# Assessing the potential of laptops for demand response applications

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ABSTRACT

Laptops are widely deployed but underused as flexibility assets, despite their potential to support the grid and reduce electricity costs for users via coordinated battery management. As curtailment of renewable energy rises globally, identifying low-cost, scalable sources of demand-side flexibility has become increasingly urgent. This work explores the novel hypothesis that laptops can function as a distributed fleet of mini-batteries, offering system-level flexibility through optimised management of charging and discharging cycles.

A simulation framework was developed using real-world electricity prices and 15-minute laptop usage profiles derived from badge data collected over a year from 93 employees; four scenarios were analysed, combining two national grid contexts (Spain and Germany) with two typical work schedules (morning and full-day).

The results confirm that the Laptop Demand Response strategy was found to be effective under all analysed scenarios, with comparable outcomes across both countries and enhanced performance when laptop consumption is misaligned with price minima, intra-day price variability is high, and surplus generation is frequent; under a full-day schedule, the strategy reduced average electricity costs by up to 47 % in Germany and 43 % in Spain, while surplus energy utilisation increased by up to 290 % and 10 %, respectively. These findings demonstrate that a negligible marginal cost, software-based coordination of existing laptop batteries can unlock measurable flexibility benefits, offering a scalable and fast deployable solution to support further renewable energy integration.

## 1. Introduction

The rapid growth of Variable Renewable Energy Sources (VRES) [1] has intensified the need for flexibility resources to maintain grid balance [2]. The direct consequence of the lack of such flexibility resources is the curtailment of clean generation [3], an issue that is becoming increasingly serious worldwide, particularly in regions with high penetration of VRES. In 2024, the California Independent System Operator (CAISO) curtailed approximately 3.4 TWh of utility-scale wind and solar power, marking a 29 % increase compared to 2023 [4]. Similar dynamics have been observed globally [5]: in Chile, solar Photovoltaic (PV) curtailment reached 1.4 TWh in 2022 (1.8 % of annual demand); in Cyprus, it rose from 3 % in 2022 to over 13 % in 2023; and in Texas, 9 % of utility-scale solar generation was curtailed in 2022. In Jordan, Laimon [6] estimated that, by 2030, VRES curtailment could reach up to 3 TWh, corresponding to 14 % of the country's annual electricity generation and resulting in economic losses up to USD 419 million. Although these figures are country-specific, they highlight the substantial environmental and economic burden that curtailment may impose in systems with limited flexibility resources. Among the existing solutions, Demand Response (DR) is the only one that consistently addresses grid requirements, thereby representing the only flexibility strategy that is steadily and increasingly remunerated by the market itself, without the need for subsidies or incentivisation mechanisms [7]. In fact, DR encourages users to increase consumption when renewable generation is high (mitigating curtailment [8]), and to decrease it during peak demand periods. Beyond the system-level benefits, this also translates into lower average electricity costs for end users, since overgeneration typically drives wholesale prices down [9]. Consistently, Merabet et al. [10] demonstrated that modulating battery charging according to tariff signals can significantly enhance the economic efficiency of the system.

While large-scale flexible resources (such as industrial processes, centralized Heat Pump (HP) systems, or Electric Vehicle (EV) fleets) have received much attention as providers of DR services [11], small distributed loads are increasingly recognized as an untapped resource [12]. Recent studies highlight that even small-load devices, when aggregated, can provide significant demand response services if properly incentivized [13]. For example, a city-scale analysis in Australia found that widespread electrification (including single EVs and electric

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|---|---|---|---|
| **Nomenclature** | | $\pi_L$ | Average electricity price for powering the laptops |
| | | *Acronyms* | |
| *Symbols* | | BESS | Battery Energy Storage System |
| E | Electricity | DR | Demand Response |
| $E_{B,SYS}$ | Battery electricity used to meet $E_{SYS}$ | ESS | Energy Storage System |
| $E_G$ | Grid withdrawals | EV | Electric Vehicle |
| $E_{G,B}$ | Grid electricity used to charge the battery | HP | Heat Pump |
| $E_{G,L}$ | Laptop demand (gross of battery charging) | LDR | Laptop Demand Response |
| $E_{G,NO\ SURP}$ | Grid withdrawals during moments of no overgeneration | FDWS | Full-Day Work Schedule |
| $E_{G,SURP}$ | Grid withdrawals during moments of grid overgeneration | SDR | Surplus to Demand Ratio |
| $E_{G,SYS}$ | Grid electricity directly used to meet $E_{SYS}$ | SOC | State Of Charge |
| $E_{SYS}$ | Laptop operating system demand | MWS | Morning Work Schedule |
| t | time | VRES | Variable Renewable Energy Source |
| $\eta_B$ | Laptop battery round-trip efficiency | | |
| $\pi$ | Electricity price (day-ahead market) | | |

hot water systems) could effectively turn an entire city into a "giant battery," with each resident enabling around 46 kWh of flexible storage through smart timing of device operation [14]. This context underscores the motivation to explore novel sources of distributed flexibility: beyond EVs, HPs and home batteries, ubiquitous small devices like laptop computers (each equipped with an onboard battery) may collectively offer a significant, largely untapped, and already available DR resource.

Concerning their significance, and assuming an average capacity of 60 Wh, over 15 GWh of new laptop battery capacity was added globally in work environments in 2024 [15], a value remarkably close to the 21.9 GWh of utility-scale Battery Energy Storage System (BESS) capacity installed in Europe in the same year [16]. Clearly, compared to the potential of new EVs sold in 2024, estimated at around 1.4 TWh (17 million units equipped with an average battery capacity of 80 kWh [17]), the flexibility potential of laptops is significantly lower. However, laptops still represent a distributed, low-cost, and immediately deployable source of flexibility that can complement larger storage assets. As for their untapped potential, laptops' batteries are typically underutilised for two reasons: first, they are commonly used only in cases of absent electrical connections; and second, they are on average discarded well before reaching the end of their technical life (500–1,000 charge cycles), due to the obsolescence-driven replacement of the laptops themselves. Regarding availability, such devices are already widespread in grid-connected environments, and their use as flexibility assets would only require the implementation of appropriate software-based control strategies.

Given these premises, the motivation for this work lies in the convergence of two trends: the critical need for flexible demand to absorb renewable oversupply, and the pervasiveness of laptops in work and study environments. Harnessing even a fraction of the global laptop fleet for DR could translate into meaningful grid-level effects at negligible marginal cost, since the hardware, as abovementioned, is already in place. Software-based coordination of laptop charging could thus transform an underutilized asset into a valuable flexibility service, while simultaneously offering electricity cost reductions for end users.

Research on leveraging distributed storage and small loads for demand response has gained increasing interest in recent years. For instance, Moreno et al. [13] proposed an incentive-based framework to engage small-load flexibility providers (residential and commercial customers with small devices), reflecting the growing attention in aggregating many small consumers for DR programs. In parallel, numerous works have examined the integration of battery storage and electric vehicles into DR schemes, demonstrating that smart charging and discharging can flatten demand peaks and accommodate more renewable generation. A recent case study showed that a large fleet of electric cars, when optimally scheduled, can serve as a major power-balancing resource for the grid during peak renewable [14]. These

studies underscore the general feasibility of distributed, software-controlled resources contributing to grid flexibility.

Against this backdrop, the idea of using laptop batteries for demand response remains a niche and scarcely explored area of the literature, although the concept itself is not entirely new. Over a decade ago, Murthy et al. [18] demonstrated in simulations that optimized management of the laptop network led to a baseload reduction during a DR event ranging from 30 % to 90 %. This early work introduced the notion of "energy-agile laptops" and showed their potential to reduce grid demand during critical periods by pausing or delaying charging. However, the scalability of their results was limited by the very short time intervals considered (1–6 h). In a related effort, Hild et al. [19] developed a smart charging prototype for portable electronics (laptops, smartphones, etc.) that responds to grid frequency signals (as an indicator of real-time supply–demand imbalance). Their system could autonomously stop or start charging based on grid conditions, effectively turning these devices into frequency-responsive loads. While Hild et al. confirmed the technical viability of controlling charging in response to grid signals, they also noted a key limitation: their algorithm did not account for real usage profiles, thereby restricting the use of batteries for demand response to a very narrow range. More recently, Nasirifard et al. [20] designed a distributed, real-time DR infrastructure specifically for networks of laptops, using purely software-based control to adjust charging in response to fast fluctuations in renewable output. Their field tests showed that such a system can rapidly execute DR commands across many devices. However, like the earlier studies, the usage profiles of the laptops were standardized, leaving uncertainty about real-world effectiveness.

In summary, the current literature still reveals three critical gaps. First, the potential of laptops to provide demand response services and user cost savings has been systematically underestimated, as demonstrated by the very limited number of studies dedicated to this topic. Second, existing analyses do not rely on empirical usage data, relying instead on idealized profiles. Third, prior works have been largely confined to short-term demand response events, without evaluating the feasibility and benefits of continuous, system-level operation.

To address these gaps, this study explores the proposal that laptops, when intelligently managed through software-based coordination, can serve as a distributed fleet of mini-batteries, providing continuous demand response services at negligible marginal cost. The novelty of this work lies in delivering the first systematic, data-driven assessment of laptop demand response potential in a real work environment, by combining year-long empirical laptop usage profiles with electricity price data. The contribution is twofold: first, it quantifies the techno-economic benefits for users and for the grid under year-long scenarios; and second, it outlines laptops as an overlooked but immediately available flexibility resource, thereby opening a novel pathway for

integrating small distributed devices into large-scale demand response programs.

The remainder of this paper is organised as follows: Section 2 describes the mathematical model underlying the Laptop Demand Response (LDR) strategy, as well as the parameters used to evaluate its performance and the scenarios in which the strategy was tested; Section 3 discusses the results.

## 2. Methods

This work evaluates the potential of laptops to provide a continuous demand response service to the power grid. The service is defined as continuous because it does not rely on responding to individual load adjustment requests from grid operators, but rather on the planned grid needs profile defined in the day-ahead market. Specifically, the LDR strategy proposed here aims to charge laptops during periods of low residual grid load and to operate them on battery during periods of high residual load. Since these periods of low and high residual load coincide, respectively, with times of low and high electricity prices, the LDR strategy supports the grid while simultaneously reducing costs for the user. In this sense, the proposed LDR strategy adopts a grid-oriented (and cost-aware) approach.

The capabilities of the LDR strategy are evaluated with reference to different scenarios, described in Subsection 2.3, which feature real grid requirements and laptop usage profiles. A mathematical model was developed to perform the simulations.

### 2.1. Mathematical model

The mathematical model, developed in MATLAB version R2024b [21] and based on the energy flows shown in Fig. 1, employs a Linear Programming optimisation algorithm that, for each 15-minute interval ($t$) of a 24-hour horizon, decides whether each laptop should draw power from the grid $E_{G,SYS}(t,n)$, operate on battery $E_{B,SYS}(t,n)$, or charge its battery $E_{G,B}(t,n)$. The linear optimization problem is solved using the "linprog" MATLAB solver, to find the minimum of the objective function, with a daily optimization horizon. This process generates a daily operation schedule for each laptop.

Since this strategy is cost-aware, the objective function of the optimization is to minimize the overall daily electricity withdrawal cost (Eq. (1)):

$$\min OF = \min \sum_{t=1}^{24 \cdot 4} (\pi(t) \cdot E_G(t)) \tag{1}$$

where $t$ is the considered time step (15 min), $\pi(t)$ is the electricity price on the day-ahead market and $E_G(t)$ is the total energy drawn from the grid by all N laptops:
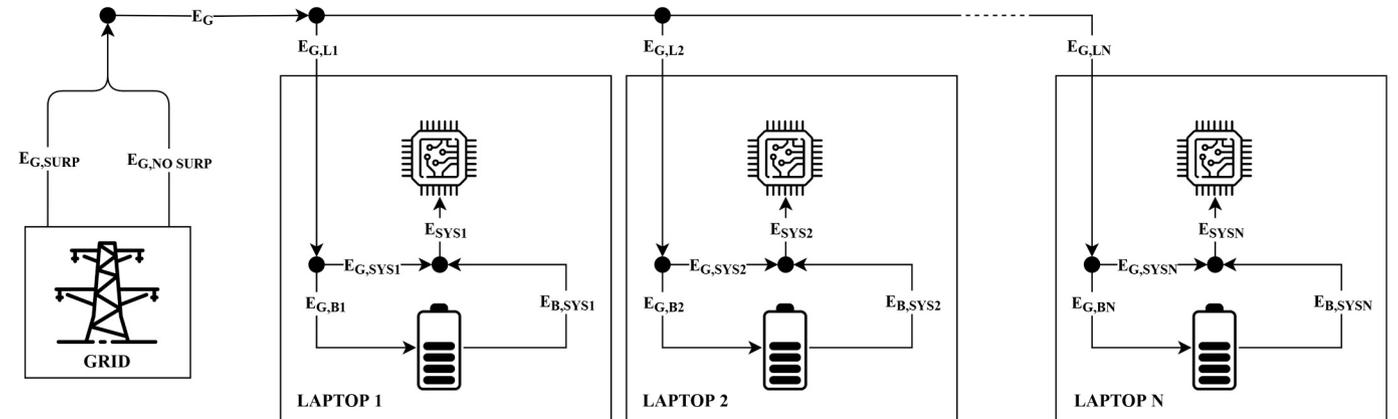
$$E_G(t) = \sum_{n=1}^{N} E_{G,L}(t,n) \tag{2}$$

As shown in Fig. 1, $E_G$ is further divided into $E_{G,SURP}$ and $E_{G,NOSURP}$. This division provides a logical distinction between electricity withdrawals occurring during periods of surplus generation in the grid and those occurring in its absence (as further detailed in Section 2.2).

Clearly, the optimization is subject to constraints related to energy balances, non-simultaneity of battery charging and discharging, battery capacity, charge/discharge limits, and to the fulfilment of each laptop's daily usage profile. In accordance with these constraints, some laptops are powered and/or some batteries can be charged even during periods of high electricity price (and high residual load). A further assumption is that laptops are always left at the workplace; therefore, an employee's laptop can be charged regardless of whether the employee is present. Moreover, the model assumes a perfect forecast [22] of each user's daily behaviour, meaning that laptop daily usage profiles are known in advance and do not deviate from expected patterns. As a result, the model simulates best-case scenarios, providing an upper bound for the achievable performance. Additional assumptions and data are reported in Table 1.

More in detail, the total energy consumption and storage dynamics are computed at the individual laptop level and then aggregated across all units. For each time step ($t \in T$), each laptop ($n \in N$) receives an energy input from the grid denoted as $E_{G,L}(t,n)$. This energy input includes both the energy used to directly meet the operating system demand $E_{G,SYS}(t,n)$ and the energy used to charge the battery $E_{G,B}(t,n)$:

$$E_{G,L}(t,n) = E_{G,SYS}(t,n) + E_{G,B}(t,n) \tag{3}$$

Each laptop battery is characterized by a State of Charge (SOC) calculated as reported in Eq. (4), where $\eta_B$ is the round-trip efficiency, assumed equal to 0.9 in order to implicitly account for performance losses due to battery degradation over time:

$$SOC_B(t,n) = SOC_B(t-1,n) + E_{G,B}(t,n) - \frac{E_{B,SYS}(t,n)}{\eta_B} \tag{4}$$

**Table 1**
Assumptions and data underlying the model.

| Parameter | Value | |
|---|---|---|
| Operating system average consumption | 15 | W |
| Battery capacity (net) | 60 | Wh |
| Battery round-trip efficiency | 90 | % |
| Maximum charge/discharge power | 45 | W |
| Initial/Final SOC (January 1st /December 31st) | 5 | % |



**Fig. 1.** Schematic representation of the energy flows.

## 2.2. Performance assessment

The performance of the LDR strategy is assessed using two indicators, both computed over a time horizon T that may vary (e.g., daily, monthly, or yearly).

The first indicator is economic in nature, as the LDR strategy follows a cost-aware approach, namely the average electricity price for powering the laptops ($\pi_L$ – Eq. (5)):

$$\pi_L = \frac{\sum_{t=1}^{T}(\pi(t) \cdot E_G(t))}{\sum_{t=1}^{T} E_G(t)} \tag{5}$$

The second indicator, instead, is energy-related: the Surplus-to-Demand Ratio (SDR – Eq. (6)) measures the fraction of electricity drawn during periods of surplus generation, compared to the total energy demand of the laptops.

$$SDR = \frac{\sum_{t=1}^{T} E_{G,SURP}(t)}{\sum_{t=1}^{T} E_G(t)} \tag{6}$$

The logical division between $E_{G,SURP}$ and $E_{G,NOSURP}$ is based on the condition defined in Eq. (7)

$$E_G(t) = \begin{cases} E_{G,SURP}(t), \pi(t) \leq 0 \\ E_{G,NOSURP}(t), \pi(t) > 0 \end{cases} \tag{7}$$

Since null or negative wholesale prices are widely recognised as reliable indicators of overgeneration [23], surplus generation is assumed to occur when the electricity price takes such values. Although this criterion does not fully capture all grid-level constraints, it remains, to the best of the authors' knowledge, the only feasible proxy, as hourly curtailment datasets are not yet available for most market areas, including those analysed in this study. Therefore, the SDR, ranging
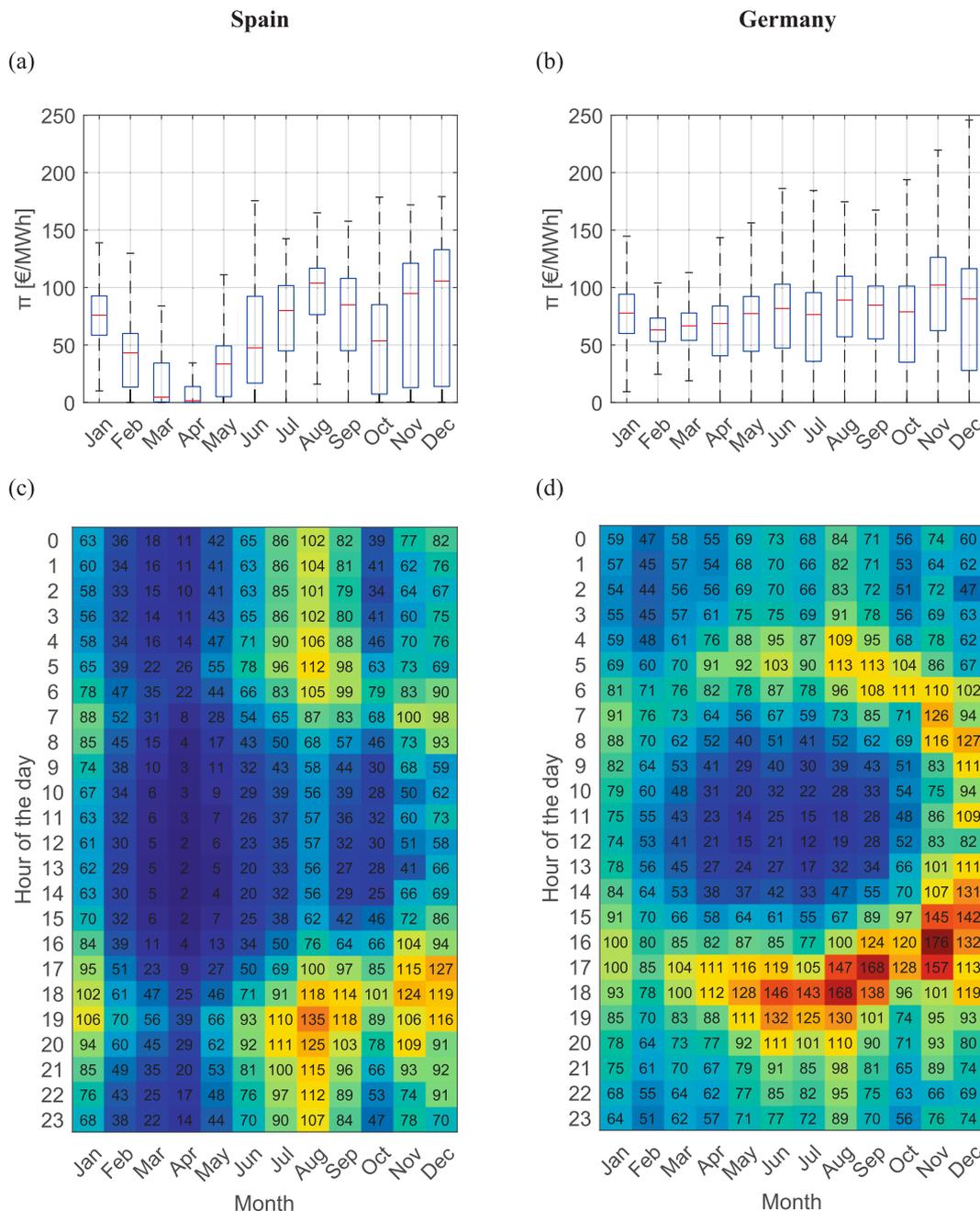


**Fig. 2.** Monthly distribution (a, b) and average hourly values (c, d) of day-ahead electricity prices in Spain and Germany (2024).

between 0 and 1, provides an energy-based measure of the effectiveness of the LDR strategy. Specifically, higher *SDR* values denote a larger portion of surplus energy, potentially subject to curtailment, within the total electricity supplied to the laptops.

### 2.3. Scenarios

The LDR performance is evaluated across four scenarios, defined by the combination of two grid requirement types (Section 3.1) and two employee work schedules (Section 3.2), which determine the corresponding laptop usage profiles. Both the grid requirements and the work schedules are based on real data: the former derive from European Network of Transmission System Operators for Electricity (ENTSO-E) operational records [24], the latter was obtained through an experimental monitoring campaign conducted at the University of Cagliari.

#### 2.3.1. Grid requirements

The grid requirements considered are those of Spain and Germany, two European countries where renewable energy surplus and curtailment levels have become among the highest. In Germany, renewable energy curtailment in 2024 accounted for approximately 3.5 % of the total renewable generation, including around 1.4 TWh of curtailed solar and 5.7 TWh of curtailed wind [25]. In Spain, nearly 15 TWh of renewable electricity was curtailed over the same year [26]. These countries' grid requirements, that the demand-response strategy tends to align with, are inferred from their wholesale electricity market conditions observed in 2024 [24] (Fig. 2a,c for Spain and Fig. 2b,d for Germany). Specifically, when electricity prices approach their minimum values, the grid requires an increase in load, and the LDR strategy prioritises battery charging. Conversely, when electricity prices approach their maximum values, the grid requires a load reduction, and the LDR strategy prioritises battery discharging. Panels (a) and (b) show the monthly distribution of day-ahead electricity prices ($\pi$) in Spain and

Germany through boxplots, while panels (c) and (d) show the average hourly values. Boxplots (a and b) summarise the hourly prices for every month, highlighting median (red line inside boxes), interquartile range, and variability.

In 2024, electricity prices in Spain (Fig. 2a) showed a clear seasonal pattern. Spring (March–April) was marked by extremely low medians (as low as 1.6 €/MWh in April) and relatively stable prices, driven by high solar output and low demand. Summer and autumn (June–October) saw a peak median above 100 €/MWh in August and intermediate variability, reflecting increasing cooling demand and moderate system stress. Winter (November–December) was characterised by medians around 100 €/MWh and maximum volatility, driven by high heating demand, low renewable output, and greater reliance on fossil fuels.

In the same year, electricity prices in Germany (Fig. 2b) exhibited a more moderate seasonal pattern. Median values remained consistently between 50 and 100 €/MWh, with both medians and maximum values increasing in the second half of the year, particularly in the last quarter. This trend was driven by reduced wind and solar output during autumn and early winter, coupled with higher heating demand and increased reliance on fossil-based generation during extended periods with low renewable production.

Focusing on hourly average values (Fig. 2c,d), it is interesting to note that, in both countries, the minimum prices occurred during the central hours of the day, while the maximum prices during the evenings.

By deducing the occurrences of surplus generation from the price trends, as defined by Eq. (7), it can be observed that in Spain (Fig. 3a) the central hours of the day from March to September were characterized, in 2024, by a relative frequency of surplus generation occurrences rarely below 30 %. This phenomenon was particularly evident in April, when surplus generation was recorded from 10 a.m. to 2 p.m. in 90 % of the cases. The situation in Germany was similar (Fig. 3b), although less extreme regarding the maximum values. Indeed, from April to September, the minimum surplus generation during the central hours of



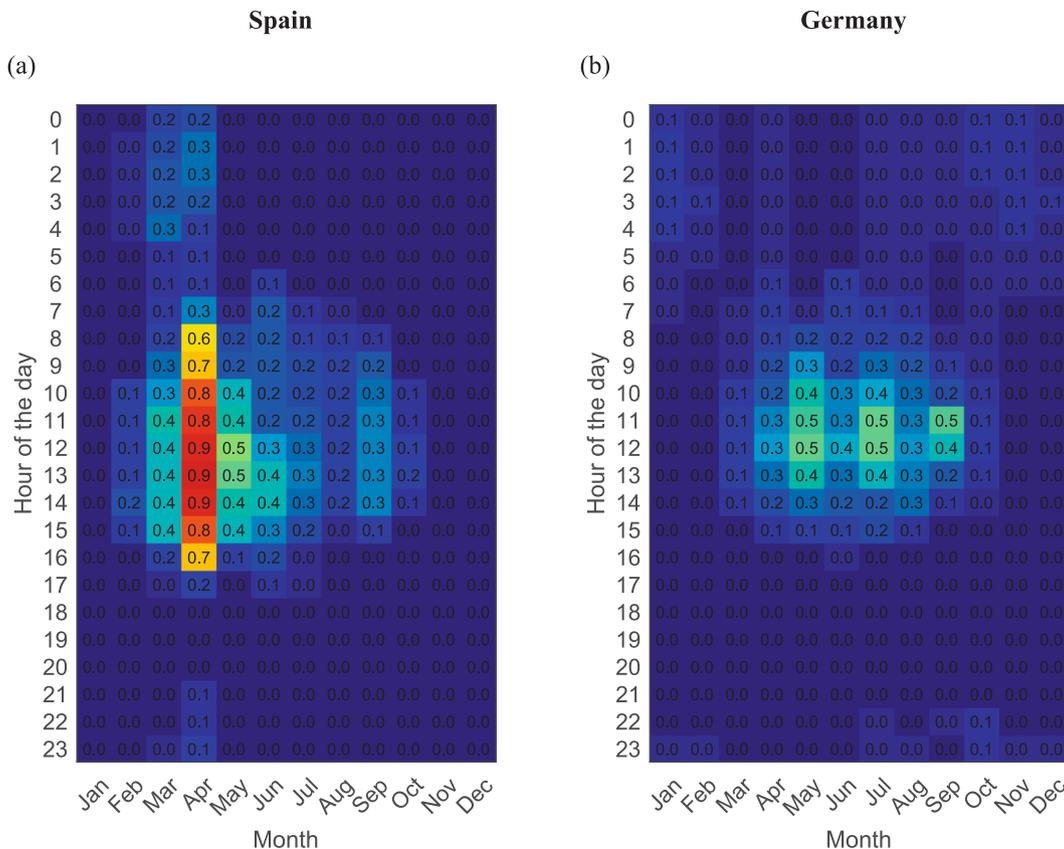**Fig. 3.** Relative frequency of surplus generation occurrences in Spain (a) and Germany (b) during 2024.

the day rarely fell below 30 % (as for Spain), but the maximum values did not exceed 50 %.

### 2.3.2. Work schedules

This study considers two contractual work schedules adopted at the University of Cagliari: the Morning Work Schedule (MWS) and the Full-Day Work Schedule (FDWS). In the MWS, employees are expected to work five mornings and two evenings per week (36 h per week), resulting in a laptop usage profile (each employee has a laptop) predominantly concentrated in the first half of the day. In the FDWS, work activity is distributed over five mornings and five evenings (40 h per week), resulting in a more extended and flexible presence and a different laptop usage pattern. Given that, as discussed in Section 3.1, the considered grids benefit most from load during the central hours of the day, the MWS is inherently more aligned with these grid requirements than the FDWS.

For each of the two contractual work schedules, presence data were collected for 93 employees via badge swipes throughout the entire year 2024. Each employee's laptop consumption profile was then estimated by multiplying the average laptop power demand (from datasheets) by the actual presence time inferred from badge activity. User presence data for the two contractual work schedules is illustrated in Fig. 4a (MWS) and Fig. 4b (FDWS) by boxplots showing the number of laptops in use (employee on site) during each 15-minute interval between 7:00 a.m. and 8:00p.m. on working days. The lower and upper bounds of each box represent the first ($25^{th}$ percentile) and third quartile ($75^{th}$ percentile), respectively, while the red line within the box indicates the median. The whiskers extend to the most extreme data points that are not classified as outliers.

Although derived from an academic setting in Italy, the two work schedules reflect typical working patterns found in broader international contexts. The MWS aligns with standard office hours commonly adopted in public administration and academic institutions across Europe and other OECD countries, while the FDWS is representative of extended or flexible working hours frequently observed in the private sector and research organisations.

It is important to note that inferring laptop usage profiles indirectly from badge data introduces two potential sources of measurement inaccuracy. First, individual laptops may use different amounts of power depending on hardware characteristics and workload intensity, which are not captured by a single average value. Second, badge-based presence data may not perfectly match actual laptop usage, since devices can be unused while the user is present or, conversely, remain powered without the user. However, this simplified approach was considered suitable for this initial assessment, which primarily aimed to establish the techno-economic potential of the strategy, and future works will refine these estimates using real measurement data of laptop consumption, motivated by the promising results obtained here.

## 3. Results and discussion

The results presented in this section evaluate the performance of the LDR strategy under the different scenarios (grid requirements and work schedules) already described in Section 2.3. As the simulations rely on a perfect forecast of user behaviour (see Section 2.1), the following results should be interpreted as best-case performances, reflecting the maximum potential of the proposed strategy under ideal information conditions.

The discussion is structured in two parts: first, the outcomes obtained in the Spanish context are analysed; then, the analysis is extended to the German case, allowing a comparative assessment and the identification of key differences. For both countries, the results are presented with reference to two temporal resolutions. Annual indicators are first used to quantify the overall benefits in terms of electricity cost reduction and surplus energy utilisation. Subsequently, a monthly-level analysis is carried out to investigate seasonal variations in performance and to better understand the influence of intra-annual dynamics.

In Spain (Table 2), under the Morning Work Schedule, the application of the LDR strategy enables a 35 % reduction in the yearly average electricity price for powering the laptops (from 46.3 €/MWh to 30.3 €/MWh). The concentration of the battery charging phase during low-price hours leads to a 75 % increase in the consumption of surplus grid energy compared to the case without LDR, resulting in a 7.9 % increase in the SDR ratio (from 11.7 % without LDR to 19.6 % with
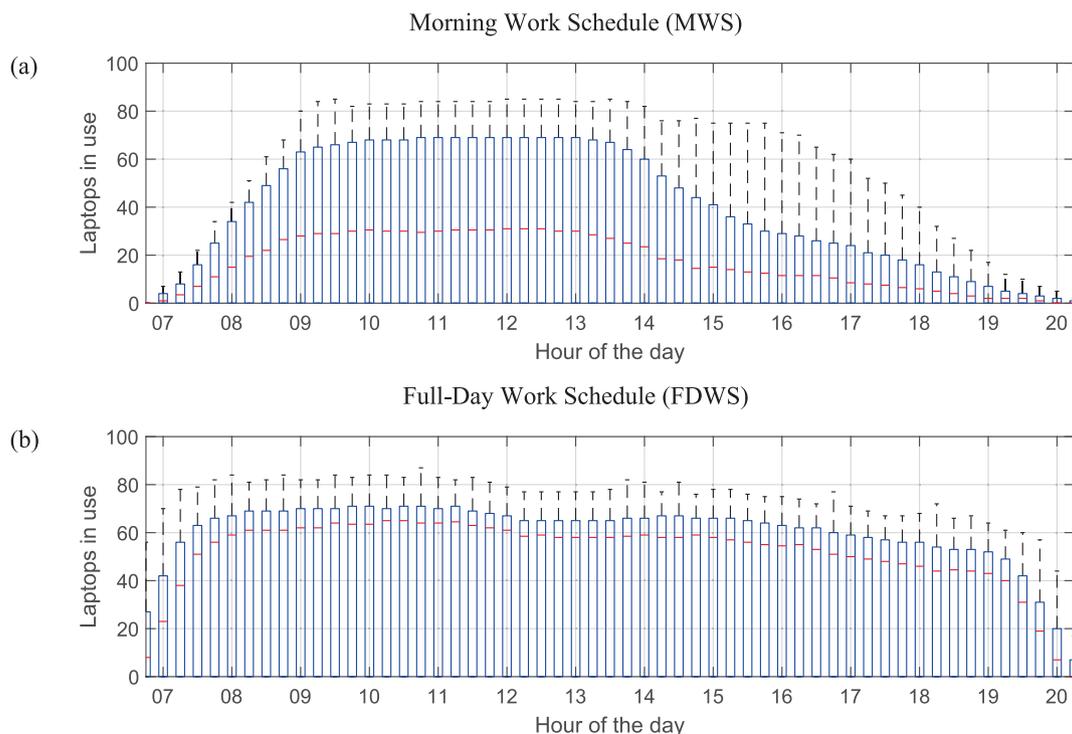


**Fig. 4.** Laptops in use (employee on site) for the two work schedules.

**Table 2**
Yearly performance of the LDR strategy under the different scenarios in Spain.

| | | | Morning Work Schedule (MWS) | | | Full-Day Work Schedule (FDWS) | | |
|---|---|---|---|---|---|---|---|---|
| | | | Without LDR | With LDR | Variation with LDR | Without LDR | With LDR | Variation with LDR |
| Average electricity price for powering the laptops | $\pi_{L,year}$ | €/MWh | 46.3 | 30.3 | − 16.0 (− 35 %) | 54.5 | 30.8 | − 23.7 (− 43 %) |
| Electricity costs | − | $\frac{€}{laptop \cdot year}$ | 0.8 | 0.6 | − 0.3 (–32 %) | 1.5 | 0.9 | − 0.6 (−41 %) |
| Surplus-to-Demand Ratio | $SDR_{year}$ | % | 11.7 | 19.6 | + 7.9 | 9.4 | 18.3 | + 8.9 |
| Energy consumption | $E_G$ | $\frac{kWh}{laptop \cdot year}$ | 18.1 | 18.8 | + 0.7 (+ 4 %) | 27.5 | 29.0 | + 1.5 (+ 5 %) |
| Surplus energy consumption | $E_{G,SURP}$ | $\frac{kWh}{laptop \cdot year}$ | 3.2 | 5.6 | + 2.4 (+ 75 %) | 2.6 | 5.3 | + 2.7 (+ 104 %) |

LDR). Under the Full-Day Work Schedule, the performance of the LDR strategy is further improved. Indeed, the application of the strategy enables a 43 % reduction in the yearly average electricity price for powering the laptops (from 54.5 €/MWh to 30.8 €/MWh). The concentration of the battery charging phase during low-price hours leads to a 104 % increase in the use of surplus grid energy compared to the case without LDR, resulting in an 8.9 percentage point increase in the SDR ratio (from 9.4 % without LDR to 18.3 %). For both schedules, the energy consumption of laptops increases by 4–5 % with the LDR strategy, compared to the case without LDR, due to losses associated with frequent battery usage. Under the LDR strategy, the maximum annual charge-discharge cycle counts are 203 for the MWS and 246 for the FDWS. These values correspond to approximately one-third of the average full-cycle lifetime of laptop batteries. Therefore, over a standard three-year professional use period, the LDR strategy is not expected to appreciably shorten the laptop lifecycle.

From the above results, it emerges that the LDR strategy performs better under the Full-Day Schedule than under the Morning Work Schedule. The reasons for this difference can be inferred by comparing the yearly average hourly profiles presented in Fig. 5. The figure shows both the average hourly day-ahead electricity price ($\pi$, blue line) and the hourly average electricity flows. Fig. 5(a) refers to MWS, while Fig. 5(b) refers to FDWS. The areas represent normalised energy contributions with respect to the maximum net laptop demand $E_{SYS}$. Positive values indicate the laptop consumption net of battery charging, supplied either directly from the grid ($E_{G,SYS}$, blue areas) or via battery discharging ($E_{B,SYS}$, orange areas), while negative values indicate battery charging ($E_{G,B}$, green areas).
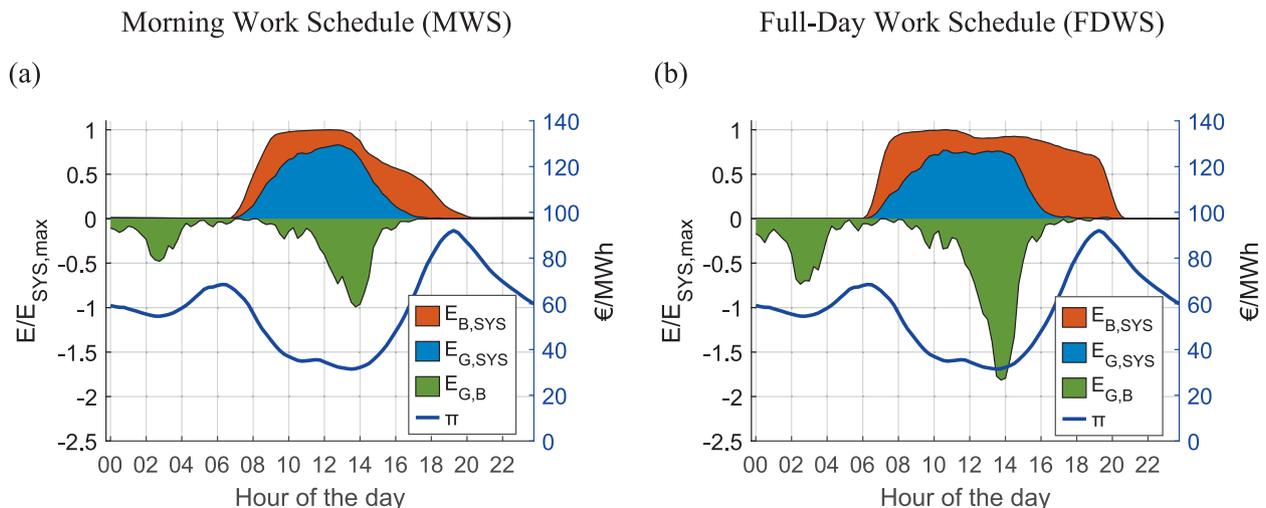
The electricity price profile exhibits an initial value around 60

€/MWh at midnight, rising during the early morning hours and reaching approximately 70 €/MWh by 7:00 a.m. A subsequent decrease is observed, with a minimum value of about 35 €/MWh occurring between 10:00 a.m. and 2:00 p.m. Thereafter, the price increases again, exceeding 90 €/MWh at 7:00 p.m. The resulting daily spread, exploitable through the LDR strategy, approaches 55 €/MWh. In both schedules, the LDR strategy shifts laptop direct power supply and battery charging to low-price hours, with charging peaking during the two daily price minima (one during nighttime and the other around 2:00 p.m.). During high-price periods, particularly in the early morning and evening, battery discharge approaches full utilisation.

Under the Full-Day Work Schedule (Fig. 5b), a more pronounced use of batteries during high-price hours and a more intensive charging during low-price hours is observed compared to the Morning Work Schedule (Fig. 5a). This results from a weaker alignment between laptop usage and low electricity prices in FDWS, which enhances the opportunity to exploit intra-day price variability. Conversely, in MWS, the peak in laptop usage coincides with the price minimum and the price maximum occurs after the end of the average working day, limiting the potential benefits of load shifting.

As a consequence, the improvements achievable in the performance indicators through the LDR strategy under the MWS scenario are lower than those obtained under the FDWS scenario, although they remain higher in absolute terms.

Once the values have been analysed on an annual basis, it is useful to examine the monthly performance of the LDR strategy. Fig. 6 presents the monthly average price to power laptops (top panels) and the monthly SDR (bottom panels), under the Morning Work Schedule (left) and the Full-Day Work Schedule (right).



**Fig. 5.** Hourly average electricity prices and energy flows with the LDR strategy under the two work schedules in Spain.
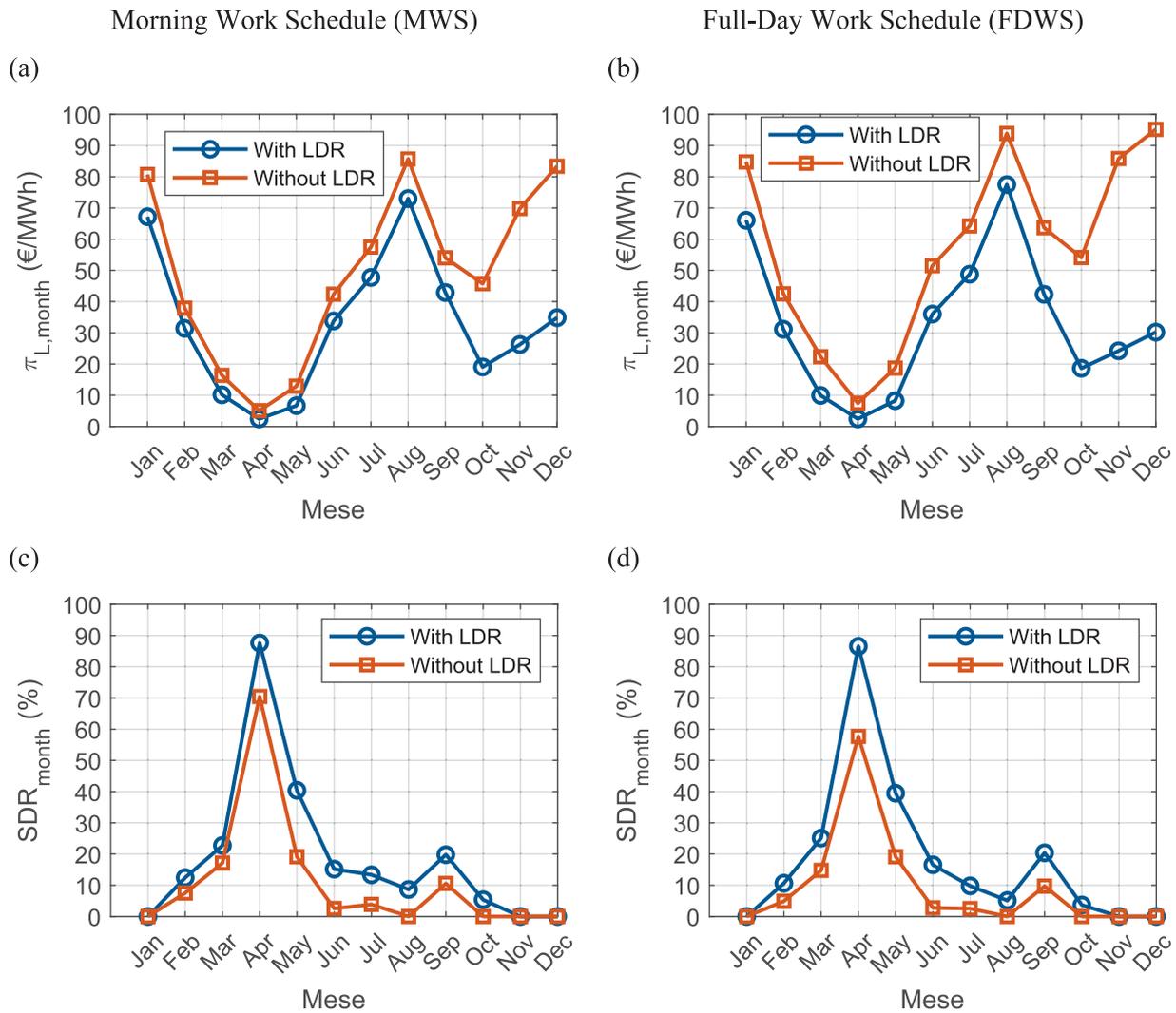
## Morning Work Schedule (MWS)

(a)



## Full-Day Work Schedule (FDWS)

(b)



(c)



(d)



**Fig. 6.** Monthly average electricity price for powering the laptops (a, b) and Surplus-to-Demand Ratio (c, d) under the different scenarios in Spain.

Regardless of schedule and strategy, the trend of $\pi_{L,month}$ shows three peaks in January, August, and December, a deep minimum in April, and a second minimum in October. This trend mirrors the day-ahead market price pattern (median) previously shown in Fig. 2a.

Under the Morning Work Schedule, the average price reduction enabled by the LDR strategy (Fig. 6a) is very limited from January to August, whereas from September to December a substantial reduction (up to 50 €/MWh) is observed. This improvement is attributable to the greater intra-day price variability occurring in these months during the working hours (see the extension of the boxplots of Fig. 2): indeed, higher intra-day price variability enhances the effectiveness of the LDR strategy. Furthermore, due to the aforementioned weaker alignment between laptop usage and electricity prices in the Full-Day Work Schedule, the average price reductions achieved with LDR under the FDWS are approximately 10 €/MWh higher (Fig. 6b).

Regarding the SDR across both strategies and schedules (Fig. 6c,d), near-zero surplus energy values for laptop power occur in January, November, and December; a significant peak occurs in April, a second peak in September, and slightly lower values during the summer months and October. These patterns, which reflect the frequency of surplus generation occurrences already shown in Fig. 3a, are typical of grids with a high photovoltaic penetration. Indeed, during the April and September peaks, photovoltaic generation in the power grid is at its maximum while load demand is minimal due to the absence of air-conditioning-related consumption. The zero SDR values, unchanged by

the LDR strategy, correspond to months without grid overgeneration and therefore with higher prices. Conversely, the peak values (April and September) correspond to months with maximum surplus generation in the power grid and, for this reason, in these months the consumption of surplus electricity under the LDR strategy can be most effectively exploited.
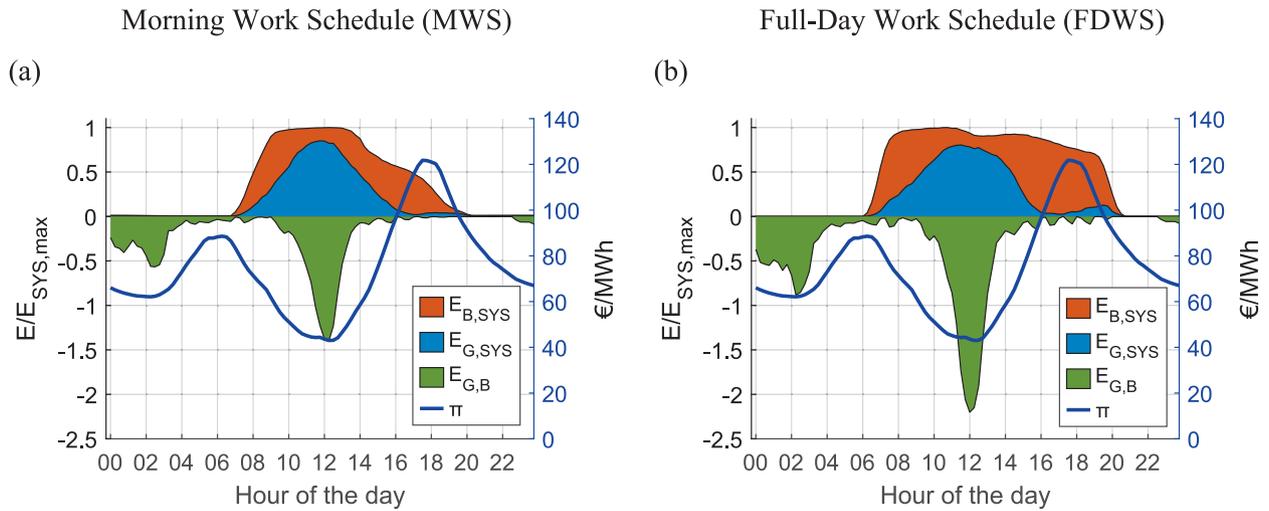
More in detail, under the Morning Work Schedule (Fig. 6c), the LDR strategy increases the SDR by approximately 20 percentage points during the April peak and by 5–15 points in other non-zero months. Under the Full-Day Work Schedule (Fig. 6d), the increase is higher, reaching approximately 30 points in April and 15–25 points in other non-zero months.

The use of the LDR strategy in Germany yields yearly results similar to those described for Spain (Table 3). The application of the strategy enables a 42 % reduction (45.2 €/MWh vs 78.0 €/MWh) in the yearly average electricity price for powering the laptops under the MWS and a 42 % reduction (45.5 €/MWh vs 85.9 €/MWh) under the FDWS. Under this schedule, the concentration of the battery charging phase during low-price hours results in a 290 % increase in the consumption of surplus grid energy. In the case of Germany, the maximum annual charge-discharge cycle counts are 233 for the MWS and 270 for the FDWS, in line with the results obtained for the Spanish scenario.

As in the case of Spain, the LDR strategy in Germany performs better under a Full-Day than under a Morning Work Schedule. Consistent with Fig. 5, Fig. 7 shows the average hourly day-ahead electricity price ($\pi$,

**Table 3**
Yearly performance of the LDR strategy under the different scenarios in Germany.

| | | | Morning Work Schedule (MWS) | | | Full-Day Work Schedule (FDWS) | | |
|---|---|---|---|---|---|---|---|---|
| | | | Without LDR | With LDR | Variation with LDR | Without LDR | With LDR | Variation with LDR |
| Average electricity price for powering the laptops | $\pi_{L,year}$ | €/MWh | 78.0 | 45.2 | − 32.8 (−42 %) | 85.9 | 45.5 | − 40.4 (− 47 %) |
| Electricity costs | – | $\frac{€}{\text{laptop} \cdot \text{year}}$ | 1.4 | 0.9 | −0.6 (−39 %) | 2.3 | 1.3 | − 1.0 (−44 %) |
| Surplus-to-Demand Ratio | $SDR_{year}$ | % | 4.6 | 16.0 | + 11.4 | 3.6 | 13.3 | + 9.7 |
| Energy consumption | $E_G$ | $\frac{\text{kWh}}{\text{laptop} \cdot \text{year}}$ | 18.1 | 19.0 | + 0.9 (+5%) | 27.5 | 29.1 | + 1.6 (+ 6 %) |
| Surplus energy consumption | $E_{G,SURP}$ | $\frac{\text{kWh}}{\text{laptop} \cdot \text{year}}$ | 1.3 | 4.6 | + 3.3 (+ 254 %) | 1.0 | 3.9 | + 2.9 (+ 290 %) |



**Fig. 7.** Hourly average electricity prices and energy flows with the LDR strategy under the two work schedules in Germany.

blue line) and the hourly average electricity flows. The trends are similar to those discussed for Spain, with some differences: the time interval of lowest average prices (about 45 €/MWh) is centred around noon and lasts approximately 2 h, and thus it is shorter than in Spain (4 h). From that point onwards, the price increases up to a maximum of 120 €/MWh at 6:00 p.m., which occurs earlier than in Spain (7:00 p.m.) and while the working day (also under the MWS scenario) is still ongoing. Moreover, the daily difference between minimum and maximum, exploitable through the LDR strategy, is potentially close to 75 €/MWh, higher than in Spain (55 €/MWh). Under both schedules, the LDR strategy reallocates laptop power supply and battery charging to periods with lower electricity prices, concentrating the charging phase around the two daily price minima, while, during high-price hours (around 5–6 p.m.), battery discharging is maximized.

Similarly to the Spanish case, the trend of the monthly average electricity price for powering laptops (with and without the LDR strategy and under both work schedules) in Germany shown in Fig. 8 follows the median price profiles already presented in Fig. 2(b). Differently from Spain, however, in Germany the implementation of the LDR strategy results in a consistent price reduction (at least 10 €/MWh) across all months. As previously highlighted for Spain, the strategy is more effective during months characterized by higher price variability (i.e., greater boxes in Fig. 2(b)), as observed in December. Also in this case, the FDWS scenario yields better results than the MWS. Regarding the SDR strategy, its impact is less extreme and more evenly distributed across all months compared to Spain, with a trend that closely reflects the curtailment occurrence already shown in Fig. 3(b).

Given the promising results obtained, future developments should

focus on the practical implementation of the proposed strategy. A preliminary step will consist of addressing the main limitations of the present study, which can be grouped into four main categories (model-related assumptions, user-related uncertainties, technical and organizational constraints and economic and market integration issues).

First, several assumptions within the modelling framework require refinement to improve realism. These include the use of averaged laptop energy consumption, which neglects the heterogeneity of devices and workloads; the assumption that laptops are continuously on-site, which does not account for hybrid or remote working arrangements; the use of negative electricity prices as a proxy for surplus generation, which may not fully capture actual curtailment dynamics; and the assumption of perfect user behaviour forecastability, which overestimates optimization performance. These aspects should be addressed through empirical consumption measurements, probabilistic modelling, and scenario-based analysis.

Second, user-related uncertainties must be considered. Variability in behavioural patterns and levels of user acceptance could significantly affect the real-world effectiveness of the proposed strategy. Understanding these factors through field tests, user surveys, and opt-in mechanisms will be essential to ensure engagement and usability.

Third, the strategy's integration within institutional and enterprise environments raises technical and organizational challenges. Potential issues include compatibility with existing Operating Systems (OS), IT infrastructures, and security protocols, as well as privacy concerns. These aspects should be systematically evaluated through implementation pilots in representative environments.

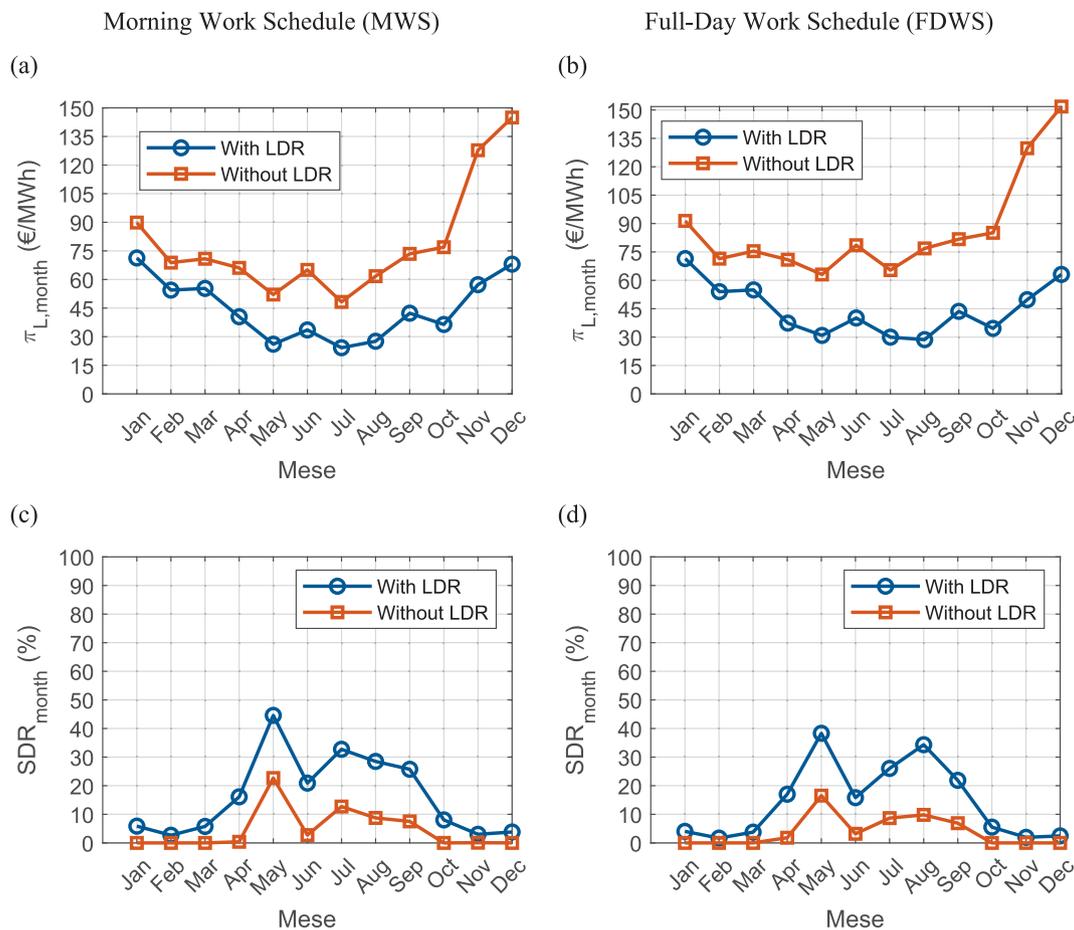Fourth, economic and market-related aspects remain open. Although

Morning Work Schedule (MWS)  Full-Day Work Schedule (FDWS)



**Fig. 8.** Monthly average electricity price for powering the laptops (a, b) and Surplus-to-Demand Ratio (c, d) under the different scenarios in Germany.

the proposed approach relies on negligible marginal costs, software development, deployment, and IT support may entail measurable expenditures. Moreover, the potential participation of aggregated laptop demand in flexibility markets remains untested. Future research should address full techno-economic assessments, aggregation mechanisms, and regulatory pathways to enable market integration.

Once these foundational issues are addressed, the strategy can progress toward real-world implementation. Pilot studies can be launched in universities and public administrations, which are natural candidates for initial deployment due to their large centrally managed laptop fleets and existing IT infrastructures. These pilots would provide essential insights into technical feasibility, user acceptance, and organizational compatibility.

Subsequent steps should aim to extend deployment to private enterprises, where operating conditions are more heterogeneous, but laptop usage is equally widespread. In this context, system administrators could coordinate implementation through enterprise power management tools, ensuring both centralized control and IT compliance.

In the longer term, the most effective solution would be native integration of the proposed strategy into operating systems. Embedding the functionality within OS-level power management would overcome compatibility and security barriers while offering a simple user interface that proposes a daily charging schedule at log-in, which the user can confirm or adjust.

Finally, large-scale adoption would require participation in flexibility markets. Collaboration with aggregators and system operators will be essential to validate the aggregated contribution of laptops to flexibility services, benchmark their role relative to other distributed loads, and define standardized protocols for their inclusion in demand response programs.

## 4. Conclusions

This study assessed the techno-economic potential of coordinating laptop battery management in response to electricity price signals, with the dual aim of supporting grid flexibility and reducing user electricity costs. The proposed strategy, based on real price conditions (Spain and Germany) and laptop usage profiles (categorized in the morning and full-day work schedules), yielded consistent performance improvements across all scenarios.

The results, representing an upper-bound estimate of the achievable benefits, confirmed that the strategy is more effective (i) when laptop energy demand is temporally misaligned with price minima, as in the Full-Day Work Schedule, (ii) when intra-day price variability is greater, as in the winter months, and (iii) when oversupply conditions are frequent.

In Spain, under the Full-Day Work Schedule, the LDR strategy achieves substantial reductions in electricity cost (−43 %) and significant increases in the consumption of surplus energy (+104 %). Under the Morning Work Schedule, performance remains notable, with cost reductions of 35 % and surplus energy utilisation increased by 75 %. In the German case, under the Full-Day Work Schedule, the laptop demand response strategy leads to a 47 % reduction in electricity costs and a 290 % increase in the utilisation of surplus energy. The corresponding values under the Morning Work Schedule are −42 %, +254 %, respectively.

While individual impacts may seem modest, the aggregated effect at system level appears promising. By extrapolating the study results to 50 % of global laptop sales in a year (~250 million units), the LDR strategy could potentially enable 300–400 GWh/year of additional surplus energy consumption, with avoided electricity costs of up to 125 M€ compared to a conventional, non-coordinated charging approach. These

figures should be considered as indicative, illustrating the potential scale of the opportunity rather than precise forecasts.

Overall, the findings illustrate the potential system-level benefits of a solution that relies solely on software-based coordination. While the practical scalability of the approach will require addressing current limitations, ranging from technical aspects, to behavioural factors, and institutional barriers, the results suggest that laptops could become a meaningful contributor to distributed demand response at negligible marginal cost.

## Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI ChatGPT in order to revise the English language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## CRediT authorship contribution statement

**Luca Migliari:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Davide Micheletto:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Daniele Cocco:** Writing – review & editing, Supervision, Project administration, Formal analysis.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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