Local Energy Communities in Service of Sustainability and Grid Flexibility Provision: Hierarchical Management of Shared Energy Storage

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***Abstract*—Local Energy Communities (LECs) can facilitate the transition towards sustainable and clean energy system infrastructure. In this work, we construct a novel hierarchical energy management framework for an LEC equipped with a community energy storage (CES) installation. The proposed two-stage approach involves end-users making self-driven, cost-optimal decisions (first stage) and said decisions being further coordinated through the CES in service of boosting the LEC's self-consumption and self-sufficiency (second stage). By complementing the approach with a real-time, predictive, envelope-based methodology for LEC flexibility quantification, a rigorous cost structure for flexibility procurement is established. The LEC is further considered to be providing higher-level ancillary services to the wider power grid, through the load flexibility provision and CES capacity sharing. The efficacy and superior performance of the proposed approach are demonstrated in an exhaustive case study. This includes a detailed comparison with conventional centralized approaches and a comprehensive analysis of the financial and environmental benefits that this envisioned LEC variant can ultimately achieve.**

***Index Terms*—Community energy storage, flexibility procurement, local energy communities, model predictive control.**

Nomenclature

Acronyms

LEC	Local energy community.
CES	Community energy storage.
MPC	Model predictive control.
HVAC	Heating-ventilation-air-conditioning.
BEMS	Building energy management system.
CEMS	Community energy management system.

Parameters

H	Prediction horizon (hours).
Δk	Sample time (minutes).
$P_{\mathrm{h,max}}$	Maximum rated power of HVAC system (kW).
$P_{\mathrm{h,min}}$	Maximum rated power of HVAC system (kW).
$\eta_{\mathrm{c}}, \eta_{\mathrm{d}}$	Charging/discharging efficiency of the CES.
$E_{\min}$	Minimum constraint on capacity of the CES (kWh).
$E_{\max}$	Maximum constraint on capacity of the CES (kWh).
$P_{\mathrm{c,CES}}^{\max}$	Maximum charging rated power of the CES (kW).
$P_{\mathrm{d,CES}}^{\max}$	Maximum discharging rated power of the CES (kW).
$P_{\mathrm{pur,LEC}}^{\max}$	Maximum power LEC can import from grid (kW).
$P_{\mathrm{sell,LEC}}^{\max}$	Maximum power LEC can export to grid (kW).
I	Initial investment into CES (€).

Continuous Variables

E_{CES}	Energy stored in the CES (kWh).
$P_{\mathrm{c,CES}}, P_{\mathrm{d,CES}}$	Charging/discharging power of the CES (kW).
$P_{\mathrm{pur,LEC}}$	Power purchased from the grid by LEC (kW).
$P_{\mathrm{sell,LEC}}$	Power sold back to the grid by LEC (kW).
P_{h}	HVAC systems' power consumption (kW).
P_{app}	Shiftable appliance's power consumption (kW).
C_{lf}	Cost of load flexibility provision (€ /kW).
C_{f}	Cost of CES capacity procurement (€ /kW).
Φ_{sc}	LEC's self-consumption.
Φ_{ss}	LEC's self-sufficiency.

Binary Varibles

$\zeta_{1,\mathrm{CES}}, \zeta_{2,\mathrm{CES}}$	Prevent simultaneous charging/discharging of the CES.
$\theta_{1,\mathrm{LEC}}, \theta_{2,\mathrm{LEC}}$	Prevent simultaneous LEC power exchange to/from the grid.

Sets and Indices

$\mathcal{H}$	Set of simulation time instants indexed by k.
$\mathcal{P}_{\mathrm{h}}$	Set for abstract HVAC model.
$\mathcal{P}_{\mathrm{app}}$	Set for abstract shiftable appliance model.
$\mathcal{N}$	Set of buildings in the LEC indexed by i.

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I. Introduction

THE European Commission's Clean Energy for all Europeans Package via its various directives has introduced the concept of Energy Communities in the EU legislation [1], [2].

The energy community initiative allows its citizens to collectively participate in the management of energy systems, serving as the impetus a variety of economic, social and environmental benefits. Examples include the substantial reduction of the end-users' energy bills, the promotion of environmental friendliness and local sustainability directives at community and individual level, and the ability to better support the power grid's operation through coordinated flexibility provision.

Specifically, the Directive on common rules for internal electricity market (EU 2019/944) establishes an outline for local energy communities (LECs) that allows the communities and their members to legally engage into energy generation, distribution, supply, consumption, storage, aggregation, and sharing [1]. The direct visible benefits are increased levels of autonomy from the power grid, advancement of energy efficiency and reduced energy costs for community citizens. The indirect benefit are increased contribution of the community citizens towards achievement of environmental goals and more cooperation within the community [3]. Moreover, the LECs can support the power grid operation by offering a variety of flexibility services through demand response, load shifting, and energy storage. With the technical advancements, declining cost, incentive schemes for renewable energy sources and energy storage devices, an ever-increasing number of energy communities has been emerging throughout Europe [4].

Various studies in the literature have investigated different strategies for energy management in LECs. The most common implementation approaches are centralized ones, in which the formulated large-scale optimization problems include exclusively community-wide objectives and constraints [5], [6]. While centralized approaches lead to globally optimal solutions (at least for linear or mixed-integer programming problems), the associated high computation time can render these approaches impractical under certain conditions, especially in real-time implementations [7]. However, the most important barrier for practical deployment is the lack of compliance with privacy concerns, since the end-users have to share detailed information with the involved central entity [8].

Decentralized and distributed approaches can overcome these shortcomings, by instead having end-users make their own independent decisions; this may (distributed) or may not include some form of bilateral or peer-to-peer communication between buildings [9], [10]. Furthermore, many studies have explored LEC energy management from a market-based energy trading standpoint incorporating different approaches such as game-theory [11], peer-to-peer energy trading [12], [13], and blockchain-based applications [14]. Generally, these approaches are used for offline operational planning rather than for real-time implementation.

A key aspect for guaranteeing the successful operation of LECs is the successful implementation of integrated community energy system [15]. These technologies include distributed renewable energy sources and energy storage at the household (individual batteries) and community (shared CES) levels, community-level generation such as micro-combined heating and power units, photovoltaic panels, fuel cells, and district heating/cooling systems. The CES is an important element of the LECs within the ICES technologies [16]. The CES fosters the self-consumption of community renewable energy sources by better matching the generation and load demand within the LEC. Moreover, in light of the real-time pricing nature of the envisioned flexible electricity tariffs, the CES can generate additional monetary benefits for end-users by matching its behavior to the shifting electricity pricing profile. Field experience has shown that CES projects are characterized by easy integration to the power grid and by substantial contribution to its regulation. For example: in Feldheim (Germany), the installed CES support the grid by providing primary frequency regulation for the transmission system operator [17]. The distribution network can utilize the CES as a flexibility service to improve the grid stability (e.g., during periods of increased power production from renewables) [18]. Therefore, CES could play an important role in realizing the transition towards efficient energy systems as evident from the great number of practical implementations in real-world industrial projects [19], [20].

Researchers have separately studied various aspects of CES integration, such as optimal sizing [21], control [22], [23], techno-economic feasibility [24], [25], etc. Different strategies have been explored for CES management including non-cooperative and cooperative game-theory [26], [27], auction-based models [28], capacity-allocation/capacity-sharing approaches [29], [30], price-based mechanisms [31], multi-objective optimization [32]. The overarching trend of these works is that these studies are generally based on off-line or day-ahead planning of CES operation.

The management of CES at the real-time/online simulation settings is a surprisingly underaddressed issue, having been touched upon by only a handful of works [22], [33]. Within the scope of operational management, a few researchers have also investigated the potential of CES being guided by model predictive control (MPC) approaches, as a counterbalance to shorter-term uncertainty [34]–[37]. Nonetheless, a prominent research gap still remains untouched upon. Indeed, the works [34], [35] consider only the aggregated building load instead of modelling the intrinsic device dynamics. On the other hand, works [36], [37] ignore the flexibility service procurement aspect of the CES. Given how all CES-driven flexibility ultimately depends on its interaction with buildings, attempting to quantify it and offer to the grid without the consideration of rigorous mathematical building models is a significant departure from reality. Addressing this issue lies at the core of this work.

Undoubtedly, one should be conscientious of the undesirable network issues that are attributed to high PV power generation (of which the LEC is responsible of), such as overvoltages and network congestion. There is a vast amount of literature proposing approaches for DSO to deal with such issues not only at the planning but also at the operation stage [51]–[54].

However, managing the above-mentioned network issues is considered as the responsibility of the DSO and not of the LEC community (unless futuristic self-management of grid issues by multiple LECs will be designed), which does not have access to and is most likely unaware of the network data and model. Accordingly, the distribution network is not explicitly included in the considered energy system structure, unlike a few recent works in literature [55]–[57].

In this work, the DSO is regarded as an entity procuring the flexibility services offered by the LEC in exchange for economic advantages. Therefore, aligning to the former research theme, the present work addresses the energy management in LECs from a purely demand-side perspective with economic and sustainability objectives while leaving the management of the network constraints to the DSO and thereby keeping it out of the scope of the paper.

Summarizing, the state-of-the-art is as follows: studies investigating CES energy management within a real-time simulation framework such as MPC are sparse. Furthermore, according to a very recent comprehensive review [38], the online provision of upstream ancillary services to the power grid by CES units has not been explored yet. The present work addresses the two gaps described above by employing a hierarchical (two-stage) energy management approach combined with MPC for an LEC with CES. The proposed strategy is based on decentralized energy management assisted by a central coordinator: instead of communicating amongst each other, end-users interact with the central entity [39]. In stage 1 of the proposed approach, LEC members determine their cost-optimal energy profiles, while in stage 2, said profiles are further coordinated using the CES in service of the overarching LEC (novel) objective, i.e., maximizing its self-consumption and self-sufficiency. The implemented real-time predictive framework additionally includes the following flexibility services in support of the grid's operation: 1) load flexibility and 2) CES capacity sharing between the LEC and grid aggregator.

The novel contributions of the paper can be summarized as follows:

- An MPC-based, two-stage hierarchical energy management framework for LECs, driven by the first stage end-user cost minimization and second stage LEC maximization of self-sufficiency and self-consumption.
- A real-time framework for the procurement of LEC-based flexibility services by the network aggregator, using an envelope-based flexibility quantification mechanism.
- A novel cost structure for the procurement of flexibility services, on the basis of the quantified flexibility.
- The first-time consideration of CES providing ancillary services to the grid, with fair profit allocation in accordance with the initial investment of the users.

II. Hierarchical Management Approach

A. System Description

Fig. 1 depicts the schematic diagram of the assumed LEC and its components. Let's denote the set of buildings in the LEC by $\mathcal{N}$ with $N = |\mathcal{N}|$ as the total number of buildings. The buildings are connected to a shared energy storage system, namely the CES, and the main power grid via AC power lines.

The LEC is assumed to be composed of three distinctly different building archetypes: residential houses, offices, and healthcare facilities. Each building archetype is equipped with size-dependent photovoltaic (PV) panels for on-site renewable energy generation, and a size-appropriate heating-ventilation and air-conditioning (HVAC) system to serve its heating/cooling demand. Residential houses further include discrete, time-shiftable appliances in their device sets, namely dishwashers, washing machines, and clothes dryers. All buildings in the LEC are assumed to be fully electrified, i.e., their entire load is served by electricity. They further posses their own private building energy management systems (BEMS), which optimally steer the operation of all controllable devices. The overarching community energy management system (CEMS) is in turn responsible for managing the CES, accounting for the signals from individual BEMSs and the grid aggregator, via a bidirectional communication.

Energy management within the LEC follows the proposed 2-stage approach, as seen in Fig. 2:

- *Individual building optimization stage* – at this stage, all individual BEMSs solve, in parallel, their own local cost minimization problem (subject to the individualized end-user preferences), thus generating their respective optimized power consumption profiles.
- *Community optimization stage* – The CEMS receives the optimized power consumption profiles from each BEMS. Through further coordination, these profiles are further refined in service of the CEMS maximizing the LEC's self-consumption and self-sufficiency.

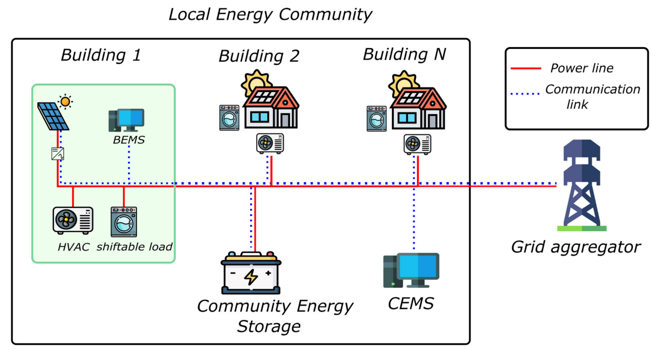

Fig. 1. Schematic lay out of the proposed LEC.

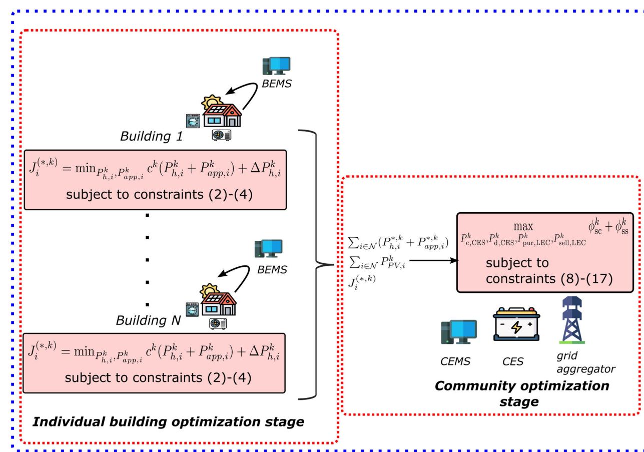

Fig. 2. Schematic representation of the proposed two-stage approach.

The following subsections explain the optimization stages in detail. Let $\mathcal{H}$ be the set of time steps with $H = |\mathcal{H}|$ as the prediction horizon and Δk as the sample time.

B. Stage 1: Individual Building Optimization Stage

We assume that each BEMS in the LEC receives real-time electricity price signals from the energy market or the system operator; aside from the binding end-user preferences, these serve as the driving force behind each building's cost minimization efforts. Do note that, at this stage, each building is essentially a self-contained entity, and the BEMS's defined operating schedule is *independent* from the CES. The cost minimization problem for any building $i \in \mathcal{N}$ can be formulated in abstract form as:

$$J_i^{(*,k)} = \min_{P_{\text{h},i}^k, P_{\text{app},i}^k} c^k(P_{\text{h},i}^k + P_{\text{app},i}^k) + \Delta P_{\text{h},i}^k \qquad k \in \mathcal{H} \quad (1)$$

subject to

$$P_{\text{h},i}^k \in \mathcal{P}_{\text{h},i} \quad (2)$$

$$P_{\text{h,min},i}^k \leq P_{\text{h},i}^k \leq P_{\text{h,max},i}^k \quad (3)$$

$$P_{\text{app},i}^k \in \mathcal{P}_{\text{app},i} \quad (4)$$

where the superscript k denotes the value of the corresponding variable/parameter at the k^{th} time step and c the electricity price. J^* is the optimal operation cost. For the general constraints (2)-(3), P_{h} refers to HVAC system's power consumption with $P_{\text{h,min}}$ and $P_{\text{h,max}}$ as the minimum and maximum rated power. Constraint (4) applies only to residential buildings, where P_{app} is the power consumption of shiftable appliances.

The sets $\mathcal{P}_{\text{h}}$ and $\mathcal{P}_{\text{app}}$ are the abstract representation for suitable mathematical models that capture intrinsic dynamics of the building's thermal behavior and shiftable appliances operation. The complete model formulation is provided in the appendix section.

ΔP_{h} is added to the objective function as an artificial penalty against abrupt activations/deactivations of the HVAC system; this helps achieve a smoother, more reliable operation. The superscript k denotes the value of the corresponding variable/parameter at the k^{th} time step. The resulting optimization problem (1)-(4) is a mixed-integer linear program (MILP).

Each BEMS, in parallel, solves the optimization problem (1)-(4) and computes the cost-optimized power consumption $P_{\text{h},i}^*$ and $P_{\text{app},i}^*$, and the optimal cost J_i^*. This information along with the PV production profile $P_{\text{PV},i}$ from each building is dispatched to the CEMS for stage 2 optimization.

C. Stage 2: Community Optimization Stage

The Stage 2, CEMS optimization problem, is built on two key performance indicators of the LEC's operation, which measure (and subsequently drive) its performance in terms of sustainability. We hereby define both.

1) Self-Sufficiency: The self-sufficiency (SS) of any all-electric entity, here the LEC, can be defined as the share C of the total load demand $A + C$ that is supplied by the renewable energy sources generation within the LEC (see Fig. 3), i.e., the ratio of load demand not supplied by the grid to the total load demand of the LEC [50].

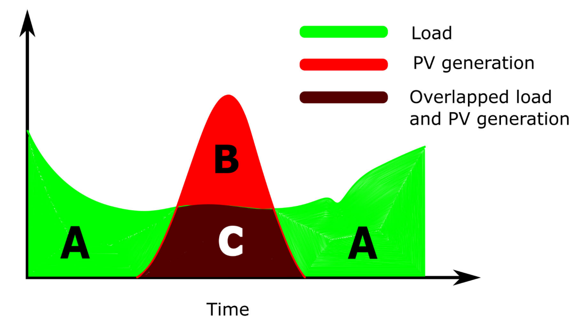

Fig. 3. Schematic representation of daily load and PV production (modified from [50]).

$$SS = \frac{C}{A + C}$$

2) Self-Consumption: The self-consumption (SC) is a metric that indicates the share C of locally generated electricity $B + C$ (PV generation in this case) that is being utilized to satisfy the load demand of the LEC, i.e., the ratio of used PV generation to total PV generation.

$$SC = \frac{C}{B + C}$$

Based on the above definitions, the LEC's SS and SC represented by Φ_{ss} and Φ_{sc}, respectively, can be expressed as:

$$\Phi_{\text{ss}} = \frac{\sum_{i\in\mathcal{N}} \sum_{k\in\mathcal{H}} (P_{\text{h},i}^k + P_{\text{app},i}^k) - \sum_{k\in\mathcal{H}} P_{\text{pur,LEC}}^k}{\sum_{i\in\mathcal{N}} \sum_{k\in\mathcal{H}} (P_{\text{h},i}^k + P_{\text{app},i}^k)} \quad (5)$$

where $P_{\text{pur,LEC}}$ denotes the power purchased for the entire LEC at the stage 2. Minimizing electricity import ($P_{\text{pur,LEC}}$) will lead to increment in self-sufficiency of the LEC.

$$\Phi_{\text{sc}} = \frac{\sum_{i\in\mathcal{N}} \sum_{k\in\mathcal{H}} P_{\text{PV},i}^k - \sum_{k\in\mathcal{H}} P_{\text{sell,LEC}}^k}{\sum_{i\in\mathcal{N}} \sum_{k\in\mathcal{H}} P_{\text{PV},i}^k} \quad (6)$$

where $P_{\text{sell,LEC}}$ is the power exported to the grid from the LEC. Therefore, lower electricity export ($P_{\text{sell,LEC}}$) to the grid will result in higher self-consumption of the LEC.

The CEMS collects the dispatched information from the stage 1. It processes the aggregated PV production $\sum_{i\in\mathcal{N}} P_{\text{PV},i}$ and optimized power consumption profiles $\sum_{i\in\mathcal{N}}(P_{\text{h},i}^* + P_{\text{app},i}^*)$ from all buildings as fixed generation and load, respectively, and coordinates them through the CES with the objective of LEC's sustainability maximization. It should be noted that the CES can purchase and sell electricity from/to the grid to assist the CEMS into maximizing LEC's sustainability. The CES is not concerned with the electricity prices, it only serves the purpose of LEC's sustainability maximization.

Therefore, the proposed approach is a trade-off between cost optimization (individual stage) and LEC sustainability maximization (community stage), with the cost minimization and the sustainability maximization taking place sequentially.

The CEMS optimization problem, i.e., the maximization of the LEC's sustainability, is formulated as follows:

$$\max_{P^k_{\mathrm{c,CES}}, P^k_{\mathrm{d,CES}}, P^k_{\mathrm{pur,LEC}}, P^k_{\mathrm{sell,LEC}}} \quad \Phi^k_{\mathrm{sc}} + \Phi^k_{\mathrm{ss}} \qquad k \in \mathcal{H} \tag{7}$$

subject to

$$E^{k+1}_{\mathrm{CES}} = E^k_{\mathrm{CES}} + \eta_{\mathrm{c}} P^k_{\mathrm{c,CES}} \Delta k - \frac{1}{\eta_{\mathrm{d}}} P^k_{\mathrm{d,CES}} \Delta k \tag{8}$$

$$E_{\min} \leq E^k_{\mathrm{CES}} \leq E_{\max} \tag{9}$$

$$0 \leq P^k_{\mathrm{c,CES}} \leq \zeta_{1,\mathrm{CES}} P^{\max}_{\mathrm{c,CES}} \tag{10}$$

$$0 \leq P^k_{\mathrm{d,CES}} \leq \zeta_{2,\mathrm{CES}} P^{\max}_{\mathrm{d,CES}} \tag{11}$$

$$\zeta_{1,\mathrm{CES}} + \zeta_{2,\mathrm{CES}} \leq 1 \qquad \zeta_{1,\mathrm{CES}}, \zeta_{2,\mathrm{CES}} \in \{0,1\} \tag{12}$$

$$0 \leq P^k_{\mathrm{pur,LEC}} \leq \theta_{1,\mathrm{LEC}} P^{\max,k}_{\mathrm{pur,LEC}} \tag{13}$$

$$0 \leq P^k_{\mathrm{sell,LEC}} \leq \theta_{2,\mathrm{LEC}} P^{\max,k}_{\mathrm{sell,LEC}} \tag{14}$$

$$\theta_{1,\mathrm{LEC}} + \theta_{2,\mathrm{LEC}} \leq 1 \qquad \theta_{1,\mathrm{LEC}}, \theta_{2,\mathrm{LEC}} \in \{0,1\} \tag{15}$$

$$\sum_k \mathrm{c}^k (P^k_{\mathrm{pur,LEC}} - P^k_{\mathrm{sell,LEC}}) \leq \sum_i J^{*,k}_i \tag{16}$$

$$P^k_{\mathrm{c,CES}} + \sum_{i \in \mathcal{N}} (P^{*,k}_{\mathrm{h},i} + P^{*,k}_{\mathrm{app},i}) + P^k_{\mathrm{sell,LEC}} = \sum_{i \in \mathcal{N}} P^k_{\mathrm{PV},i} + P^k_{\mathrm{d,CES}} + P^k_{\mathrm{pur,LEC}} \tag{17}$$

where (8) and (9) represent the power dynamics of the CES with η_{c} and η_{d} as the charging and discharging efficiencies and E_{CES} as the energy stored in the CES. (10)–(12) enforce the charging and discharging power of the CES to remain below the maximum allowed charging ($P^{\max}_{\mathrm{c,CES}}$) and discharging power ($P^{\max}_{\mathrm{d,CES}}$). The binary variables $\zeta_{1,\mathrm{CES}}$ and $\zeta_{2,\mathrm{CES}}$ prevent the simultaneous charging and discharging of the CES. Similarly, (13)–(15) constrain the maximum purchasing ($P^{\max}_{\mathrm{pur,LEC}}$) and selling ($P^{\max}_{\mathrm{sell,LEC}}$) of power from/to the grid and the binary variables $\theta_{1,\mathrm{LEC}}$ and $\theta_{2,\mathrm{LEC}}$ avoid the simultaneous selling and purchasing of power. Equation (16) ensures that the total cost of the LEC does not exceed the total optimal cost (for all buildings) from the stage 1, i.e., the optimal cost for end-users (stage 1) should not be jeopardized in pursuit of the LEC's sustainability maximization (stage 2). Equation (17) represents the power balance for the entire LEC. The power balance ensures that the requested power from the individual stage is met at the community stage.

The resulting CEMS optimization problem (7)-(17) is an MILP. The problem is solved repetitively at each time step employing the MPC strategy.

Maximizing any of the metrics, Φ_{sc} and Φ_{ss}, and their summation, encourages the buildings to consume the locally PV generated electricity within the LEC and essentially reduces the energy exchange (import/export) between the LEC and the main grid, thus improving the sustainability of the community.

III. Flexibility Services Provision by LEC

In addition to focusing on its sustainability, the LEC also plays the role of flexibility service provider to the grid. Specifically, the present work concentrates on load flexibility provision and storage capacity sharing services. We remark that the proposed hierarchical framework can function in a flexibility reluctance (no flexibility provision requested) mode as well.

The following subsections describe these services in detail.

A. Load Flexibility

With the ability to reduce, increase, or shift their energy consumption, the buildings possess significant potential for load flexibility provision. In addition to taking up a considerable portion of any building's energy load, HVAC systems may at the same time serve as major sources of flexibility. In this work, we assume that all available building-driven load flexibility stems from HVACs, which can respond in real-time to network flexibility requests. In this work, the term "flexibility request" defines an explicit power profile demanded by the grid, to be followed as much as possible by the building in question.

Even though the grid may in theory request for flexibility provision within any arbitrary time-frame, this work operates on the basis that all flexibility requests are "locked" within a pre-specified time duration $[k_{\mathrm{lb}}, k_{\mathrm{le}}]$ denoted as *load flexibility provision period* (LFPP); this allows the building sufficient time to re-adjust its operating schedule. The LFPP has the same time resolution as the sample time of the optimization problem at each stage. k_{lb} and k_{le} are the time steps corresponding to the beginning and ending of LFPP. Flexibility provision works in the following manner:

- At the time step $k_{\mathrm{lb}} - 2$, each BEMS, along with the building's expected power profile, sends the amount of load flexibility the building can offer to the power aggregator via the CEMS.
- At the time step $k_{\mathrm{lb}} - 1$, the grid aggregator sends its flexibility requirements to the CEM, which are further communicated to the buildings as their new power consumption target during the LFPP.
- At the next time step, each BEMS solves a quadratic optimization problem to track the new power consumption for the time horizon $[k_{\mathrm{lb}}, k_{\mathrm{le}}]$.

1) Flexibility Quantification: In order to offer load flexibility to the grid, it is first crucial to quantify the amount that a building is capable of providing. The HVAC system operates to maintain building's indoor within the comfort range (accounting for the electricity prices). It allows the HVAC system to have inherent flexibility that can be utilized to increase (upward flexibility) or reduce (downward flexibility) the building's energy consumption while respecting the thermal comfort.

To properly quantify the flexibility stemming from HVAC systems, we adapt the concept of the flexibility envelope [40], which gauges the available flexibility with respect to a baseline case and a strict deviation floor (lower limit) and ceiling (upper limit), see Fig. 4. The flexibility envelopes represent the technically feasible range within which the power consumption level may lie, subject to internal building constraints. In this work,

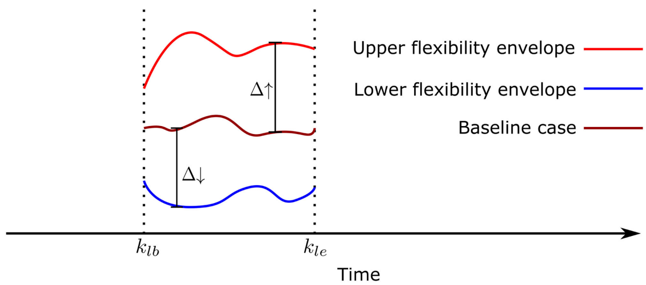

Fig. 4. Flexibility quantification with flexibility envelope approach.

the cost optimal power consumption of the building (Stage 1) is considered as the baseline case for constructing the flexibility envelope.

To obtain the upper flexibility envelope ($\Delta_k\uparrow$) for the building $i \in \mathcal{N}$, the BEMS solves the following optimization problem

$$\min_{P^k_{\mathrm{h},i}, P^k_{\mathrm{app},i}} (P^k_{\mathrm{h},i} - P_{\mathrm{h,max}})^2 \qquad k \in [k_{\mathrm{lb}}, k_{\mathrm{le}}] \tag{18}$$

subject to constraints (2)–(4) where $P_{\mathrm{h,max}}$ is the maximum power consumption capacity of the HVAC system. We opt for a quadratic objective to avoid the undesired effect of a linear objective (i.e., jumping through extreme points).

Similarly, for the lower flexibility envelope ($\Delta\downarrow$), the following optimization problem is solved

$$\min_{P^k_{\mathrm{h},i}, P^k_{\mathrm{app},i}} (P^k_{\mathrm{h},i} - 0)^2 \qquad k \in [k_{\mathrm{lb}}, k_{\mathrm{le}}] \tag{19}$$

subject to constraints (2)–(4)

As per (18) and (19), the controller's objective is to achieve the maximum and minimum overall power consumption for the HVAC system, respectively (during LFPP), while respecting all the constraints. Consequently, the upward ($\Delta\uparrow$) and downward ($\Delta\downarrow$) flexibility can be calculated as

$$\Delta_k\uparrow = P^{k,\mathrm{up}}_{\mathrm{h},i} - P^{k,*}_{\mathrm{h},i}, \qquad \Delta_k\downarrow = P^{k,*}_{\mathrm{h},i} - P^{k,\mathrm{low}}_{\mathrm{h},i} \tag{20}$$

where $P^{k,\mathrm{up}}_{h,i}$ and $P^{k,\mathrm{low}}_{\mathrm{h},i}$ is the power consumption of the HAVC system corresponding to upper and lower flexibility envelope, respectively. $P^{k,*}_{\mathrm{h},i}$ is the HVAC system's power consumption with baseline case (cost minimization).

The operation cost of the HVAC system will increase with upper and lower flexibility envelopes. Let's denote the cost increment by $\Delta J_i\uparrow$ and $\Delta J_i\downarrow$, which can be calculated as

$$\Delta J_i\uparrow = J^*_{\mathrm{up}} - J^*_i, \qquad \Delta J_i\downarrow = J^*_{\mathrm{down}} - J^*_i \tag{21}$$

where J^*_{up} and J^*_{down} is the operation cost of the building with upper and lower flexibility envelope. J^*_i is the optimal cost during the LFPP for the i^{th} building.

We use this increment in the operation cost to set a per-unit price for the load flexibility service. The per-unit cost for the load flexibility service (C_{lf}) is assigned as the ratio of increased operational cost due to the service provision and the total flexibility over the LFPP.

$$C_{\mathrm{lf}}\uparrow = \frac{\Delta J_i\uparrow}{\sum_{k=k_{\mathrm{lb}}}^{k_{\mathrm{le}}} \Delta_k\uparrow} \tag{22}$$

$$C_{\mathrm{lf}}\downarrow = \frac{\Delta J_i\downarrow}{\sum_{k=k_{\mathrm{lb}}}^{k_{\mathrm{le}}} \Delta_k\downarrow} \tag{23}$$

Note that we use cost for per unit procurement of the load flexibility service since the grid aggregator may not always request for the maximum available flexibility.

2) Power Consumption Readjustment: After receiving the amount of available load flexibility, the power grid aggregator sends flexibility requests to the buildings through CEMS to reduce or increase their power consumption. Let us denote the requested flexibility amount from the power grid by $\tilde{\Delta}$, which can be positive (upward flexibility) or negative (downward flexibility) depending upon the grid requirements. In response, the local BEMS for building $i \in \mathcal{N}$ runs the following tracking optimization problem in order to adjust the building's power consumption as per the flexibility request.

$$\min_{P^k_{\mathrm{h},i}, P^k_{\mathrm{app},i}} \left(P^k_{\mathrm{h},i} - P^{k,*}_{\mathrm{h},i} - \tilde{\Delta}_k\right)^2 \qquad k \in [k_{\mathrm{lb}}, k_{\mathrm{le}}] \tag{24}$$

subject to constraints (2)–(4)

According to the objective (24), the HVAC system strives to adjust its power consumption as per the flexibility request, while respecting all the constraints. A total cost of $\sum_{i\in\mathcal{N}} \sum_{k=k_{\mathrm{lb}}}^{k_{\mathrm{le}}} C_{\mathrm{lf}} \times \tilde{\Delta}^k_i$ occurs to the grid aggregator for the flexibility service procurement.

B. CES Capacity Sharing

In this work, the CES is considered to act as a multi-service energy device. In addition to serving the LEC for energy storage purposes, it can provide flexibility services to the grid in case of grid congestion due to the high penetration of renewable energy generation. The grid aggregator can send a flexibility requirement signal to the CEMS in advance. In that case, the CEMS will allow the grid aggregator to use a part of the energy storage capacity of the CES as a flexibility service. The grid aggregator is charged for the flexibility service, and the profit is divided among the building owners of the LEC according to their initial investment in the CES.

Note that, with this service, the optimization problem at the stage 2 will be solved with the reduced CES capacity. Therefore, the optimal cost for the building owners will increase. So the amount paid by the grid aggregator needs to at least cover the increased cost for the building owners. The cost for the flexibility service procurement (C_{f}) is determined according to the following linear cost function.

$$C_{\mathrm{f}}(E_{\mathrm{CES}}) = \psi_0 + \psi_1 \times (E_{\mathrm{CES}}) \quad \psi_0, \psi_1 > 0 \tag{25}$$

where ψ_0 is the base cost to procure the flexibility service, the base cost ensures that the building owners' optimal cost is not imperiled. The value of ψ_0 is established as the total increased cost for the building owners due to renting out the CES capacity as a flexibility service to the grid aggregator as:

$$\psi_0 = J^*_{\mathrm{LEC}}\uparrow - J^*_{\mathrm{LEC}} \tag{26}$$

where $J^*_{\mathrm{LEC}}\uparrow$ is the optimal cost for the LEC at the community optimization stage with reduced capacity of the CES; the upper arrow is used to denote that the cost will increase. J^*_{LEC} is the optimal cost for the LEC at the community stage with the full capacity of the CES (7).

The second term in (25) represents the profit made by the LEC by providing the flexibility service to the grid aggregator. The value of ψ_1 can be mutually agreed between the LEC and the grid aggregator based upon the curtailment cost of excess power incurred to the grid. The profit for each building owner (ρ_i) is assigned based upon their initial investment (I_i) into the CES as follows:

$$\rho_i = \frac{\mathrm{I}_i}{\sum_i \mathrm{I}_i} \times \psi_1 \times (E_{\mathrm{CES}})^2 \tag{27}$$

IV. Case Study

A. Optimization Problem Setup and Assumptions

First, the performance of proposed approach is demonstrated on a 3-building LEC; a proof-of-concept mentality. While varying in size, the buildings are assumed to have same thermal parameters (thermal resistance and capacitance), which were identified using the R toolbox CSTM-R [41], based on real measurements from a one-story residential building in Aarhus, Denmark [42]. The three buildings are assigned different temperature set-point schedules according to ASHRAE standard 55 guidelines [43], to properly capture the thermal behavior of each archetype (residential, office, healthcare facility).

Concerning the energy storage system, the SAMSUNG SDI-ESS (Lithium-ion storage 3.6 kWh [44]) is assumed as the smallest unit for simulation purposes. The sizes of the three building archetypes are kept in a $1:2:3$ ratio; therefore, without the loss of generality, a CES of 21.6 (6*3.6) kWh is considered, according to the building size.

In the absence of dynamic retail prices, the historical electricity prices from wholesale NordPool market [45] are scaled up to estimate the retail electricity prices. The external weather data (ambient temperature and solar irradiance) are generated for the specific location using Meteonorm.

All optimization problems are formulated in MATLAB through the YALMIP toolbox [46] and solved using CPLEX with an optimality gap of 10^{-4}. All simulations are performed for one-week period with a sampled time Δk of 15 min and a prediction horizon of H of 96 time-steps (24 hr).

B. Performance of Involved Entities

1) Behavior of Building Archetypes: We start by analyzing the different types of building thermal dynamics derived from Stage 1, with HVAC systems serving as the only flexible load for the buildings. Fig. 5 shows the weekly indoor air temperature evolution for each building archetype. As expected, each BEMS comfortably maintains the temperature within the acceptable comfort range. Do note that, as a result of the various individual and collective optimization objectives, each building archetype's thermal profile consistently lies at its user-defined limit. Nonetheless, for real-time applications, the risk of encountering major violations in terms of thermal comfort is negligible, as observed in [49]. Due to the smaller size of the residential building, which translates to faster thermal dynamics, its temperature progression presents minor peaks, which do not however create any issues of note.

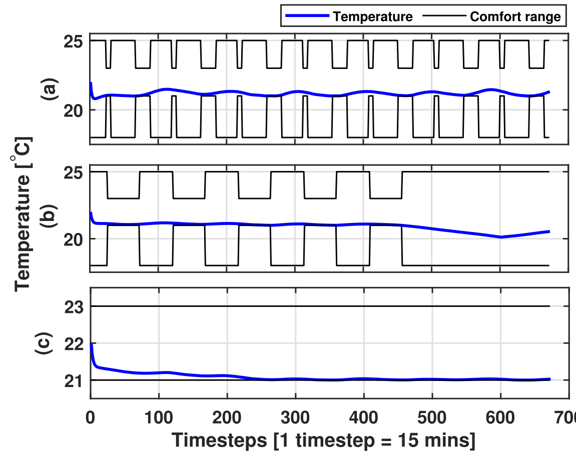

Fig. 5. Stage 1: Indoor air temperature dynamics in (a) residential building, (b) office building, and (c) healthcare facility building.

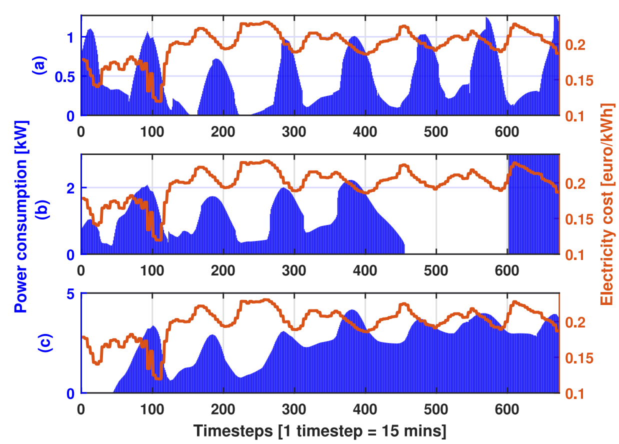

Fig. 6. Stage 1: Power consumption of HVAC system over a week for (a) residential building, (b) office building, and (c) healthcare facility building.

Fig. 6 presents the weekly power consumption of the HVAC system in each building derived from Stage 1. In order to drive down the building costs, the HVAC system reserves its intense operation for periods when the electricity prices are low. It also demonstrates a natural, continuous consumption pattern, a direct result of the ramping rate penalty in (1). Do also observe how the consumption pattern directly reflects the implicit occupancy and its needs per archetype: the residential HVAC demonstrates a repeating up-and-down pattern (people leaving and coming back from work), the office HVAC shuts down during the weekend and restarts towards the start of the first work day, and the healthcare HAVC maintains a cost-optimal, yet consistently active operation. The calculated power consumption profiles are subsequently transmitted to the CEMS for the upcoming Stage 2.

2) Performance of the LEC: Fig. 7(a) shows the CES's charging and discharging dynamics. Rather than purchasing power from the grid, the CES opts for storing energy during periods of high PV production in the LEC; energy which is used to

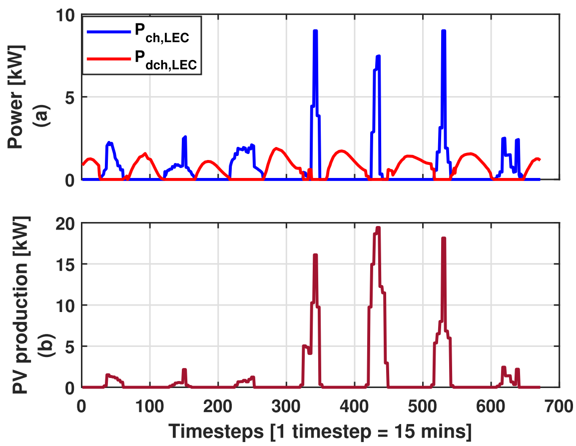

Fig. 7. (a) Stage 2: Charging and discharging power dynamics of the CES, (b) PV power generation.

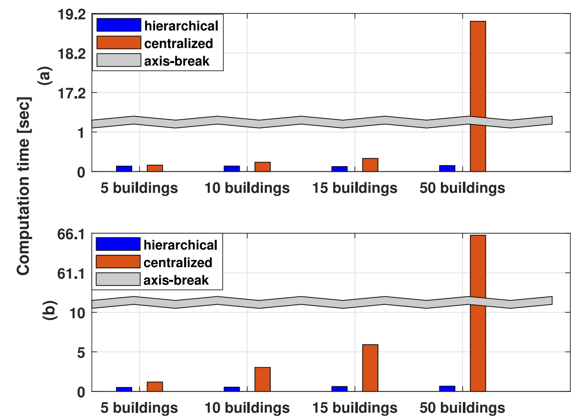

Fig. 8. Computation times of hierarchical and centralized approaches with 5, 10, 15, and 50 buildings in the LEC, (a) without and (b) with shiftable appliances.

TABLE I
KEY PERFORMANCE INDICATORS FOR THE LEC OPERATION THROUGHOUT THE YEAR

Month	Φ_{ss}	Φ_{sc}
Jan	0.16	0.81
Feb	0.23	0.78
Mar	0.47	0.51
Apr	0.64	0.37
May	0.75	0.32
Jun	0.77	0.18
Jul	0.97	0.13
Aug	0.90	0.14
Sep	0.74	0.28
Oct	0.40	0.51
Nov	0.24	0.73
Dec	0.25	0.77

later compensate the high HVAC demand during the late afternoon/night. If the CES happens to max out its charging capacity, any excess PV production directly serves the HVAC demand, with any "leftovers" being finally fed into the grid. By design, there is only minimal exchange of energy between the LEC and the grid, leading to the maximization of its sustainability, as expressed by the relevant self-sufficiency and self-consumption metrics.

Table I shows the key performance indicators of the 2-stage LEC management approach, over a four-week simulated period for each month of the year. An interesting feature to note is that the self-sufficiency and self-consumption metrics are in fact contradictory: for example, the LEC exhibits maximum self-sufficiency during the summer, when the PV production supplies most of the load demand, either directly or indirectly (through the CES). The self-consumption takes a deep dive during this period, owing to a significant amount of excess PV power which is fed back into the grid by default. The LEC's yearly averages in terms of self-sufficiency and self-consumption are 0.54 and 0.46, respectively, thereby contributing significantly to the LEC's sustainability.

The LEC's self-sufficiency and self-consumption are clearly dependent on the sizing of the energy devices. However, the optimal sizing aspect is outside this paper's scope; the reader is referred to [21], [47] for more details.

C. Centralized vs. Hierarchical Approach

To evaluate the performance of the hierarchical approach, it is mandatory that we compare it to the standard benchmark, i.e., a hypothetical centralized approach which skips Stage 1 and which tasks the CEMS with centrally managing every single energy device in the LEC, across all buildings. We examine three different cases of LEC size, with 5, 10, 15, and 50 buildings. Without loss of generality, all considered buildings are treated as residential dwellings, without (case **a**, LP problem) and with shiftable appliances (case **b**, MILP problem). The computation times for solving both cases under the centralized and hierarchical strategies are shown in Fig. 8.

The computation time under the centralized approach proportionally increases with the number of buildings in the LEC, whereas the hierarchical approach demons rates consistently low computation times, apparently fully independent from the number of simulated buildings. This is a direct result of running the individual BEMS optimization problems of Stage 1 in parallel. Notwithstanding that the computation time for the centralized approach is higher in magnitude compared to the hierarchical approach, it may still be acceptable for practical implementations concerning a small number of buildings (though the centralized approach is expected to decline in reliability for cases with dozens of buildings). However, as was previously mentioned, centralized approaches are notoriously weak choices when issues of privacy or cyber-security are involved, especially when the number of end-users (not just buildings) grows substantially. Despite not having directly quantified these advantages, the hierarchical approach is unquestionably more robust in terms of information trafficking and of reliance on some central entity.

Similar observations can be drawn for the case which includes shiftable appliances (i.e., binary variables) in the model. While the computation time expectedly increases for both approaches, the hierarchical approach is maintains its crucial characteristics of independence from the number of buildings in the LEC, thus proving its superiority over the centralized approach in terms of scalability for real-life implementation as the computation time remains steady with increasing the number of building. One would expect said superiority to come at the cost of a worse

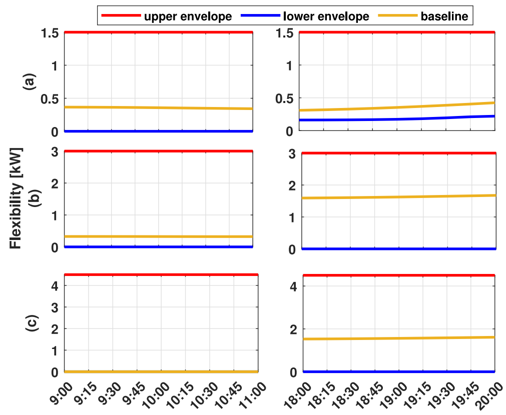

Fig. 9. Upper and lower flexibility envelops during LFPP for (a) residential building, (b) office building, and (c) healthcare facility.

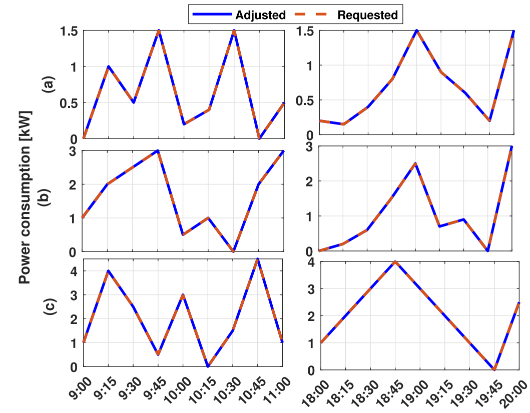

Fig. 10. The adjusted power consumption during the LFPP for (a) residential building, (b) office building, and (c) healthcare facility.

(sub-optimal) solution for the LEC's objective function. However, the average objective deterioration lies at around 1.37% (against the centralized approach's solution), a relatively minute trade-off for the substantial gains in terms of scalability and the implicit privacy; the proposed approach's pros clearly outweigh the minor cost increases.

D. Load Flexibility Provision

To investigate the flexibility services provision, we consider the two peak-demand periods of the day as the LFPP, namely [09:00-11:00] and [18:00-20:00]. As outlines in Section II.A, the LEC transmits the available flexibility to the grid aggregator at 08:30 and 17:30, with the aggregator returning its flexibility requests (power adjustment signals) at 08:45 and 17:45, respectively. The LEC is simulated for a one-day period.

Fig. 9 illustrates the results of the building flexibility quantification, i.e., the operating envelopes that are derived based on the objectives (18)-(19), subject to (2)-(4). Each building may offer to alter the HVAC's power consumption up to its maximum or minimum value (comfort-dependent), except for the residential building during evening hours, which must maintain an acceptable level for the indoor temperature. Do note that in case a building is already operating at its minimum or maximum power (see healthcare facility in Fig. 9(c), the baseline profile overlaps with the flexibility envelope's technical limits. Each BEMS forwards its own flexibility envelope to the grid aggregator (via the CEMS), which subsequently transmits new (requested) power consumption profiles to each end-user.

To examine the inner working of this process, we first define random power profiles within the quantified flexibility ranges. Fig. 10 shows the randomly requested and subsequently adjusted power consumption of each buildings during the LFPP. Evidently, all BEMSs successfully track the requested power profiles without any meaningful deviations. Table II shows the total profit made by the LEC by providing flexibility services to the grid aggregator. Although small for a single-day LFPP, the yearly profit may in fact be non-negligible, depending on the available flexibility, the amounts requested, and of course, the electricity prices. For instance, if one applies the exact same conditions for each day of the year, and assuming that the maximum amount of flexibility is always requested, the LEC can make a yearly profit of 3,952 €, split 16-30-54 between the residential, office, and healthcare buildings (HVAC size-dependent).

TABLE II
TOTAL PROFIT (IN €) OF THE LEC DUE TO FLEXIBILITY PROVISION

Building	LFPP [12:00 - 14:00]	LFPP [18:00 - 20:00]
Residential	0.67	0.51
Office	1.69	1.47
Healthcare facility	2.78	1.58

TABLE III
TOTAL COST (IN €) FOR THE LEC AND THE GRID AGGREGATOR WITH CES CAPACITY PROCUREMENT

Procured capacity	LEC operation cost	Aggregator	
		Base cost (ψ_0)	Total cost (C_f)
0%	453.78	0	0
25%	483.98	30.2	31.71
50%	490.7	36.92	39.94
75%	594.13	140.35	144.89
100%	776.58	322.8	328.85

E. CES Capacity Sharing

This section investigates the other flexibility service, i.e., sharing the CES's capacity with the grid aggregator, to be independently "deployed" during times of high renewable energy production. To illustrate how the process works, a 15-building LEC is considered, hosting a CES with a capacity of 108 kWh (30*3.6). It is assumed that the grid aggregator reserves a portion of the CES's capacity for the period [11:00-14:00], i.e., the one with the highest renewable energy production. By running simulations for the standard four-week period, we can calculate the costs incurred to the LEC and the grid aggregator for varying amounts of requested and reserved CES capacity, see Table III. The cost is calculated with value of $\psi_1 = 0.002$ € /kWh, which is the general flexibility provision cost for storage devices, see [48]. As expected, as the LEC offers more of its capacity to the grid aggregator, its profit increases (though not proportionally). The profit generated from the service is fairly allocated according to the initial investment in the CES.

F. Discussion on End-User Privacy

The proposed hierarchical approach inherently preserves the end-users privacy since they only share their aggregated electric load profile. However, with the increasing digitization of energy systems (e.g., wireless communication, smart metering systems) no communication channel can be fully safeguarded against cyber-attacks. For instance, a versed adversary could intrude into the system and obtain sensitive information about the building's occupants and can potentially gain knowledge about the occupant's activities (e.g. presence, absence, sleep and wake cycles), including LEC-related data. This may require installation of proper cyber-security protocols, though what these are not within paper's scope. However, the inherent privacy of the proposed approach could be further strengthened through well-established protection mechanisms to tackle the aggregated load (originating from smart meters) privacy issues reported in the literature as well as in practice [58]. The fundamental idea is to obfuscate the data in order to prevent inference of sensitive information. The most common strategies are either using data manipulation techniques to alter smart meter data [59] or user demand shaping through physical devices such as an energy storage system or flexible thermal devices [60], [61].

On the contrary, with the centralized approach, the amount of information shared with the central entity is higher. For instance, the end-user will have to share their preferred time period to run the shiftable appliances, their thermal comfort preferences, and the intrinsic dynamics of their energy devices with the central entity, which could disregard EU's General Data Protection Regulation [62]. Furthermore, this leads to a larger volume of data shared within LEC and hence higher value of observable features metric [63], thus making it more prone to privacy intrusion. As such, based on the shared information characteristics, it would be much easier for the adversary to learn about the occupant's activities.

V. Conclusion

This work has presented a novel MPC-based hierarchical two-stage energy management approach for diverse LECs (various building archetypes) including a CES. Not only does the approach accommodate the desire of each building to optimally steer its energy devices in service of its own individual objective (Stage 1), but it also substantially improves the sustainability and grid friendliness of the LEC (Stage 2), as these are expressed through the self-sufficiency and self-consumption metrics. The real-time-based framework also gave the LEC the "ability" to quantify its available flexibility range (through operating envelopes) and to subsequently offer it to the grid aggregator through various kinds of ancillary services (load flexibility and CES capacity sharing).

Aside from the apparent financial and environmental benefits recorded for the LEC (and by definition its members), alongside its implicit contribution to improving the grid's operation by providing ancillary services, the proposed approach vastly outperformed its centralized counterpart in terms of computational performance. Setting aside the superiority in terms of privacy and communication trafficking, the employed hierarchical strategy's performance proved to be consistent and effectively *independent* of the number of buildings in the LEC, thus opening the door for scaling up to large-scale, real-life cases; the deterioration in terms of objective function could even be viewed as negligible. The operating envelope technique for quantifying the available building flexibility demonstrated remarkable ease-of-use, providing the grid aggregator with a practical tool for managing and reserving flexibility in real-time. This granted substantial monetary benefits to end-users, either through direct load flexibility provision or through sharing their corresponding shares of the CES capacity.

At the current stage, the work assumes a perfect weather forecast. Including uncertainties in the weather forecast [49] is a possible avenue for future work. Another interesting idea would be to explore the optimal sizing of the energy devices and its effect on the LEC's sustainability. Another future work is to validate the proposed approach in a real-life setting, implementing the MATLAB simulation model developed in a hardware-in-the-loop simulation with real-time digital simulators.

Appendix
Modeling of Flexible Load Devices

This section presents the detailed models for intrinsic dynamics of the energy devices ($\mathcal{P}_{\mathrm{h}}$ and $\mathcal{P}_{\mathrm{app}}$) introduced in constraints (2)-(4).

A. Thermal Dynamics of Building and HVAC

The thermal dynamics of a building are mainly affected by ambient air temperature (T_{a}), solar irradiance (ϕ_{s}), and heating/cooling power supplied by the HVAC system. The overall dynamics are modeled employing a lumped-capacitance method with indoor air temperature (T_{i}) and the internal heat-accumulating medium temperature (T_{m}) as states. Internal mass such as furniture, floor, and ceiling, are lumped into the internal heat-accumulating medium. The thermal dynamics of the building are captured by the following first-order differential equations [49] (later descritized with 15 min sample time), which represent the detailed version of abstract set $\mathcal{P}_{\mathrm{h}}$:

$$C_{\mathrm{m}}\dot{T}_{\mathrm{m}} = \frac{(T_{\mathrm{i}} - T_{\mathrm{m}})}{R_{\mathrm{im}}} + A_{\mathrm{w}}.\mathrm{p}.\phi_{\mathrm{s}} \tag{28}$$

$$C_{\mathrm{i}}\dot{T}_{\mathrm{i}} = \frac{(T_{\mathrm{m}} - T_{\mathrm{i}})}{R_{\mathrm{im}}} + \frac{(T_{\mathrm{a}} - T_{\mathrm{i}})}{R_{\mathrm{ia}}} + \eta_{\mathrm{h}}\phi_{\mathrm{h}} + A_{\mathrm{w}}.(1-\mathrm{p}).\phi_{\mathrm{s}} \tag{29}$$

where C_{m} and C_{i} are the heat capacities of indoor air and heat accumulating medium. R_{im} and R_{ia} is the thermal resistance against heat transfer between indoor air and heat accumulating medium, and external air, respectively. A_{w} is the effective window area of the building and p is the fraction of solar irradiance which directly affects T_{m}. The HVAC system is modeled as a heat pump with a constant coefficient of performance η_{h} with ϕ_{h} as the compressor power consumption.

B. Shiftable Appliances

The operation of shiftable appliances is modeled considering different energy phases within each appliance. The detailed model of the abstract set $\mathcal{P}_{\text{app}}$ is defined as follows:

$$\begin{aligned}
&\sum_{k\in\mathcal{H}}\alpha_j^k=\Omega_j && \forall j\in\mathcal{M}\\
&\alpha_j^k=0 && \forall k\in\mathcal{F}_j\\
&\alpha_j^k+\beta_j^k\le 1 && j\in\mathcal{M},k\in\mathcal{H}\\
&\alpha_j^{k-1}-\alpha_j^k\le\beta_j^k && j\in\mathcal{M},k=2,3\ldots H\\
&\beta_j^{k-1}\le\beta_j^k && j\in\mathcal{M},k=2,3\ldots H\\
&\alpha_j^k\le\beta_{j-1}^k && k\in\mathcal{H},\ j=2,3,\ldots M\\
&\gamma_j^k=\beta_{j-1}^k-(\alpha_j^k+\beta_j^k) && k\in\mathcal{H},\ j=2,3,\ldots M\\
&D_j^{min}\le\sum_{k\in\mathcal{H}}\gamma_j^k\le D_j^{max} && j=2,3,\ldots M
\end{aligned}$$

where $\mathcal{M}=\{1,2,\ldots,M\}$ is the set of appliance's energy phases. $\mathcal{F}$ represents the set of time instant when the appliance is not allowed to operate. Ω is the specific duration for which appliance needs to run for. α,β and γ are binary variables. α denotes the on/off status of the energy phase, β is an auxiliary variable to indicate the finishing status of energy phase by taking the value of 1 at its completion. γ is another auxiliary variable to assist in keeping track of the waiting time between the energy phases. D_j^{min} and D_j^{max} is the minimum and maximum delay allowed between the energy phases.

C. Centralized Approach Problem Formulation

With the considered centralized approach (section-IV C), the CEMS centrally and directly manages the energy devices of the buildings within the LEC. The optimization problem is formulated as:

$$\min_{\substack{P^k_{\text{h},i},P^k_{\text{app},i},P^k_{\text{c,CES}},\\ P^k_{\text{d,CES}},P^k_{\text{pur,LEC}},P^k_{\text{sell,LEC}}}} c_{\text{k}}(P^k_{\text{pur,LEC}}-P^k_{\text{sell,LEC}})\quad k\in\mathcal{H} \tag{30}$$

subject to

$$P^k_{\text{h},i}\in\mathcal{P}_{\text{h},i}\quad\forall i\in\mathcal{N} \tag{31}$$

$$P^k_{\text{h,min},i}\le P^k_{\text{h},i}\le P^k_{\text{h,max},i}\quad\forall i\in\mathcal{N} \tag{32}$$

$$P^k_{\text{app},i}\in\mathcal{P}_{\text{app},i}\quad\forall i\in\mathcal{N}$$

$$(8)\text{-}(15) \tag{33}$$

$$P^k_{\text{c,CES}}+\sum_{i\in\mathcal{N}}(P^k_{\text{h},i}+P^k_{\text{app},i})+P^k_{\text{sell,LEC}}= \sum_{i\in\mathcal{N}}P^k_{\text{PV},i}+P^k_{\text{d,CES}}+P^k_{\text{pur,LEC}} \tag{34}$$

Acknowledgment

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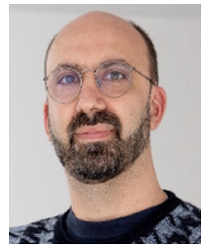

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