quad & \sum_{k=1}^{T} w_k\alpha_{k,i}^2\\
\text{s.t.} \quad & P_{k,i}^{\text{HP,el}}, P_{k,i}^{\text{HP,heat}} \in \mathcal{X}_{\text{i}}^{\text{HP}}\\
& P_{k,i}^{\text{ESS,c}}, P_{k,i}^{\text{ESS,d}} \in \mathcal{X}_{\text{i}}^{\text{ESS}}\\
& P_{k,i}^{\text{app}}, E_{k,i}^{\text{app}} \in \mathcal{X}_{\text{i}}^{\text{app}}\\
& P_{k,i}^{\text{heat,min}} \le P_{k,i}^{\text{HP,heat}} + \frac{\bar{P}_k^{\text{CHP,heat}}}{N} \le P_{k,i}^{\text{heat,max}}\\
& P_{k,i}^{\text{el}} = P_{k,i}^{\text{HP,el}} + P_{k,i}^{\text{app}} + P_{k,i}^{\text{ESS,c}} - P_{k,i}^{\text{ESS,d}} - P_{k,i}^{\text{PV}}\\
& -\alpha_{k,i} + \bar{P}_{k,i}^{\text{el,PD}} \le P_{k,i}^{\text{el}} \le \alpha_{k,i} + \bar{P}_{k,i}^{\text{el,PD}}\\
& -\alpha_{k,i} + \bar{P}_{k,i}^{\text{el,PD}} \ge -P_{k,i}^{\max}\\
& \alpha_{k,i} + \bar{P}_{k,i}^{\text{el,PD}} \le P_{k,i}^{\max}\\
& \alpha_{k,i} \ge 0\\
& \sum_{k=1}^{T} c_k^{\text{grid}}\alpha_{k,i} \le \eta_i^{\kappa,\max},
\end{aligned}$$

where $w_k$ is a penalty factor and $\eta_i^{\max} \le \beta_i$ is another cost parameter assigned to a microgrid $i$, which represents the maximum cost affordable for deviating from the power profile required by the aggregator. This cost does not have to be greater than the cost saving $\beta_i$, since the final cost saving is $\beta_i - \eta_i^{\max}$. It could be also agreed that a minimum cost saving has to be guaranteed at the end of the planning horizon, denoted by $\beta_i^{\min}$, which implies that $\eta_i^{\max} = \beta_i - \beta_i^{\min}$.

As $\beta_i$, also $\eta_i^{\max}$ has to be updated at each point in time of the MPC scheme, yielding $\eta_i^{\kappa,\max}$. If the remaining time to the end of the planning horizon, $T^{\kappa}$, is less than the prediction horizon $T$, the last constrain of Problem 3 must be replaced with $\sum_{k=1}^{T^{\kappa}} c_k^{\text{grid}}\alpha_{k,i} \le \eta_i^{\kappa,\max}$.

Since we can reasonably assume that power deviations can be partially compensated in fully interconnected and coordinated microgrids, a net unmet power can be computed at each time step as $\alpha_k^{\text{net}} = \sum_{i=1}^{N}\alpha_{k,i}$. Thus, the energy costs of the overall system is $J^{\text{AGG}} + \sum_{k=1}^{T} c_k^{\text{grid}}\alpha_k^{\text{net}}$, which is lower than $\sum_{i=1}^{N} J_i^{\text{IN}}$ resulting from the initialization phase because of the last constraint of Problem 3.

Hence, the overall energy costs resulting from the power distribution phase is upper bounded by $\sum_{i=1}^{N} J_i^{\text{IN}}$ and lower bounded by $J^{\text{CN}}$: $J^{\text{CN}} < J^{\text{AGG}} + \sum_{k=1}^{T} c_k^{\text{grid}}\alpha_k^{\text{net}} < \sum_{i=1}^{N} J_i^{\text{IN}}$, where $J^{\text{CN}}$ denotes the optimal solution of the centralised formulation of the overall energy management problem. The centralized problem aims at minimizing the energy costs of the overall systems without accounting for individual costs, profits of the local energy subsystems, and a fair allocation of the micro-CHP power outputs. Because of that, the optimal cost of the centralised formulation will be the lowest possible. We point out that all these cost parameters, $\beta_i$, $\beta_i^{\min}$ and $\eta_i^{\max}$, are to be carefully estimated based on microgrid specific features and agreed with the aggregator. Comfort constraints, i.e., thermal comfort and time preferences for shiftable loads, can be softened up to an agreed amount, depending on bilateral contract between the microgrid and the aggregator. This will increase the flexibility capacity.

*Remark 1:* In this study we consider, without loss of generality, fully interconnected microgrids, which entails that an energy surplus in one microgrid can be utilized to compensate for an energy deficit in another microgrid. The energy management framework can easily be applied to a more general scenario, where the local energy system consists of $N_s$ clusters of fully interconnected microgrids. In this more general scenario, the power balance constraint in Problem 2 is replaced with $\sum_{j=1}^{N_s} P_{k,j}^{\text{grid}} = P_k^{\text{grid}}$ and $P_k^{\text{grid}} + P_{k,\text{CHP}}^{\text{el}} = 0$ and $\sum_{i \in SN_j} P_{k,i}^{\text{el}} = P_{k,j}^{\text{grid}}$, where $SN_j$ is the set of microgrids belonging to the cluster $j$, $j = 1, \dots, N_s$.

*3) Power Redistribution Phase:* The last phase of the distributed coordination algorithm is executed if $\alpha_k^{\text{net}} \neq 0$ for at least one $k$. We denote by $\bar{P}_{k,i}^{\text{el,PDU}} = P_{k,i}^{\text{el}}$ the optimal power profile computed by solving Problem 3. The following problem is to be solved sequentially until the unmet power is redistributed among the microgrids, whereas feasible.

We start with microgrid $i = 1$. While $i \leq N$ and there is still unmet power to redistribute, the following Problem 4 is solved.

*Problem 4:* Redistribution problem for microgrid $i$

$$
\begin{aligned}
\min \quad & -\sum_{k=1}^{T} r_k \gamma_k \\
\text{s.t.} \quad & P_{k,i}^{\text{HP,el}}, P_{k,i}^{\text{HP,heat}} \in \mathcal{X}_{\text{i}}^{\text{HP}} \\
& P_{k,i}^{\text{ESS,c}}, P_{k,i}^{\text{ESS,d}} \in \mathcal{X}_{\text{i}}^{\text{ESS}} \\
& P_{k,i}^{\text{app}}, E_{k,i}^{\text{app}} \in \mathcal{X}_{\text{i}}^{\text{app}} \\
& P_{k,i}^{\text{heat,min}} \leq P_{k,i}^{\text{HP,heat}} + \frac{\bar{P}_k^{\text{CHP,heat}}}{N} \leq P_{k,i}^{\text{heat,max}} \\
& P_{k,i}^{\text{HP,el}} + P_{k,i}^{\text{app}} + P_{k,i}^{\text{ESS,c}} - P_{k,i}^{\text{ESS,d}} - P_{k,i}^{\text{PV}} \\
& \quad = \bar{P}_{k,i}^{\text{el,PDU}} + \text{sgn}(\alpha_k^{\text{net}})\gamma_k \\
& \quad\quad - P_{k,i}^{\max} \leq \bar{P}_{k,i}^{\text{el},red} + \text{sgn}(\alpha_k^{\text{net}})\gamma_k \leq P_{k,i}^{\max} \\
& 0 \leq \gamma_k \leq |\alpha_k^{\text{net}}|,
\end{aligned}
$$

where $r_k$ is a reward factor. If the problem is infeasible, $P_{k,i}^{\text{el}} = \bar{P}_{k,i}^{\text{el,PDU}}$, otherwise the profile of unmet power is updated at each iteration, $|\alpha_k^{\text{net}}| = |\alpha_k^{\text{net}}| - \gamma_k$, $\forall k = 1, \dots, T$, the microgrid $i$ is rewarded, and the total energy cost of the overall system is reduced by $\sum_{k=1}^{T} c_k^{\text{grid}} \gamma_k$. Problem 4 is then solved for the remaining microgrids, as long as there is still unmet power to redistribute.

We introduce the variable $\bar{P}_{k,i}^{\text{el,RED}}$, which is defined as $\bar{P}_{k,i}^{\text{el,RED}} = \bar{P}_{k,i}^{\text{el,PDU}} + \text{sgn}(\alpha_k^{\text{net}})\gamma_k$ and $\bar{P}_{k,i}^{\text{HP,heat}} = P_{k,i}^{\text{HP,heat}}$. If there is still unmet power after the loop above is completed, the second phase problem at aggregator level, Problem 2, is solved to reschedule the shared resource micro-CHP, considering an updated power balance constraint, $P_k^{\text{grid}} = \sum_{i=1}^{N} \bar{P}_{k,i}^{\text{el,RED}} - P_k^{\text{CHP,el}}$, an updated thermal comfort constraint, $P_{k,i}^{\text{heat,min}} \leq \bar{P}_{k,i}^{\text{HP,heat}} + \frac{P_k^{\text{CHP,heat}}}{N} \leq P_{k,i}^{\text{heat,max}}$, and the capacity constraint on the aggregated power, $-P_k^{\text{grid,max}} \leq P_k^{\text{grid}} \leq P_k^{\text{grid,max}}$. The computed optimal cost is denoted by $J^{\text{AGG,RED}}$, which is closer to the optimal solution of the centralised problem, $J^{\text{CN}} < J^{\text{AGG,RED}} <= J^{\text{AGG}} + \sum_{k=1}^{T} c_k^{\text{grid}} \alpha_k^{\text{net}} < \sum_{i=1}^{N} J_i^{\text{IN}}$.

*Remark 2:* The obtained solution of the algorithm is a feasible solution of the centralised formulation since the computed power profiles satisfy the constraints at microgrid level and the coupling constraints at aggregator level.

## IV. Simulation and Result Discussion

### A. Multi-Location Co-Simulation Environment

The proposed method is evaluated in a virtual testing environment that integrates accurate emulators of the energy systems forming the microgrids. This multi-location co-simulation environment interconnects resources available in geographically distributed laboratories. The data distribution platform based on a virtual private network (VPN) is placed on top of the public Internet using open-source OpenVPN software [36], assuring both required information security and message integrity. A lightweight routing entity in combination with a straight-forward message protocol ensures the application specific messaging between the VPN clients of the connected labs. Three research facilities across Europe [33], have been connected, integrating a comprehensive set of DER including co-generation, PV systems, batteries, heat pumps as well as electrical and thermal building loads.

### B. Simulation Setup

Three different case studies are implemented and simulated in the virtual laboratory:

- Virtual Lab Experiment 1 ($\text{VE}_1$): the local energy system comprises 5 microgrids and the simulation horizon is 1 day (3 November 2014). The aim of this experiment is to show that our proposed framework yields energy profiles very similar to the centralised formulation, considered as the benchmark;
- Virtual Lab Experiment 2 ($\text{VE}_2$): the local energy system comprises 15 microgrids and the simulation horizon is 1 day (3 November 2014). The aim of this experiment is to show that the proposed cooperative energy management framework is beneficial to the microgrids, for cost saving, and to the network operator, in terms of power exchanged with the distribution network, with respect to the non-cooperative strategy.
- Virtual Lab Experiment 3 ($\text{VE}_3$): the local energy system comprises 15 microgrids and the simulation horizon is 7 days (week commencing 3 November 2014). The aim of

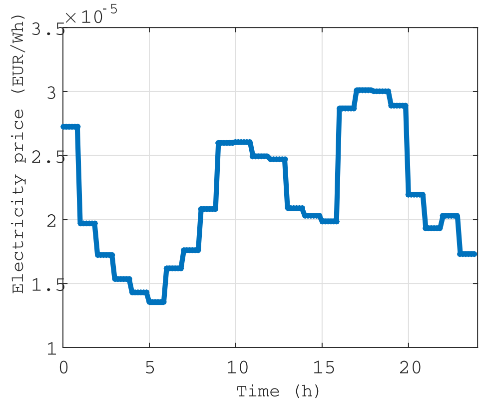


Fig. 2. Electricity price on Monday, 3 November 2014.

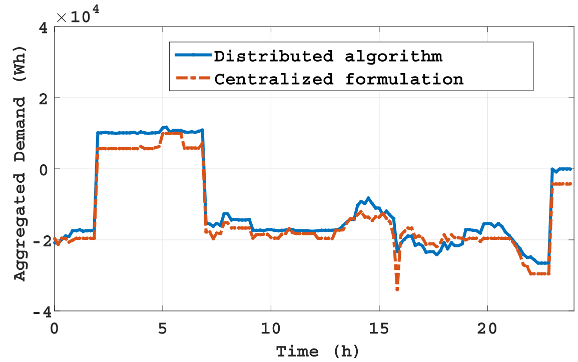


Fig. 3. Comparison between the distributed algorithm and the centralised formulation on Monday, 3 November 2014 ($VE_1$).

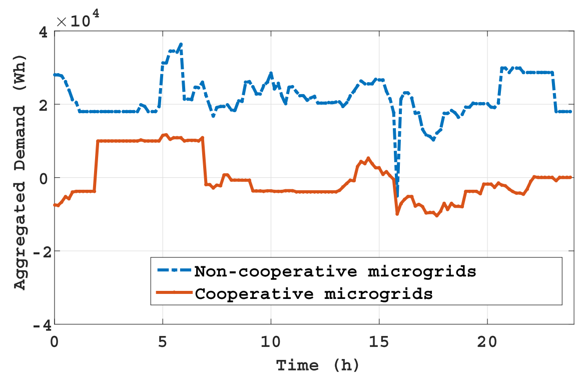


Fig. 4. Comparison between cooperative and non-cooperative microgrids on Monday, 3 November 2014 ($VE_2$).

this experiment is to show that the potential cost saving yielded by the proposed cooperative energy management framework increases as the simulation horizon increases. Each microgrid is connected to the distribution network and equipped with a heat pump, a 1 kWh/kWp PV plant and an ESS. Three shiftable loads are included in each microgrid: a washing machine, a dryer and a dishwasher. Not all three smart appliances are to be scheduled in each microgrid, which entails that some microgrids have an higher electrical energy demand than others. Furthermore, different time preferences are considered, hence time requirements for some microgrids are more stringent than others.

The implemented heat pumps have a rated electrical power of 2000 W and a minimum electrical power of 500 W. Each ESS has 1.0 kWh capacity and 0.85 as charging/discharging efficiencies. The micro-CHP implemented as a shared resource 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 are taken from the Nordic market Nordpool. 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 and the sampling time is 10 minutes. The minimum cost saving required by each cooperative microgrid $i$ ($\beta_i$ in the distributed algorithm formulation) is 10%. The energy costs include the cost of corrective actions compensating for actual power imbalances (e.g., additional power will be bought in case of power deficit), which are computed at each time step based on the actual values of weather conditions and power outputs produced by the energy resources, like PV and heat pumps.

### *C. Result Evaluation*

Here we discuss the results of the three experiments performed with the virtual laboratory [33]. Figure 2 depicts the electricity prices and solar generation on the simulated day.

Figure 3 shows the profile of the aggregated energy exchanged with the grid resulting from the experiment $VE_1$. We compare the results obtained by applying two different MPC strategies: *i)* centralised MPC, where the centralised energy management problem is solved at any time step; *ii)* distributed MPC, where the energy management plan is computed, at any time step, by applying the distributed algorithm described in Section III. As mentioned in Section III, the optimal cost of the centralised formulation is the lowest possible; hence, the centralised MPC is considered as the benchmark. It can be clearly seen that the two energy profiles obtained by the centralised and distributed MPC formulations are really similar. However costs yielded by the distributed MPC are slightly higher (5%), it takes around 2 minutes on average to compute a feasible solution, whilst the solver time of one iteration of the centralized formulation takes at least 2 hours. We also notice that energy is mainly purchased between 2-8 am and after 11 pm, because electricity prices are lower (see Figure 2).

Figure 4 depicts the energy profiles of the aggregated energy exchanged with the grid resulting from the experiment $VE_2$. We consider cooperative and non-cooperative microgrids. Cooperative microgrids are managed through our proposed framework and are coordinated via an aggregator; non-cooperative microgrids optimise their own energy resources in order to minimise their energy costs only, through their local energy management system (the MG-EMS in

TABLE II
RESULTS EVALUATION

| Virtual experiment | Average saving (%) | Minimum saving (%) | Maximum saving (%) |
|---|---|---|---|
| $VE_1$ | 15.2 | 13.8 | 16.3 |
| $VE_2$ | 21 | 15.6 | 25 |
| $VE_3$ | 48 | 36 | 51 |

Figure 1). It can be seen that the energy exchange with the distribution grid resulting from the cooperation of the microgrids is beneficial not only in terms of cost saving but also for the substantial reduction in the amount of energy exchanged with the grid.

We point out that the computational time of the centralised formulation is prohibitive for a higher number of microgrids. The solver takes over 2 days to solve one single MILP for the local energy system of 15 microgrids considered in the experiment $VE_2$, whilst our distributed algorithm takes 5 minutes on average per iteration to compute the solution.

Lastly, Table II shows that the potential cost saving increases as the number of microgrids and the simulation horizon increase. Besides, the yielded cost saving per microgrid is always higher than the minimum agreed saving of 10%.

Incidentally, we mention that the overall average energy imbalance yielded in the virtual experiment $VE_3$ is 110.7 Wh, with a minimum of $-500.2$ Wh and maximum of 960.4 Wh. Hence, the framework can potentially be beneficial also for reducing imbalances.

## V. CONCLUSION

In this paper we present a novel cooperative MPC framework for networked microgrids sharing a distributed energy resource. The operation of the microgrids, along with the shared resource, are coordinated such that a common goal is achieved. The proposed framework is flexible and can handle microgrids with different local generation capabilities and energy requirements, technical and operational features. Numerical results in a virtual laboratory co-simulation testing environment show the potential benefits offered by the proposed distributed framework. Extensive simulations continue, accounting for longer planning horizons, different microgrid configurations and different tuning parameters (e.g., $\alpha$, $w$, $r$).

We point out that, while the proposed framework is scalable and can coordinate an arbitrary number of microgrids, the computational time depends on the solving time of single MILP problems, which are known to be NP complete. The MILP formulations are under study in order to analyse and improve their structure, and possibly derive an upper bound on their worst-case computational time.

In addition, stability and constraints satisfaction should be guaranteed under uncertainty (e.g., enough energy is stored in storage elements to counteract an unpredicted change in demand and RES generation). This can be ensured by a terminal set for the storage level which is a robust control invariant set or by constraints tightening. Stochastic approaches are under study in order to address more effectively the uncertainty challenge, as well as to improve on the system reliability and minimise power imbalances. In particular, robust approaches to demand response [34] and stochastic approaches for microgrid energy management [32] will be integrated in the proposed framework.

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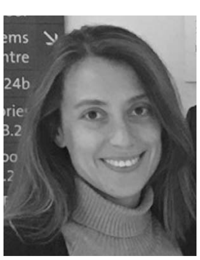

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