From Smart to Sustainable to Grid-Friendly: A Generic Planning Framework for Enabling the Transition Between Smart Home Archetypes

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***Abstract*—The concept of nearly zero energy (nZE) or sustainable buildings is prominently featured in the EU's energy strategy. However, transitioning to the envisioned era of "smartness" and "sustainability" involves overcoming several technoeconomic barriers: the difference in nature between different building archetypes, the simultaneous management of daily and yearly objectives by the energy management system (EMS), the impact on distribution grids and the required modelling detail. Focusing on addressing such concerns in the scope of the residential sector, this work proposes a generic mixed-integer linear programming (MILP) framework for modelling smart appliances (conventional and new advanced approaches) as well as for the seamless transition of residential homes from passive to smart, to sustainable and finally to grid-friendly entities. The framework includes an adaptive rolling horizon strategy accounting for the yearly nZE objective and a cost-grid impact trade-off strategy for handling flexibility requests. The energy management framework and all developed models are validated in several different scenarios, including a comprehensive sensitivity analysis.**

***Index Terms*—Energy management system, multi-step optimization, shiftable loads, smart sustainable building.**

Nomenclature

Sets

$\mathcal{D}$	Set of days (indexed by d)
$\mathcal{T}$	Set of time periods within a day (indexed by t)
$\mathcal{T}^{off}$	Set of time periods when SLs must be "OFF"
$\mathcal{T}^{nc}$	Set of time periods when EVs cannot charge
$\mathcal{U}$	Sets of consumption levels order (indexed by u)

Parameters (devices & general problem)

CT	SL cycle time, number of periods
EC	Battery energy capacity of EV or ES, kWh
η	Conversion efficiency of EV or ES, %
$P_{d,t}^{D}$	Fixed active power demand, kW
P^{rate}	Rated power EV, ES or SL, kW
P^{temp}	SL temperature maintenance power, kW (% of P^{rate})
$P_{\text{d,t}}^{\text{gen}}$	PV active power generation, kW
P^{cd}	SL cool-down power, kW (% of P^{rate})
P^{wu}	SL warm-up power, kW (% of P^{rate})
E^{nZE}	Yearly nZE net energy target, kWh
$p_{\text{d,t}}^{\text{el}}$	Electricity price, €/kWh
$p_{\text{d,t}}^{\text{fit}}$	Feed-in tariff, €/kWh
ϵ	Consumer maximum profit deterioration, %

Variables (continuous & binary)

$P_{\text{d,t}}^{\text{I}}$	Power imported from the grid, kW
$P_{\text{d,t}}^{\text{E}}$	Power exported to the grid, kW
$P_{\text{d,t}}^{\text{inj}}$	PV active power injection, kW
$P_{\text{d,t}}^{\text{ch}}$	Active power charge of EV or ES), kW
$P_{\text{d,t}}^{\text{dis}}$	Active power discharge of EV or ES, kW
$SoC_{\text{d,t}}$	State of charge of EV or ES, %
$\beta_{\text{d,t}}$	SL is maintaining temperature (P^{temp}) or "OFF"
$\delta_{\text{d,t}}$	Conventional SL is "ON" (P^{rate}) or "OFF"
$\zeta_{\text{u,d,t}}$	Advanced SL is "ON" (P_u^{rate}) or "OFF"
$c_{\text{d,t}}$	Conventional SL is cooling down (P^{cd}) or "OFF"
$w_{\text{d,t}}$	Conventional SL is warming up (P^{wu}) or "OFF"

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I. Introduction

A. Motivation

THE increased consumption of fossil fuels for the purpose of electricity production has led to the escalation of environmental pollution. Buildings take up a major portion of the "blame"; according to recent studies, they could be contributing up to 40% to global CO_2 emissions [1]. In mobilizing recent decarbonization efforts, the concept of nearly zero energy (nZE) or sustainable buildings is extensively promoted in the EU, with good strides having been taken in some countries [2]. Strictly speaking, a nZE building is not smart per se; it simply must balance its yearly energy use and on-site renewable energy production [3]. This target is, however, somewhat myopic, as existing smart buildings (SBs) can evolve to serve superior, more encompassing objectives, transitioning to more sustainable and grid-friendlier entities.

The nZE status is primarily equipment-dependent and easily achievable, assuming (on-paper) sufficiently high on-site production potential. However, from the perspective of owners and distribution system operators (DSOs) alike, it is often desirable

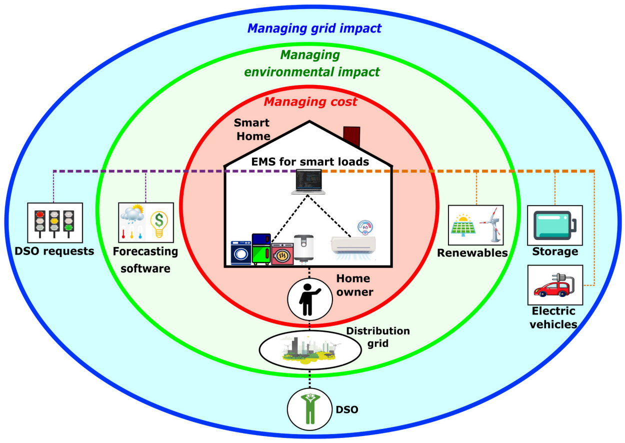

Fig. 1. Involved "actors," systems, equipment, objective layers.

for buildings to also be smart. This carries higher potential for monetary gains and flexibility provision opportunities [4], thanks to the buildings' energy management systems (EMS). Nonetheless, when buildings evolve to serve additional objectives, their original objectives must not be compromised. The aforementioned evolution should not be a brute-force conversion, but rather a seamless transition that allows for the serving of multiple objectives in a clear hierarchy. While the original objectives remain dominant, all objectives are ultimately served to such an extent that the building's nature effectively changes.

This conceptual evolution is illustrated in Fig. 1. When the only objective is cost management, the EMS does not consider the building-grid relation. At the inclusion of the secondary environmental impact layer, the interaction with the grid must be closely monitored, albeit not at the expense of the primary objective. At the inclusion of the tertiary grid impact layer, the relation between building and DSO also comes into play through energy flexibility provision. Again, this must not compromise the secondary, much less the primary objective. All objectives should also remain centered around building owners, the main beneficiaries of the optimization process.

B. Literature Review

The topic building optimization has always attracted significant attention. The most common objective is minimizing operating costs, often complemented with flexibility provision schemes or user-related restrictions. However, the inclusion of environmental impacts is rarely considered [5]. The SB's behavior is optimized by its EMS, which manages various devices. Controllable devices could include flexible loads, electric vehicles (EVs), both conventional and advanced (vehicle-to-grid or V2G), photovoltaics (PVs), energy storage (ES) and shiftable loads (SL) [6]–[13]. The resulting problems are predominantly linear/mixed-integer linear programming (MILP). It is SLs whose modelling presents a consistent challenge. It can range from approximated representations, continuous or discrete, to highly complex ones with device-specific constraints [11], [12], [14]–[18]. The former approaches involve many simplifying assumptions, resulting in tractable, yet inaccurate problems [19]. The latter are more accurate, but result in highly complex formulations which also require a lot of multidisciplinary information about the devices and the building; these are not always available or easy to determine [11], [13]. Because researchers opt for case-specific models each time, a generic and comprehensive modelling framework does not currently exist. This gap partially motivated this work.

Residential flexibility provision is most commonly implemented through grid-driven dynamic pricing schemes [9], [12], [20], [21], which often lead to high end-user costs or to underaddressing the system's needs [22]–[24]. These issues have been addressed by penalizing local line overloads, constraining the interactions with the grid, or re-adjusting the building's profile to meet the DSO's requests [7], [16], [18]. Ultimately, all approaches pass down increased responsibilities to end-users. Most schemes are one-sided, with the DSO having direct authority over the building's consumption [25], the flexibility remuneration being highly lucrative for end-users but expensive for the DSO [9], [25], or the flexibility being procured in bulk by aggregated buildings with no consideration of internal electrical issues [13]. Fairer approaches have been proposed, though these require establishing some local energy market structure [26], [27]. Aside from the infrastructural upgrades and the inadequate energy literacy of end-users, there is no clear consensus on how to best implement such a market [28], [29]. Currently, one very rarely encounters flexibility-based approaches that are reasonably simple to implement and that can achieve positive outcomes without giving too much authority to the DSO or too much responsibility to end-users.

Special mention should be made of longer-term objectives, especially as they pertain to nZE buildings. Due to the yearly temporal nature of the nZE mandate, it is almost always included in a deterministic fashion [4], [30], with the day-to-day optimization taking place under the assumption that the nZE mandate cannot be violated. In the day-ahead planning process, the issue of uncertainty has been tackled with various degrees of success [17], [31], though this kind of shorter-term uncertainty is becoming easier to handle with the development of more sophisticated forecasting tools. The nZE buildings are usually assumed to be able to meet their energy targets by design [3]; some have considered the possibility of that target being jeopardized, but only within microgrid settings [32], [33]. That way, the microgrid's resources can support the building in managing its environmental goals. However, the case of a nZE building optimizing its profile while keeping track of its environmental mandate is an underaddressed issue which we want to tackle through a rolling horizon algorithm technique. A topic that is also surprisingly underaddressed is the simultaneous consideration of (conflicting) environmental and flexibility-based objectives, so that a nZE building would be able to provide *"clean flexibility"* through energy-neutral actions. This is another issue addressed in this work.

C. Contributions

In this paper, we ask two important questions: a) how could an existing EMS naturally adopt additional tasks without compromising pre-existing objectives and b) what is the appropriate level of device modelling detail? We propose a novel, multi-step strategy to "upgrade" SBs along three axes: the seamless transition of SBs to higher levels of sophistication, the co-management of objectives with different temporal bases, and the modelling of smart devices in a generic manner. Accordingly, our main novel contributions are the following:

- We describe an envisioned 3-stage strategy for transitioning between different building archetypes: SB → sustainable SB (SSB) → grid-friendly SSB (GF-SSB).
- We propose an adaptive version of the "Relax and Reduce Algorithm" of [34] to bridge the gap between daily objectives and yearly targets for SSBs and GF-SSBs.
- We develop a novel, energy-neutral flexibility provision algorithm for GF-SSBs that considers owner willingness to trade off potential profits for supporting the grid.
- We propose a generic framework for the modelling of SLs, applicable to a wide variety of smart appliances.

While the developed concepts and device models are generic, our focus is primarily on the residential sector. As such, we use the terms "building" and "home" interchangeably. The remainder of the work is structured as follows. The examined device models are detailed in Section II. The building objectives and their practical realization are analyzed in Section III. The case study is presented in Section IV. Conclusions and future research avenues are outlined in Section V.

II. Device Modelling

Variables are characterized by day, $d \in \mathcal{D}$, and time period, $t \in \mathcal{T}$. We assume a yearly horizon of 365 days, each of 24 hourly intervals. The year starts at January 1st and each day at midnight; *any starting time could be viewed as equally valid*. All devices are represented by their steady-state operation equivalent. Power fluctuations during activation, deactivation, operation or temperature management are assumed to be in the order of a few Watts, see [35], [36]. Accordingly, fast device dynamics, typically orders of ms are approximated by the steady-state power consumption level of each time interval.

A. Classical Renewable and Low Carbon Technologies

1) Photovoltaics: The generated PV active power can be curtailed, up to a limit M^{PV}, at the inverter level:

$$(1 - M^{\text{PV}}) \cdot P^{\text{gen}}_{\text{d,t}} \leq P^{\text{inj}}_{\text{d,t}} \leq P^{\text{gen}}_{\text{d,t}} \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{1}$$

2) Energy Storage: ES is represented by two generators, one charging (negative) and one discharging (positive). Their operation is limited by (2)–(3), where η^{ES} is the charging/discharging efficiency. The state of charge (SoC) should lie within predefined limits (4), and start-close the day at the same level (5). The SoC change is described by (6) $\forall d \in \mathcal{D}, \forall t \in \mathcal{T}$:

$$-P^{\text{rate,ES}} \leq P^{\text{ch,ES}}_{\text{d,t}} \leq 0 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{2}$$

$$0 \leq P^{\text{dis,ES}}_{\text{d,t}} \leq P^{\text{rate,ES}} \cdot \eta^{\text{ES}} \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{3}$$

$$SoC^{\text{ES}}_{\text{min}} \leq SoC^{\text{ES}}_{\text{d,t}} \leq SoC^{\text{ES}}_{\text{max}} \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{4}$$

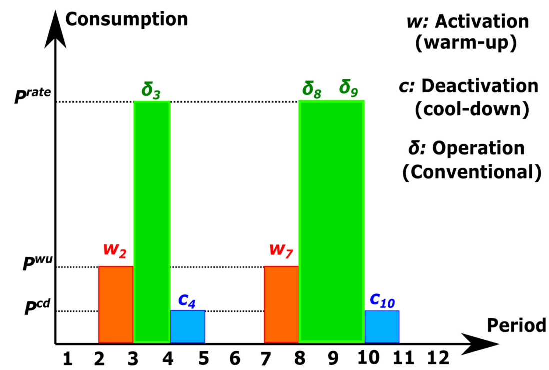

Fig. 2. Interruptible SL example ($CT = 3$).

$$SoC^{\text{ES}}_{\text{d,t=1}} = SoC^{\text{ES}}_{\text{d,t=24}} \quad \forall d \in \mathcal{D} \tag{5}$$

$$SoC^{\text{ES}}_{\text{d,t+1}} - SoC^{\text{ES}}_{\text{d,t}} = -\frac{\eta^{\text{ES}} \cdot P^{\text{ch,ES}}_{\text{d,t}}}{EC^{\text{ES}}} - \frac{P^{\text{dis,ES}}_{\text{d,t}}}{EC^{\text{ES}} \cdot \eta^{ES}} \tag{6}$$

3) Electric Vehicles: There is an ongoing debate on whether EVs should be connected directly to buildings or to public charging stations; both approaches have their pros and cons [37]. In this paper, we adopt the former, more commonly employed approach. The ES model can similarly be employed to model EVs, i.e., constraints (2)–(4), (6), with or without the V2G capability. EVs may not interact with the grid while the resident is absent, see $\mathcal{T}^{nc}$ and (7). If the first element of set $\mathcal{T}^{nc}$ is t^*, the EV's SoC must always be above an owner-defined limit, SC^{drive}, at that point (8); this ensures that the EV will always have enough "fuel" to complete its daily drive:

$$P^{\text{ch,EV}}_{\text{d,t}} = P^{\text{ds,EV}}_{\text{d,t}} = 0 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T}^{nc} \tag{7}$$

$$SoC^{\text{EV}}_{\text{d},t^*} \geq SoC^{\text{drive}} \quad \forall d \in \mathcal{D} \tag{8}$$

B. Conventional Shiftable Loads

The potential of SLs to contribute to cost minimization and flexibility provision is well-documented [38], [39]. They are usually modelled by discrete formulations. Continuous models are convenient for problems that are computationally heavy or that involve the aggregation of SLs. However, the latter are not reliable for capturing the behavior of individual SLs. This work opts for making explicit use of discrete models.

1) Interruptible SLs: The most common approach is to model SLs by employing binary variables ($\delta_{\text{d,t}}$) and a single consumption value. The SLs are either "ON" and consuming their rated power ($\delta_{\text{d,t}} = 1$) or "OFF" ($\delta_{\text{d,t}} = 0$). The SLs must fulfil their energy mandate, i.e., operate for the duration of their cycle time (CT) (9). This ensures that they complete their operation within the examined day and do not "spill over" to the next day. Finally, most SLs are programmed to not operate during nighttime, see $\mathcal{T}^{off}$ and (10), see [19]. SL that may re-activate multiple times are called interruptible. An illustration of a conventional interruptible SL is presented in Fig. 2:

$$\sum_{t \in \mathcal{T}} \delta_{\text{d,t}} = CT \quad \forall d \in \mathcal{D} \tag{9}$$

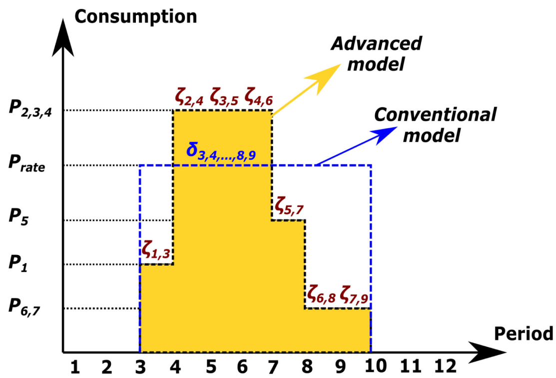

Fig. 3. Uninterruptible SL example ($CT = 7$ for conventional or 7 consumption levels for advanced).

$$\delta_{\mathrm{d,t}} = 0 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T}^{off} \tag{10}$$

2) Uninterruptible SLs: Uninterruptible SLs must complete their operation without interruption. This is modelled by the set of constraints (11), guaranteeing that the the first positive binary variable $\delta_{\mathrm{d,t}}$ is followed by an appropriate number (CT-1) of consecutive positive variables. An illustration of a conventional uninterruptible SL is presented in Fig. 3:

$$\sum_{t'=t}^{t+CT_s} \delta_{\mathrm{d,t'}} \geq CT \cdot (\delta_{\mathrm{d,t+1}} - \delta_{\mathrm{d,t}}) \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{11}$$

C. Proposed Advanced Models

1) Interruptible SLs: An issue that is often overlooked is that during the activation and deactivation of SLs, there are intermediate consumption values before reaching the desired level. When an SL turns "ON" or "OFF," it must usually go through a "warm-up" and a "cool-down" stage, respectively.

The above are modelled by introducing two sets of binary variables: the warm-up, $w_{\mathrm{d,t}}$, and the cool-down variables, $c_{\mathrm{d,t}}$. The former are activated before regular operation starts (12), while the latter are activated after it ends (13). The warm-up (P^{wu}) and cool-down (P^{cd}) powers must be defined, and the energy mandate (9), must also hold. An illustration of an advanced interruptible SLg is presented in Fig. 2:

$$(1 - \delta_{\mathrm{d,t}}) \cdot \delta_{\mathrm{d,t+1}} - w_{\mathrm{d,t}} = 0 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{12}$$

$$(\delta_{\mathrm{d,t+1}} - 1) \cdot \delta_{\mathrm{d,t}} + c_{\mathrm{d,t+1}} = 0 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{13}$$

The nonlinear constraints (12)–(13) can be re-formulated to linear equivalents by introducing auxiliary variables, $\xi_{\mathrm{d,t}}$:

$$\delta_{\mathrm{d,t+1}} - \xi_{\mathrm{d,t}} - w_{\mathrm{d,t}} = 0 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{14}$$

$$\xi_{\mathrm{d,t}} - \delta_{\mathrm{d,t}} + c_{\mathrm{d,t+1}} = 0 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{15}$$

$$\xi_{\mathrm{d,t}} \leq \delta_{\mathrm{d,t+1}} \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{16}$$

$$\xi_{\mathrm{d,t}} \leq \delta_{\mathrm{d,t}} \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{17}$$

$$\xi_{\mathrm{d,t}} \geq \delta_{\mathrm{d,t+1}} + \delta_{\mathrm{d,t}} - 1 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{18}$$

2) Uninterruptible SLs: In practice, uninterruptible SLs have varying consumption patterns, represented by specific time series. Shiftable time series have been minimally explored [15], [16], usually avoided altogether by employing inefficient brute force algorithms to optimally position them.

This work proposes an original formulation for modelling uninterruptible SLs, based on enhanced versions of the original binary variables $\delta_{\mathrm{d,t}}$, here represented by $\zeta_{\mathrm{u,d,t}}$, based on (19)–(20). For an SL with U different consumption levels, P_{u}, we require U sets of binary variables. Their sum must be equal to 1, ensuring that each consumption level is observed only once (19). The difference between variables separated by exactly one set and time period must equal zero (20), so that all levels are reached in proper sequential order. An illustration of an advanced uninterruptible SL is presented in Fig. 3:

$$\sum_{t \in \mathcal{T}} \zeta_{\mathrm{u,d,t}} = 1 \quad \forall u \in \mathcal{U}, \forall d \in \mathcal{D} \tag{19}$$

$$\zeta_{\mathrm{u+1,d,t+1}} - \zeta_{\mathrm{u,d,t}} \leq 0 \quad \forall u \in \mathcal{U}, \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{20}$$

D. Special Categories

1) Freezer: A freezer is in constant operation in order to regulate its internal temperature. It may be interrupted, but only for a limited time, so as to ensure that the temperature does not increase above an upper bound [40]. For a generic freezer, the aforementioned requirement can be modelled by assuming that for X consecutive periods, there can be at most Y interruptions without compromising temperature limits, where $Y < X$. Thus, (21) is formulated:

$$\sum_{t}^{t+X} \delta_{\mathrm{d,t}} \geq X - Y \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{21}$$

2) Electric Water Heater (Boiler): A water heater has a minimum uninterrupted operating time to heat up the stored water. This is modelled by the standard continuity mandate (11). Depending on the user-defined time-of-use, t^{use}, and on when the heater was first activated, it may need to operate for additional periods. This is assuming that the temperature is unacceptable after Z consecutive "OFF" time periods. These requirements can be modelled by introducing the binary variables $\beta_{\mathrm{d,t}}$, which represent temperature maintenance, and by additionally enforcing (22)–(24):

$$\sum_{t \in \mathcal{T}} \beta_{d,t} \geq \alpha \cdot \delta_{\mathrm{d},(t^{use} - \alpha \cdot Z)} - 1 \quad \alpha \in \{1, 2, 3, \ldots\} \tag{22}$$

$$\delta_{\mathrm{d,t}} + \beta_{\mathrm{d,t}} \leq 1 \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{23}$$

$$\sum_{t'=1}^{t} \beta_{\mathrm{d,t'}} \leq \sum_{t'=1}^{t} \delta_{\mathrm{d,t'}} \quad \forall d \in \mathcal{D}, \forall t \in \mathcal{T} \tag{24}$$

Eq. (22) determines the number of additional operating periods based on how close to the time of use the heater is activated. For example, if the boiler is activated up to $2 \cdot Z$ hours before use (positive binary for $\alpha = 2$), then one additional re-activation is required. The same logic applies for all other values of α. These only hold in *conjunction with* (23)–(24), which also ensure that the water warming stage and temperature maintenance stage do not coincide, and that the former stage precedes the latter one.

3) Tumble Dryer: A dryer should only commence its operation after the washing machine has completed its own. This is modelled by employing versions of (23)–(24), adapted for the specific variables to be utilized.

It is worth re-stating the SL-related novelty: appliances that usually require intricate considerations such as user-related or thermal constraints to be accurately modelled can now easily be represented by generic mathematical equations. While the analysis is contained to a few specific appliances, the models are fully extendable to devices of similar natures.

E. Technical Constraints Including Advanced SLs

The power inputs, i.e., grid import, PV injection, EV and ES discharging must always match the power outputs, i.e., grid export, EV and ES charging, fixed load demand and combined SL demand, $D^{\text{SL}}_{\text{d,t}}, \forall d \in \mathcal{D}, \forall t \in \mathcal{T}$:

$$P^{\text{I}}_{\text{d,t}} + P^{\text{inj}}_{\text{d,t}} + P^{\text{dis,EV}}_{\text{d,t}} + P^{\text{dis,ES}}_{\text{d,t}} = P^{\text{ch,EV}}_{\text{d,t}} + P^{\text{ch,ES}}_{\text{d,t}} + P^{\text{E}}_{\text{d,t}} + P^{\text{D}}_{\text{d,t}} + \sum_{\text{all SLs}} D^{\text{SL}}_{\text{d,t}} \tag{25}$$

Conventional SL demand is always $D^{\text{SL,conv}}_{\text{d,t}} = \delta_{\text{d,t}} \cdot P^{\text{rate}}$. For advanced models, the demand is described by (26):

$$D^{\text{SL,adv}}_{\text{d,t}} = \begin{cases} \sum_{u \in \mathcal{U}} \zeta_{\text{u,d,t}} \cdot P^{\text{rate}}_{\text{u}} & \text{(Washer)} \\ \delta_{\text{d,t}} \cdot P^{\text{rate}} + c_{\text{d,t}} \cdot P^{\text{cd}} + w_{\text{d,t}} \cdot P^{\text{wu}} & \text{(Dryer)} \\ \delta_{\text{d,t}} \cdot P^{\text{rate}} + \beta_{\text{d,t}} \cdot P^{\text{temp}} & \text{(Boiler)} \\ \delta_{\text{d,t}} \cdot P^{\text{rate}} & \text{(Freezer)} \end{cases} \tag{26}$$

F. Remarks

The constructed problems consist of the device models (1)–(8), the conventional (9)–(11) or advanced (12)–(24) SLs, the power balance (25) plus (26) for advanced SLs, and one or more linear objectives (see Section III). The complete problem formulation is thus MILP. The developed models consider discrete comfort-related aspects that can be planned for ahead of time, such as restricting the operation of SLs during daytime or ensuring that the water heater temperature has reached a certain level at t^{use}. The models of devices that are tied to continuous comfort-related aspects (e.g., HVACs) are simpler and well-established in the literature; they are assumed to be part of the building's fixed/owner-controlled load. Our focus is on SLs, whose modelling has not yet been fully explored.

III. Multi-Period Planning Formulation and Objective Realization

A. Main Assumptions

This work is contained within the scope of daily EMS operation, mimicking its decisions. The main contributions revolve around SL modelling and building archetypes, as enhanced features to be integrated in an advanced EMS, which can later be modelled using more sophisticated approaches, e.g., model predictive control [41]. The main assumptions are:

1) The (strong) forecasting software predicts day-ahead developments with minimal error. For the remainder of the year, all forecasts are updated daily, assumed to differ randomly by -15% to 15% from the previous estimate. The further away a period is, the higher the uncertainty.
2) Temporal aspects such as seasonality or type of day type (e.g., weekend, holiday, etc.) are considered. EVs deplete their SoC by 10% during workdays. This is an average depletion rate for an EV driving at an average of 50 km/h, according to [42]. However, since the model is generic, any depletion rate could be used.
3) We focus on the P-constant active power characteristics of the problem. In addition, we assume an all-electric building, whose thermal characteristics such as room temperature maintenance are, as explained, *implicitly incorporated into the building's fixed load.*
4) All relevant adoption barriers have been overcome, such as adoption of proper ICT infrastructure, existence of appropriate market structures and sufficient knowledge regarding building-grid interactions [43].

B. Objectives and Realization

The EMS is responsible for optimally managing the building's resources. In this work, we consider objectives of increasing "smartness," corresponding to three building archetypes:

1) Smart Building (SB): The EMS maximizes the building owner's profit on a daily basis, without considering its environmental or electrical impact. No grid flexibility is offered. For any random day d, the objective, F_1, is expressed by (27):

$$\max F_1 = \sum_{t \in \mathcal{T}} (P^{\text{E}}_{\text{d,t}} \cdot p^{\text{fit}}_{\text{d,t}} - P^{\text{I}}_{\text{d,t}} \cdot p^{\text{el}}_{\text{d,t}}) \tag{27}$$

2) Sustainable Smart Building (SSB): The EMS also aims for environmental sustainability, translated to a yearly nZE target. No grid flexibility is offered. The nZE target should ideally adhere to (28), which may not always be possible:

$$\sum_{t \in \mathcal{T}, d \in \mathcal{D}} (P^{\text{I}}_{\text{d,t}} - P^{\text{E}}_{\text{d,t}}) \leq E^{\text{nZE}} \tag{28}$$

ARnR algorithm: The nZE target is a yearly one. The profit maximization should ideally be done on the same temporal basis. In reality, the envisioned optimal planning may be compromised by uncertainty, rendering the one-time solution of the yearly problem inaccurate. To address this, we adapt and enhance the "Relax and Reduce" (RnR) algorithm [34]. Contrary to conventional algorithms, the adaptive RnR (ARnR) algorithm utilizes constantly updated daily forecasts to create an adaptive yearly nZE constraint.

A visualization of the proposed algorithm is presented in Fig. 4. At each iteration, the planning is split into two sub-problems: current day, which is subject to objective F_1 according to (27), and the remainder of the year (expressed by the flexible set $\mathcal{D}^{\text{rem}}$), which is subject to the modified objective F_1^{mod}, representing the expansion of the daily objective to a yearly basis, according to (29). The former represents the certainty region and the latter the uncertainty region. The EMS plans its yearly cost-optimal operation by considering sub-problem one in its complete form and sub-problem 2 in a relaxed form,

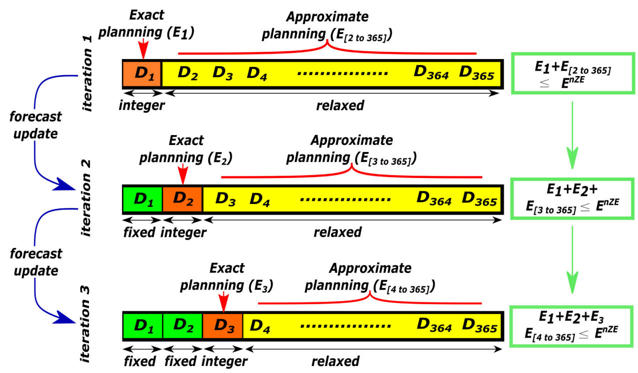

Fig. 4. Proposed ARnR algorithm (evolved from [34]).

i.e., all binaries relaxed. Each sub-problem yields a pair of results, representing the guaranteed and the envisioned cost and electricity bought/sold. In subsequent days, past daily energy values are known. Updated forecasts are also available. The constantly reducing optimization problem is re-solved with new inputs. The adaptive nZE constraint, (28), is updated for each day d according to (30):

$$F_1^{\mathrm{mod}} = \sum_{d \in \mathcal{D}^{\mathrm{rem}}} \sum_{t \in \mathcal{T}} (P_{\mathrm{d,t}}^{\mathrm{E}} \cdot p_{\mathrm{d,t}}^{\mathrm{fit}} - P_{\mathrm{d,t}}^{\mathrm{I}} \cdot p_{\mathrm{d,t}}^{\mathrm{el}}) \tag{29}$$

$$\sum_{z=1}^{d-1} E_{\mathrm{z}} + E_{\mathrm{d}} + E_{[(\mathrm{d}+1) \text{ to } 365]} \leq E^{\mathrm{nZE}} \tag{30}$$

If, at any iteration, E^{nZE} is deemed too restrictive, i.e., the planning problem is infeasible, the nZE target is instantly adjusted. Do note that this approach also *provides a method to estimate the feasible lower bound of the yearly nZE mandate.* It should finally be mentioned that if the nZE target is set very high at the start, the building essentially behaves as a pure SB.

3) Grid-Friendly SSB (GF-SSB): The EMS additionally aims for grid friendliness, i.e., limiting its local impact on the voltage and on the power lines. This is achieved be limiting the building's import and export capabilities and by incorporating a flexibility provision scheme into the planning process, in collaboration with the DSO.

Flexibility provision algorithm: The building may also provide flexibility to alleviate local grid issues. Most flexibility provision schemes revolve around dynamic pricing [44]. Two pitfalls to consider are: a) they can elicit inconsistent customer behaviors, resulting in varying degrees of effectiveness [45], and b) depending on the operational issues, undesirably high costs could be incurred by end-users [18], [23].

In this work, flexibility is assumed to be provided following explicit requests by the DSO. The EMS performs its daily planning, calculates its optimal daily profit, F_1^{optimal}, and transmits its profile to the DSO. The DSO may or may not make a specific flexibility request, accompanied by fixed remuneration. The EMS then seeks to maximize the provided flexibility without deteriorating the optimal daily profit beyond an acceptable point, ϵ, see (31). The sign function is added in case F_1 is negative, i.e., the building is making a profit:

$$F_1 \leq F_1^{\mathrm{optimal}} \cdot [1 + \mathrm{sign}(F_1^{\mathrm{optimal}}) \cdot \epsilon)] \tag{31}$$

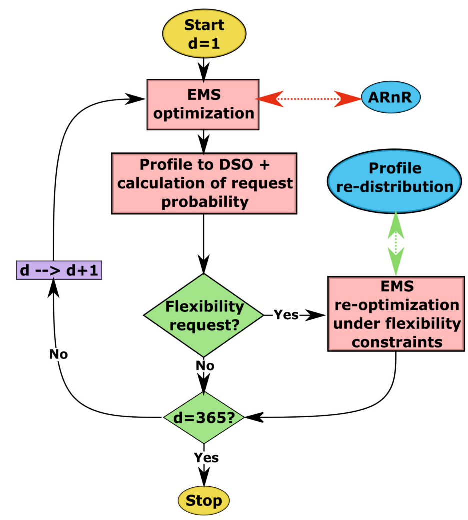

Fig. 5. Proposed flexibility provision algorithm.

Depending on how close the hourly profile is to the import/export limit, the chances of the DSO making a flexibility request increase. This assumption is based on the common observation that, in distribution feeders hosting a dominant *type* of customer, when a customer is more active, the trend of increased activity is exhibited in a relatively uniform manner across the feeder, resulting in increased electrical issues [23], [46]. This drives the DSO towards seeking flexibility more often and in larger amounts [24], [25]. In this work we consider a linear probability distribution function. Thus, if the import/export limit is P^{limit}, the probability of the DSO making a flexibility request, $Pr\{request\}$, is described by (32):

$$Pr\{request\} = \left[\max\{P_{\mathrm{d,t}}^{\mathrm{I}}, P_{\mathrm{d,t}}^{\mathrm{E}}\}\right] \cdot (P^{\mathrm{limit}})^{-1} \tag{32}$$

To minimize the impact of the re-adjustment on the overarching nZE mandate, the net daily changes should be energy-neutral (33). If we define P_d^{first}, P_d^{second}, FL as the highest import/export, the 2nd highest import/export and the requested flexibility amount, respectively, constraints (34)–(35) ensure that re-adjustment creates no additional need for flexibility:

$$E_{\mathrm{d}}^{\text{re-adjusted}} \leq E_{\mathrm{d}}^{\mathrm{original}} \tag{33}$$

$$P_{\mathrm{d,t}}^{\mathrm{I}} \leq \max\{(P_d^{\mathrm{first}} - FL), P_d^{\mathrm{second}}\} \tag{34}$$

$$P_{\mathrm{d,t}}^{\mathrm{E}} \leq \max\{(P_d^{\mathrm{first}} - FL), P_d^{\mathrm{second}}\} \tag{35}$$

The flexibility remuneration price is assumed fixed, though this is adjustable. To maintain a manageable problem size, the daily flexibility request is *limited to the hour with the highest import or export.* The request is assumed to be a season-dependent alteration: 10–20% for Spring/Fall, 25–50% for Summer/Winter. The process is depicted in Fig. 5.

IV. Case Study

A. Examined System and Scenarios

All objectives and SL models are examined for the residential building presented in Fig. 6. The examined devices are: PV, ES, EV, washing machine (uninterruptible, fixed CT), tumble dryer

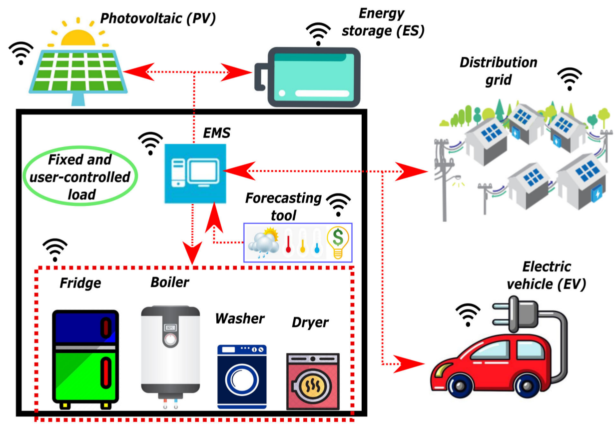

Fig. 6. Examined residential building.

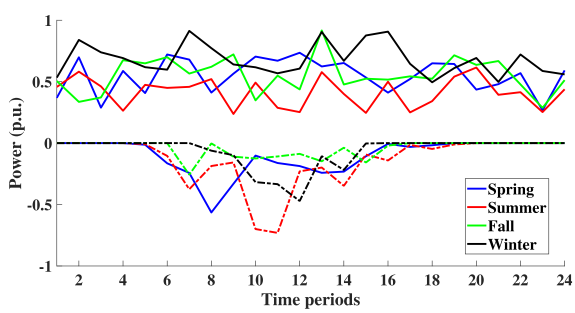

Fig. 7. Typical daily profiles for fixed load (positive, 1 kW base) and PVs (negative, 10 kW base) per season.

TABLE I
TECHNICAL CHARACTERISTICS OF BUILDING DEVICES

Device	Daily consumption (kWh)	Rated or average power (kW)	Capacity (kWh)
PV	Season-dependent	10	–
ES	∼0	2	6.4
EV[a]	Optimization-dependent	3	24
Fridge	2	0.1	–
Washer[b,c]	1.5	0.5	–
Dryer[b,d]	2.4	0.8	–
Boiler[e]	5.2	1.75	–
Fixed load	Season-dependent	1	–

[a] $\mathcal{T}^{nc} = \{8$ a.m. - 18 p.m.$\}$,
[b] $\mathcal{T}^{off} = \{10$ p.m. - 7 a.m.$\}$,
[c] for the advanced model $P^{\text{rate}}_{1,2,3} = \{0.9, 0.4, 0.2\}$kW,
[d] for the advanced model $P^{\text{wu}} = 0.1 P^{\text{rate}}$, $P^{\text{cd}} = 0.05 P^{\text{rate}}$,
[e] $P^{\text{temp}} = 0.5 P^{\text{rate}}$

(interruptible, fixed CT), freezer (interruptible, constant operation) and electric water heater (uninterruptible, minimum CT). All other devices are assumed to be part of the fixed load. The typical seasonal load and PV profiles are presented in Fig. 7. The technical characteristics of each device are presented in Table I. The employed device specifications and profiles correspond to typical residential building in the Luxembourg-Germany-France area, see [47]–[49]. Three building archetypes with the same composition are examined:

- SB: Cost minimization. SL model, EV type vary. The minimum EV charging level varies between 40/60/80%.
- SSB: The nZE mandate is additionally enforced, the target varying between 0/50/100 kWh.

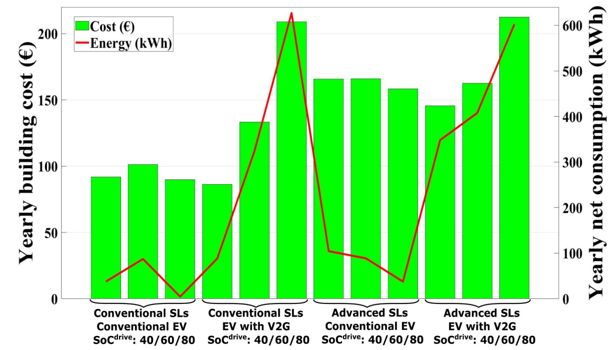

Fig. 8. Yearly costs and net consumption (SB).

- GF-SSB: Grid friendliness is considered. Conventional SLs and EVs. ϵ varies between 0/0.15/0.25 and the flexibility price (FP) varies between 0/0.15 € /kWh.

The MILP problems are solved using CBC through GAMS. ARnR is realized through MATLAB. All simulations were performed on a PC of 2.7-GHz and 8-GB RAM.

B. Results: Smart Building

1) General Behavior and Main Observations: Cases of yearly costs and net consumptions for the SB are presented in Fig. 8. Adhering to no overarching mandate, the net consumption highly depends on the electricity price and PV production. Left to sheer chance, it ranges approximately from 0 to 600 kWh. While its value is lower than that of a regular building, its behavior is uncontrolled. The representations based on advanced SL models produces higher consumption levels, as conventional SL models fail to realistically capture SL behavior (e.g., reheating or power level transition). This translates to higher yearly costs, indicating that conventional models lead to under-conservative results.

When conventional EVs are employed, the energy consumption and costs are similar for all minimum charging levels. This is to be expected; by default, a fixed SoC depletion rate translates to a conventional EV charging by the same amount each day. On the contrary, energy consumption and costs increase when the minimum charging level of V2G EVs increases: EVs plan their behavior for a single day at a time. However, if the EV closes said day with a very low charging level (which is quite common, since the EV discharging reduces the building's costs), it must then engage in mandatory charging for the day after, with little regard for the underlying cost. Due to the lack of communication between consecutive days, i.e., no preparation for the day to come, the EV may be *forced* to charge the following day; a mandatory, yet financially poor decision for the building. However, this issue is limited to the SB optimization process, taking place on a daily basis; as will be discussed, the other building archetypes are optimized along a rolling *yearly* horizon, virtually eliminating the issue of non-communication between days.

2) Impact of SL Models: The typical operation of all examined SLs and remaining devices is depicted in Figs. 9, 10, with several behavioral differences being recorded. The conventional tumble dryer shuts on and off during the day, while the

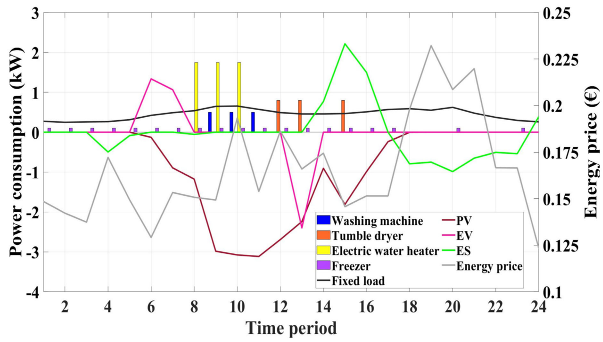

Fig. 9. Typical daily device behaviors (conventional SLs).

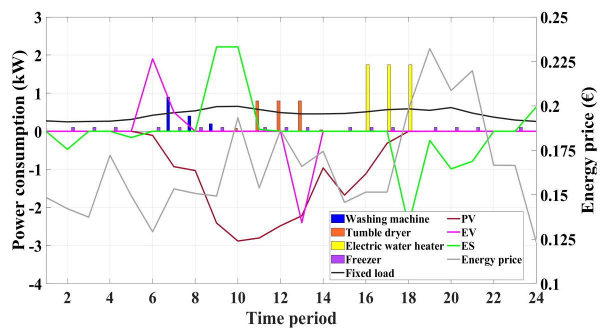

Fig. 10. Typical daily device behaviors (advanced SLs).

advanced one maintains a continuous operation. This is because the conventional one disregards the warm-up and cool-down periods, which increase the building's demand. The conventional water heater operates during early morning where electricity prices are lower. However, it disregards its internal temperature maintenance, which would normally require re-activations. The advanced model cannot activate during the same period of low prices; because it does consider the temperature maintenance aspect, had it activated at the same time, it would necessarily re-activate, thus driving up the costs. As such, it initiates its operation much later. The profiles of the washing machine and the freezer also exhibit differences, namely the activation at different periods, or the frequency of and distance between deactivations. The above showcase the substantial impact of the SL models on the building's profile.

Throughout the simulation, the solver deals with consecutive MILP problems that are easy to manage (192 continuous variables and 96 or 264 discrete variables for conventional and advanced SL modelling, respectively). On average, each "conventional" simulation requires 0.5 seconds (182 seconds in total), while each "advanced" simulation requires 0.9 seconds (5.5 minutes in total). The problem is computationally light and manageable by off-the-self solvers.

C. Results: Smart Sustainable Building

1) Differences With Respect to the SB: Cases of yearly costs and net consumptions for the SSB are presented in Fig. 11. For those directly comparable, the SSB exhibits about 5-15% higher yearly costs than the SB. However, it also maintains its yearly net consumption to much lower levels. For the cases with the

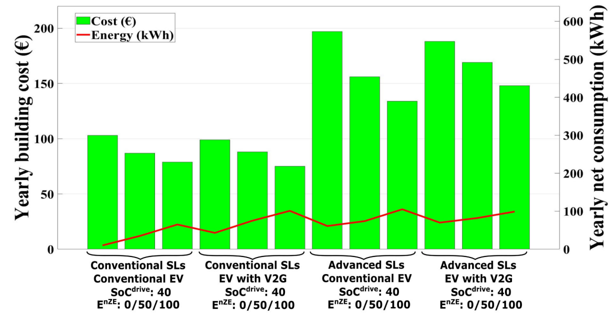

Fig. 11. Yearly costs and net consumption (SSB).

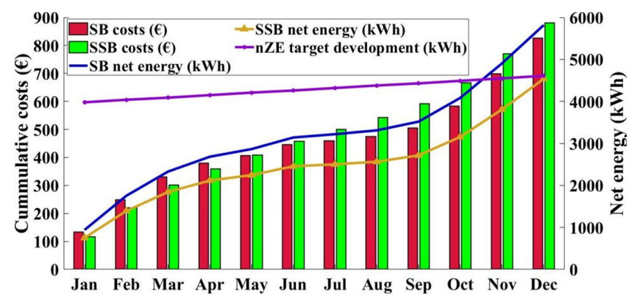

Fig. 12. SB vs SSB under reduced PV production (conv. SLs).

strictest nZE target ($E^{\mathrm{nZE}} = 0$), the net reduction ranges between 15-50%. Setting more relaxed nZE targets places less constraints on the building, which subsequently uses the opportunity to drive down its costs at the expense of higher net consumption levels. For the application of the ARnR algorithm, do note that the simplified representation of the remainder of the year in combination with the several involved uncertainties can often cause overly restrictive nZE targets to be overshot, thus requiring adjustments within the year. However, the proposed approach also provides some estimate of the *realistic lower bound for the nZE target*. After all, it heavily depends on the uncertain parameters, which may in fact not favor its realisation. It should finally be stated that if the nZE is set very high, the SSB achieves lower costs than the SB, at similar net consumption levels; this is because the ARnR algorithm still utilizes a yearly temporal basis, hence combating previous issues associated with "lack of communication" between days.

2) The ARnR Algorithm Under Extreme Conditions: To better demonstrate the effectiveness of the ARnR algorithm, an extreme case is presented in Fig. 12, where the PV production is artificially reduced by 60%. The initially set nZE target of 0 is deemed unrealistically conservative; it is also constantly being re-adjusted throughout the year. The SB makes extensive use of its two batteries (ES, EV) to reduce its costs. Because they always exhibit a positive net consumption, the building's own consumption steadily increases. Contrary to the SB, the SSB also has the nZE mandate to co-manage. In attempting to drive down its net consumption, it under-uses its batteries, thus missing out on "buy-low/sell-high" opportunities. During the year, the SSB consistently maintains lower levels of net consumption than the SB. At the end of the year, the SB ends up with a higher net consumption than the SSB, the difference

TABLE II
SSB Problem Computational Data

SL modelling	Variables 1st iteration (continuous)	Constraints 1st iteration (total)	Variables removed per iteration	Constraints removed per iteration
Conventional	69,696	63,525	465	175
Advanced	69,696	194,205	465	535

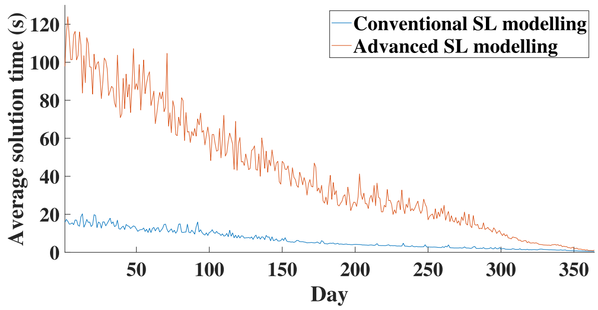

Fig. 13. Development of ARnR solution time per iteration (SSB).

TABLE III
Yearly Requested/Provided Flexibility per Scenario

Scenario	Flexibility request (kWh)	Flexibility provision (kWh)
FP:0.00, ϵ:0.00, nZE:–	247	187 (75.6%)
FP:0.15, ϵ:0.00, nZE:–	300	296 (98.7%)
FP:0.00, ϵ:0.00, nZE:0	246	168 (68.1%)
FP:0.15, ϵ:0.00, nZE:0	273	263 (96.3%)
FP:0.00, ϵ:0.15, nZE:0	390	313 (80.3%)
FP:0.15, ϵ:0.15, nZE:0	257	256 (99.7%)
FP:0.00, ϵ:0.25, nZE:0	323	297 (91.9%)
FP:0.15, ϵ:0.25, nZE:0	277	270 (97.3%)

being about 1500 kWh (~35%). The SSB ends up with higher operational costs (~6%), but with *high environmental savings*. The increased expenses could essentially be viewed as the "CO $_2$ mitigation cost". The above showcase the effectiveness of the ARnR algorithm in *enabling the SB→ SSB transition.*

3) Impact of SL Models: The yearly costs are similar between SB and SSB when employing the conventional SL models. With the advanced SL models the average yearly costs are only slightly higher. This indicates that, *assuming on-site renewable production is present*, transitioning from SBs to SSBs may require minimal monetary burdens. The true financial barrier to overcome may only be converting traditional buildings to SBs. For the SSB, the first iteration of the solution requires approximately 70 000 variables and 64 000 or 194 000 constraints (Table II). The remainder of the year sub-problem decreases in size for each day simulated (465 variables and 175 or 535 constraints removed). A problem that is initially slow to solve (about 18 or 110 seconds per iteration) gradually becomes more easily solvable, see also Fig. 13. The entire simulation requires 30 minutes (conventional SLs) or 4 hours (advanced SLs). However, the computation times for a single yearly planning simulation is very reasonable.

D. Results: Grid-Friendly Sustainable Smart Building

1) Flexibility Provision and Impact on Building: Cases of yearly costs, net consumptions and provided flexibility for the GF-SSB are presented in Fig. 14, Table III. Even in extreme cases ($\epsilon = 0$, FP $= 0$), the building can still support the grid with

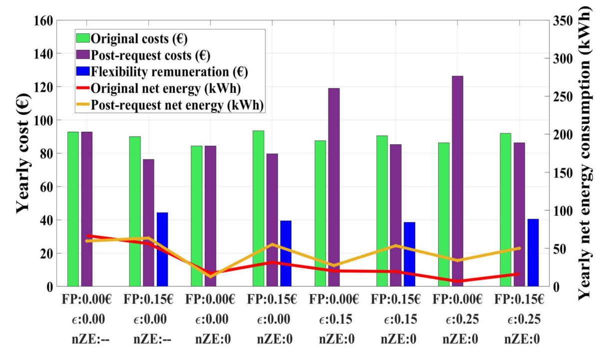

Fig. 14. Yearly operational costs, flexibility remunerations, net consumptions under various scenarios (S_3, convectional SLs).

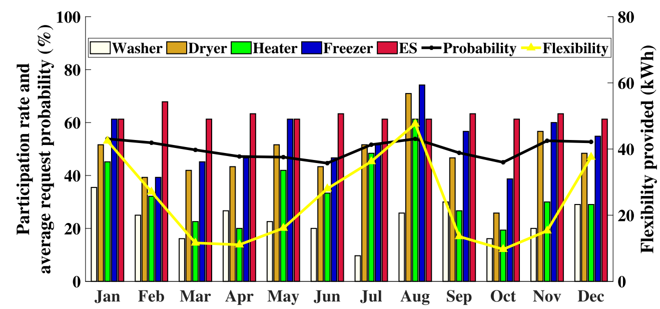

Fig. 15. Seasonal flexibility request probability and breakdown of "providers" ($\epsilon = 0.15$, $\mathrm{FP} = 0.15$ € /kW, conventional SLs).

virtually no negative impact on the its costs. When the FP is set at reasonable levels (here, slightly above the feed-in-tariff), it is usually in the owner's interest to provide flexibility as the original import costs decrease and the additional income from providing flexibility improves the financial outcome. It is important to stress that flexibility provision implicitly reduces import costs and maintains export costs (export are re-distributed), thus decreasing pure operating costs, *without accounting for flexibility remuneration.*

Higher values of ϵ (owner willingness to incur extra cost for assisting the DSO) translate to providing more flexibility. However, when the FP is reasonable, the EMS exhibits practically the same behavior regardless of the value of ϵ, providing similar flexibility amounts (~265 kWh per year, i.e., 98% of the requested amount). The exact amounts provided are a product of the flexibility provision algorithm structure, i.e., requests are limited to a single hour of the day. Nonetheless, the results indicate that as long as the building is requested to assist within a limited time-frame, it can fully respond without issue. Providing flexibility tends to increase the yearly net consumption (50% average increase). However, given the overarching nZE mandate and energy neutrality constraint, the energy profile is still kept low, making the increase negligible. As such, it could be claimed that *reasonable levels of flexibility provision do not seriously jeopardize environmental goals.*

2) Flexibility Provision Breakdown and Application: It is important to highlight the characteristics of the flexibility provision process, i.e., how it is actually realised. An illustration is depicted in Fig. 15. The monthly average probability of a flexibility request is statistically a coin flip (close to 50%, with

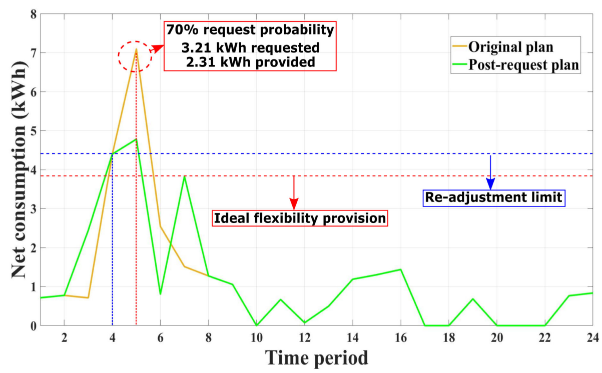

Fig. 16. Application of flexibility incorporation algorithm.

small deviations). The provided flexibility is noticeably higher during Winter and Summer months (~45% higher); this is to be expected, as these months have been observed to be more stressful for distribution grids [23]. The ES plays the most active role in flexibility provision, participating in 60% of all re-adjustment actions. The freezer and heater also participate to a high extent, the former due its extremely flexible nature and the latter due to its easily shiftable, high consumption value level. The washing machine and tumble dryer are less involved (~30-40%), due to their additional user-driven constraints (e.g., no nighttime operation or coupled operation cycles), which somewhat limit their flexibility potential.

An example of the flexibility incorporation algorithm's application is presented in Fig. 16 (ϵ and FP equal to 0). Originally, the import at time period 5 are about 7 kW (import limit of 10 kW), meaning that the probability of receiving a flexibility request is 70%. In the Winter, the request amount varies between 25-50% of the original amount (Section III), the flexibility request ending up at 3.21 kWh. According to (34), the second highest import value (4.3 kW) is chosen as the re-adjustment limit. Due to ϵ being 0, i.e., no cost deterioration allowed, the building can re-adjust its daily profile to provide about 72% of the requested flexibility, while keeping all imports (except the one for period 5) below 4.3 kW. The process repeats whenever a flexibility request is made, with different probabilities and enforced limits.

V. Conclusions and Outlook

In this paper, we addressed important research questions concerning SBs and their potential evolution to environmentally-friendly (SSBs) and grid-friendly (GF-SSBs) entities. To that end, we proposed a novel strategy that allows SBs to seamlessly transition to SSBs through a novel rolling horizon algorithm that minimizes the building's operating costs while keeping track of the yearly nZE mandate. In the case of extremely low yearly PV production, the SSB achieved 35% less net consumption at only 6% increased cost. SSBs could then seamlessly transition to GF-SSBs, through an efficient flexibility provision algorithm that respected the owner's willingness to bear some extra cost for assisting in the management of grid-related issues. Even in extreme cases were no remuneration would be offered, the devised energy-neutral (on a daily basis) scheme would always result in the provision of substantial amounts of flexibility (~300 kWh per annum on average), with very small environmental impact. The contribution to mitigating network issues would often come with either zero or a positive financial impact.

We also proposed generic mathematical models, conventional and novel advanced ones, to represent shiftable loads (SLs), and examined their behavior. While the applications were limited to only a few SLs, all of the modelled constraints correspond to a variety of different smart appliances and can thus be employed accordingly. The inefficiencies of the conventional models where highlighted, as well as the clear behavioral changes of the building when more accurate, advanced models were employed. All of the solved problems were MILP, meaning they are reliably scalable. Due to the generic nature of the SL models and the proposed strategies, and the variety of scenarios examined per building archetype, we believe this paper may serve as a guideline for researchers in the areas of device modelling and smart home design.

In the future, the authors plan to also consider aspects of real-time optimization and to adapt the framework to other building types (e.g., commercial). The inaccuracies of the day-ahead planning process can thus be properly considered and addressed in a more sophisticated manner.

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