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Remote work might unlock solar PV's potential of cracking the 'Duck Curve'

Kumar Biswajit Debnath [a,*], David P. Jenkins [b], Sandhya Patidar [b], Andrew D. Peacock [b]

[a] Hub for Biotechnology in the Built Environment (HBBE), School of Architecture, Planning & Landscape, Newcastle University, Newcastle upon Tyne, United Kingdom
[b] School of Energy, Geoscience, Infrastructure and Society (EGIS), Heriot-Watt University, Edinburgh, United Kingdom

HIGHLIGHTS

- Analysed 1-minutely grid and decentralised solar PV energy demand data from 100 houses in a southwestern UK city.
- Average electricity consumption decreased by 1.4—10% in April—August 2020 compared to 2019.
- Grid electricity consumption was reduced by 24—25%, and from solar PV self-consumption increased by 7—8%.
- Increased solar PV self-consumption was prominent in the morning and afternoon.
- Might unlock solar PV's potential of resolving the 'Duck Curve.'

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ABSTRACT

Integrating renewable energy technologies into a decentralised smart grid presents the 'Duck Curve' challenge — the disparity between peak demand and solar photovoltaic (PV) yield. Smart grid operators still lack an effective solution to this problem, resulting in the need to maintain standby fossil fuel-fired plants. The COVID-19 pandemic-induced lockdowns necessitated a shift to remote work (work-from-home) and home-based education. The primary objective of this study was to explore mitigating strategies for the duck curve challenge by investigating this notable shift in behaviour by examining the effect of remote work and education on grid and decentralised solar PV electricity use in 100 households with battery energy storage in the southwest of the UK. This study examined 1-min granular grid electricity and decentralised solar energy consumption data for April–August 2019 and 2020. The findings revealed statistically significant disparities in energy demand. Notably, there was a 1.4—10% decrease in average electricity consumption from April to August 2020 (during and following the lockdown) compared to the corresponding months of 2019. Furthermore, household grid electricity consumption was reduced by 24—25%, while self-consumption from solar PV systems increased by 7—8% during the lockdown in April and May 2020 compared to 2019. This increase in self-consumption was particularly prominent in the morning and afternoon, possibly attributed to the growing prevalence of work-from-home and home-based education. The dynamic shifts in energy consumption patterns emphasised the role of decentralised solar PV energy in meeting the evolving needs of households during unprecedented societal changes. Additionally, remote work might unlock decentralised solar PV's potential in resolving the 'Duck Curve', urging further investigation into the implications for energy infrastructure and policy development.

1. Introduction

Extreme events like heatwaves, flash floods, or pandemics can profoundly impact individuals' lives, leading to significant changes in daily routines and behaviour. For instance, the COVID-19 pandemic triggered widespread disruptions worldwide, prompting measures such as lockdowns and remote work arrangements. In response to the escalating situation, the UK government implemented lockdown measures in late March 2020, including closing schools, restaurants, and social venues [1]. By 03 March 2021, the UK had reported 4.2 million confirmed COVID-19 cases and 123,530 deaths [2]. Subsequent waves of infections led to additional lockdowns in November 2020 and January 2021 [2].

* Corresponding author.
E-mail address: Kumar.Debnath@newcastle.ac.uk (K.B. Debnath).

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Key workers, constituting 25.7% of the UK's total working-age population [3], faced varied work arrangements during the pandemic. While some could work remotely, most did not have this option, leading to job losses or furlough [4,5,6]. Data from the Office for National Statistics (ONS) indicated that approximately 47% of employed individuals adapted to remote work arrangements in April 2020, a substantial increase from pre-pandemic levels [5]. Around 9.4 million individuals were also on furlough by 30 June 2020 [4].

Several studies and reports have illustrated the profound impact of the lockdown on people's behaviours, evident not only in the UK but also in electricity demand profiles across various countries [7,8,9,10]. The lockdown induced an 18% decrease in morning electricity demand in the UK, with a comparatively lesser impact on weekend demand [11]. This decline aligns with expectations, considering the widespread closure of offices, schools, universities, and industries, leading to an overall reduction in grid-level electricity demand [7,12]. Given that residential sectors play a dominant role in nationwide electricity consumption [13,10,14], understanding the specific patterns and behaviours of household consumption during the lockdown becomes crucial. Several studies reported reduced electricity demand during the COVID-19 lockdown in Spain, Portugal, Italy, the UK, and Belgium [9,10,15] and increased demand in the UK [16]. A study reported 13.49% power demand and 32.61% CO_2 emissions reduction in Spain due to March and April 2020 lockdown measures compared to 2019 [9]. The electricity demand study in Spain, Italy, Belgium, the UK, Netherlands, and Sweden during April 2020 and 2019 showed Spain's highest (25%) Demand Variation Index (DVI) reduction. Also, Italy, Belgium, and the UK had 17.7%, 15.6% and 14.2% DVI reduction due to strict lockdown measures during the studied period. The Netherlands (with less restrictive measures) and Sweden (with no lockdown) showed an 11.6% reduction and a 2.1% increase in DVI, respectively [10]. Another study showed a 30% increase in energy consumption in the USA's residential sector. In contrast, the electricity demand was lower due to the lockdown on the commercial buildings and manufacturing sectors [13]. Carvalho et al. showed a 7–20% decrease in electricity consumption in different Brazilian regions, with the lowest 7% in the residential sector dominating the northeast subsystem [17]. A study reported that commercial and industrial activity and in-process heat and heating/cooling demand reduction were likely to contribute to lower-than-trend electricity consumption during the day during the UK's lockdown [7]. A sharp drop in electricity demand was reported as governments worldwide imposed lockdown restrictions, impacting the load composition and daily load profile [18]. Snow et al. analysed the drivers behind the Australian residential electricity demand due to the COVID-19 restriction of 491 houses. They pointed out a significant increase in household electricity use with increased cooking and digital device use. However, overall energy use among most monitored Queensland households decreased during lockdown compared to the pre-lockdown period due to reduced air conditioner use as the weather cooled [19]. Kirli et al. showed a 25% reduction in aggregated electricity demand in Great Britain during lockdown [12]. El-Khozondar, H. J. et al. developed a hybrid off-grid energy system to power a COVID-19 quarantine centre in Gaza economically and sustainably, as demonstrated by HOMER-Pro analysis [20]. Their findings highlighted the system's capacity to deliver environmentally friendly, cost-effective, and affordable electricity to the quarantine facility compared to a standalone diesel generator system. However, studies and reports suggested that considerable uncertainties existed on the long-term impact of COVID-19 on the UK's energy demand [21,7]. National Grid Electricity System Operator (ESO) showed a reduction in total energy consumption during the lockdown compared to the pre-COVID market [8], primarily due to working from home and children being home.

In January 2010, the total installed capacity of solar PV was 22.45 MW, including 10.22 MW of domestic capacity. By January 2024, the UK's solar PV install capacity was cumulatively 15,721.45 MW, of which domestic was 4623.31 MW (29.41%) [22]. Among the total solar PV installed capacity of 0 to $\leq$4 kW, 4 to $\leq$10 kW, 10 to $\leq$50 kW, 50 kW to $\leq$5 MW, 5 to $\leq$25 MW, and > 25 MW size were 3614.2 MW, 829.3 MW, 1272.1 MW, 3693.6 MW, 4440.1 MW and 1857.5 MW, respectively. In 14 years, the total installed capacity increased by 700 times, whereas the total installed capacity increased by 452 times compared to domestic capacity. Despite the massive increase in installed capacity, the UK aims to double its solar capacity by 2030. Yet, this alone may not suffice to achieve a net zero economy by 2050, and a quadrupling of national green energy output by 2050, potentially reaching 80-120GW of solar capacity, is crucial. Achieving this could reduce carbon emissions by 21.2 million tonnes annually, create 13,000 jobs, generate £17 billion in economic activity, and maintain a Compound Annual Growth Rate of 11% [23]. Solar PV in the UK benefits from ample sunlight and government incentives but faces challenges such as intermittent generation, limited grid capacity, and land use conflicts [24]. Technology, policy support, and distributed generation offer opportunities. However, policy uncertainty, market saturation, and regulatory barriers pose threats [25].

Many studies have been conducted on solar PV and grid electricity control. Saxena, V. et al. introduced an AWFSOGI-based direct power control strategy for grid-connected solar PV systems, ensuring power quality and voltage regulation under adverse grid conditions [26]. Kumar, N. et al. introduced a novel voltage sensor(less)-based model predictive control (VSPC) scheme for efficient maximum power harvesting from a photovoltaic array in a solar-powered electric vehicle charging system, demonstrating its effectiveness in experimental validation [27]. Zafeiropoulou, M. et al. developed the F-channel platform, using AI and cloud computing to address balancing and congestion management issues in the Greek power system, enhancing TSO-DSO coordination and facilitating congestion, frequency, and voltage control services [28]. Pavlatos, C. et al. presented an electrical load forecasting methodology using bidirectional long short-term memory (LSTM) neural networks, achieving better accuracy compared to previous models, with the bidirectional LSTM's mean absolute error (MAE) of 0.122 outperforming recurrent neural networks (RNN), LSTM, and gated recurrent units (GRU) by approximately 25%, 46%, and 26%, respectively, highlighting its potential for precise energy planning and market management in power systems [29]. Pavlatos, C. et al. introduced a Python-based framework utilising RNN for precise electrical load prediction [30]. They achieved a root mean square error of 0.033, demonstrating its effectiveness in capturing data patterns and trends for energy-planning applications.

Moreover, several studies also explored the mitigation strategies for the 'Duck curve'— a daily power production graph revealing the timing misalignment between peak energy demand and solar power generation. It shows a distinct dip during daylight hours when solar generation peaks, resembling a duck's silhouette [31,32,33]. Wang, Q. et al. presented a mitigation strategy for the duck-shaped net load power curve problem in high PV penetration systems, replacing thermal power stations with Concentrated solar power (CSP) stations [34]. It utilised the thermal storage system's ability to dispatch and CSP unit fast output regulation to minimise overall cost and enhance system flexibility, as demonstrated through nonlinear optimisation. Hou, Q. et al. demonstrated high PV penetration reshaped net-load curves, leading to proposed probabilistic duck and ramp curves to model uncertainty. Empirical validation showed considerable uncertainty, with flexible resource planning enhancing power system flexibility, notably through coal-fired unit retrofitting in Qinghai, China [35]. Sheha, M. et al. presented a novel approach to citywide dynamic modelling using a bilevel programming algorithm, optimised dynamic pricing profiles leveraging air-conditioning systems and distributed storage to flatten demand curves, with an economic study showing levelized storage costs below \$0.457/kWh and several cases with simple payback periods shorter than the system's lifetime [31]. Calero, I. et al. investigated pre-cooling strategies in residential households to mitigate the "duck curve" effect caused by the massive deployment of small-scale PV generation [36]. It demonstrated the technical feasibility of pre-cooling through thermal models and simulations. It proposed an aggregation technique to evaluate its effects on large grids in California and Texas, concluding that such techniques significantly flattened the system net demand curve. Olczak, P. et al. showed, in Poland, a surge in installed photovoltaic capacity, notably since 2018, led to the "duck curve" phenomenon, characterised by low daytime grid energy consumption and higher evening consumption, particularly on days with high sunlight [37]. This study analysed 608 PV installations, estimating a maximum daily difference of 3.9 kW per household in 2019 and a median value of 2.08 kW. Connecting 400,000 prosumer households was estimated to cause a maximum power fluctuation of about 1.6 GW in the national grid. Kalair, A. R. et al. developed a solution to the "duck curve" challenge through smart load-shedding devices in micro and nano grids, leveraging ICT technologies and Internet of Things (IoT)-based demand-side management to optimise energy consumption and mitigate peak-hour demands on the national grid, with future integration of big data technologies for utility-scale load management [38]. Pandey, H. W. et al. addressed the challenges of integrating renewable energy sources (RES) into the grid, mainly focusing on the "duck curve" phenomenon observed in the Indian grid scenario [39], which proposed strategies to mitigate it and employed TOPSIS to rank these strategies based on multi-criteria decision-making analysis. Watari, D. et al. proposed an optimal strategy for a resource aggregator (RA) to address the global problem of the duck curve, utilising dynamic pricing and battery systems at both RA and prosumer levels based on a model-free deep reinforcement learning (DRL) algorithm, with simulation experiments demonstrating significant improvements in net load metrics [40].

The existing literature did not explore the potential of remote working in mitigating the 'Duck curve.' This study aimed to understand the initial shifts in behaviour during the onset of the lockdown, observe the easing of these changes as restrictions were lifted, and then examine a return to more conventional practices as we transition out of lockdown, exploring the possibility of some changes becoming enduring. It focused on the first COVID-19 pandemic lockdown, which commenced on 23 March 2020 and gradually relaxed from mid-May in the UK. This study examined the period from April to August 2020, encompassing the summer and autumn months. Furthermore, 1-min intervals of residential grid electricity and decentralised solar energy generation and consumption data from 100 homes in the southwest of the UK were analysed. The primary objective was to scrutinise the grid electricity consumption and self-consumption of photovoltaic (PV) energy, as residential occupancy (and consequently, demand) might undergo significant shifts to better align with solar PV generation during this timeframe. This study aimed to shed light on how energy practices evolved during the lockdown's and subsequent phases' unique circumstances, offering insights into the potential of enduring impact on energy consumption patterns and mitigating the 'Duck curve.'

2. Methodology

2.1. Data source and description

This study used data from the Local Energy Market (LEM) Residential database within the Cornwall LEM project, a venture partially supported by the European Regional Development Fund through the European Structural and Investment Funds Programme 2014–2020 [41]. The dataset featured 1-min intervals of electricity demand, and generation data gathered from 100 residences in the southwest of the UK from August 2016 to December 2020. The project's objective centred on creating a LEM trading platform tailored for homes and equipped with solar PV and behind-the-meter battery energy storage systems (BESS) (Fig. 1). Each site was outfitted with diverse measurements, encompassing on-site energy consumption, energy generated by the Solar PV system, energy charge/discharge to and from the BESS, energy imports and exports to and from the grid, along with intricate details regarding

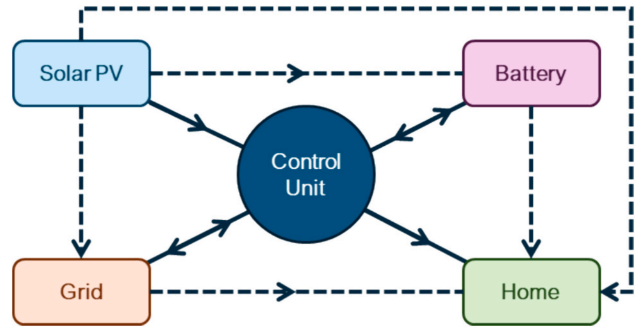

Fig. 1. Energy systems and flow in the monitored houses. The solid lines refer to the energy flow, while the dashed ones refer to the energy destination.

the allocation of energy from the Solar PV system and the BESS. These measurements included PV & BESS standby loads, BESS state of charge, and power-related parameters like active power, voltage, frequency, and power factor for the grid, BESS, and PV systems. Despite the primary compilation of the dataset for LEM trading experiments, our study focused primarily on consumption data. Performance data for PV and BESS was deliberately omitted to underscore the impact of COVID-19 on the broader population. Additionally, site-specific metadata associated with the time-series dataset was integrated, offering insights into dwelling characteristics and household composition, enriching our analysis.

The real power (P_{PV}) of the PV panel under actual operation and climatic conditions following Eq. (1) and Eq. (2), adopted from [42].

$$P_{PV} = P_{STC}\left[1+\beta_p(T_{cell}-T_{STC})\right]\frac{H_t}{H_{STC}} \tag{1}$$

$$T_{cell} = T_a + 7\times 10^{-2}H_t \tag{2}$$

Where: P_{PV} was the real power according to the operating conditions (W); P_{STC} was the power of the module at the standard test condition; T_{cell} was the surface cell temperature (°C); T_{STC} and H_{STC} were the cell surface temperature (°C) and solar radiation (W/m^2) at Standard Test Conditions (STC), respectively; β_p was the power temperature coefficient (W/°C), and H_t was the actual solar radiation incident on the PV module (W/m^2). Also, T_a was the air temperature (°C). Usually, T_{STC}, P_{STC}, β_p, H_t, and H_{STC} could be retrieved from the data sheet of the PV module, but the T_{cell} had to be estimated with Eq. (2).

The state of charging and discharging (SoC) of the conducted deep cycle battery (integrated type of the battery lithium-ion) as a chemical reaction can be mathematically expressed in Eq. (3) and Eq. (4), adopted from [43]. The equation calculates the battery's charge state at a time (t) based on the previous state of charge, the self-discharge rate, the difference between power generation and power consumption (considering efficiencies), and the efficiency of charging and discharging the battery. Eq. (5), adopted from [43], represented the calculation of the power supplied by an inverter $P_{inv}(t)$ at time (t).

$$SoC(t) = SoC(t-1).(1-\sigma) + \left((P_{PV}(t)+P_{WT}(t)) - \frac{P_L(t)+P_{EVDem}}{\eta_{inv}}\right)\times\eta_b \tag{3}$$

$$SoC(t) = SoC(t-1).(1-\sigma) + \left(\frac{P_L(t)+P_{EVDem}}{\eta_{inv}} - (P_{PV}(t)+P_{WT}(t))\right)\times\eta_b \tag{4}$$

$$P_{inv}(t) = \frac{P_l^m(t)}{\eta_{inv}} \tag{5}$$

Where: $SoC(t)$ and $SoC(t-1)$ were the estimated State of Charge at a time (t) and (t-1), respectively; σ was the Self-discharge rate of the battery, representing the loss of charge over time; $P_{PV}(t)$ was the power generated by the photovoltaic (PV) system at time (t); $P_{WT}(t)$ was the power generated by the wind turbine system at a time (t); $P_L(t)$ was the power consumed by loads at the time (t); P_{EVDem} was the power demand from electric vehicles at a time (t); η_{inv} was the efficiency of the inverter, representing the conversion efficiency of DC power to AC power or vice versa, and η_b was the efficiency of the battery's charging and discharging, representing losses during energy conversion and storage processes. $P_{inv}(t)$ was the power supplied by the inverter at the time (t), which was the output power of the inverter, which converts DC power to AC power (or vice versa) in systems like renewable energy systems or electric vehicles; $P_l^m(t)$ was the power demanded by loads at a time (t), which could be the total power consumed by various electrical loads connected to the system. The BESS battery systems and sizing details were here [41].

Also, to explore the influence of weather on electricity consumption, weather data for 2019 and 2020 from the Meteoblue database (www.meteoblue.com) for southwestern UK. The metadata named European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis 5th Generation (ERA5, ERA5T) had a 30 km spatial and hourly temporal resolution [44]. However, it is crucial to acknowledge the inherent complexities associated with the estimation process, including underlying assumptions, potential inaccuracies, and uncertainties, as extensively expounded upon in [45,46]. Any error in these variables could significantly affect the accuracy and reliability of the results obtained.

2.2. Data analysis methodology

Residential electricity consumption during the COVID-19 lockdown in the southwestern UK was examined using data from the Cornwall LEM database accessed through the MySonnenBatterie (MSB) portal. The analysis encompassed aggregated 1-min electricity consumption data from 100 houses, comparing disruptive periods from April to August 2020 with the same period in 2019. Kernel Density Estimate (KDE) was employed to analyse data distribution, including mean, maximum, and minimum range differences. Weekday and weekend electricity consumption patterns were also evaluated separately for both years. Additionally, we clustered houses based on heating fuel type (gas, oil, electricity) to assess the lockdown's impact on each cluster's electricity consumption. Paired *t*-tests were conducted to determine the statistical significance of differences in weekday and weekend consumption for different fuel types.

Additionally, to deepen our comprehension of specific household activities, such as work and education, during disruptive periods like lockdowns, houses using primary heating fuels—gas, oil, and electricity— were analysed. This analysis aimed to delineate the discernible impact of the lockdown on high-resolution (minutely) electricity consumption data. The 1-min average electricity consumption data for each heating fuel cluster was categorised into five periods within a day, spanning from morning to late night, for each month from April to August in 2019 and 2020. This segmentation allowed us to scrutinise differences in data distribution (KDE), mean, maximum, and minimum ranges during distinct parts of the day: Morning (5:00–11:59), afternoon (12:01–17:59), evening (18:00–20:59), early night (21:00–23:59), and late night (24:00–04:59). This detailed approach enables the inference of occupant activity at a granular level and facilitates the drawing of more detailed conclusions regarding the intricate interplay between a highly disruptive event and household responses.

Thirdly, the analysis delved into the aggregated 1-min electricity consumption data encompassing the Grid and Battery Energy Storage System (BESS). This investigation aimed to assess the impact of the lockdown on the energy system variables outlined in Fig. 1. Subsequently, a detailed examination of grid and solar PV electricity consumption was conducted across different segments of the day, providing insights into the effects of lockdown on user demand. Furthermore, the study employed the Seasonal-Trend Decomposition (STL) method [47] on grid and solar PV electricity data from 100 households. This approach allowed for a thorough exploration of changes in seasonal trends within total residential demand during the disruptive periods spanning from April to August 2020. A comparative analysis with the corresponding period in 2019 provided valuable context. The R code (from [48]) facilitated the execution of this analysis. Additionally, the research investigated the correlation between hourly electricity consumption data and the average outdoor temperature in the studied locations, as depicted in Supplementary Fig. 1. This inquiry sought to ascertain whether weather conditions significantly influenced electricity consumption patterns.

2.3. Household details

Of the 100 houses, 46 houses had Sonnen ECO 9.43 batteries, and the rest had Sonnen Hybrid 9.53 batteries, where the Solar PV size was 1.71–4.86 kW, and BESS size was 2.5 kW or 3.3 kW (Fig. 2A and B). In terms of Floor area, 67 featured a floor area ranging from 41 to 191 m^2 (Fig. 2C). The distribution included 56 detached residences (comprising 30 houses and 26 bungalows), 12 semi-detached houses, three mid-terrace houses, and six end-terrace houses. Among the 100 monitored homes, 213 occupants resided in 66 houses (34 had no available data). The demographic breakdown revealed 40 children, 138 adults aged 16 and above, and 35 individuals over 65 (Fig. 2D). To examine the construction history of these residences, nine out of the 66 houses (with 34 having no available data) were constructed before 1945, while 25 were built between 1945 and 1980. Another 22 houses were established between 1981 and 2016, and three were newly built. Window configurations varied, with 63 out of 77 houses featuring double-glazed windows, while eight had high-performance, partially double, and single-glazing. Wall constructions ranging from cavity walls with no insulation to various forms of insulation, including partial and complete insulation, were found in the homes. The U-value of the wall constructions ranged from 0.10 to 0.03 W/m^2K. Among the 66 households (with 34 lacking income data), seven reported annual household incomes below £16,000. Fourteen and 19 households fell within the income brackets of £16,000–25,000 and £25,001-45,000, respectively. Additionally, 23 and three households reported annual incomes within the £45,001–70,000 and £70,001–£100,000 ranges.

In terms of household appliances (data available for 66 houses), over 90% of the houses were equipped with essential appliances such as fridges, freezers, microwaves, ovens, toasters, kettles, washing machines, TVs, PC/laptops, and vacuum cleaners (Fig. 2E). Furthermore, high ownership rates were observed for smartphones (86%), dishwashers (85%), tablets (83%), hairdryers (76%), digital/skybox/Apple TV (70%), hair straighteners (52%), and game consoles (33%). Conversely, only a few houses possessed fewer common appliances, such as food processors, blenders, mixers, heat pumps, spas, dehumidifiers, and printers.

Households, on average, exhibited an annual heating demand of 15,933 kWh, with a range spanning from a maximum of 59,130 kWh to a minimum of 1807 kWh. Additionally, the average yearly hot water demand stood at 2624 kWh. The highest and lowest annual hot water demands were recorded among the monitored households at 5396 kWh and 1132 kWh, respectively. Regarding heating appliances, boilers were prevalent in 55 households (Fig. 2F). Of these, 34 relied on gas, while 18 were fuelled by oil (Fig. 2G). Also, 19 houses utilised electric heating systems, encompassing underfloor heating, portable heaters, heat storage, air source heat pumps, and ground source heat pumps (Fig. 2F). Only four households employed unconventional heating sources such as coal, wood logs, and wood pellets. The diversity in heating methods reflected the varied approaches adopted by households to meet their heating and hot water needs.

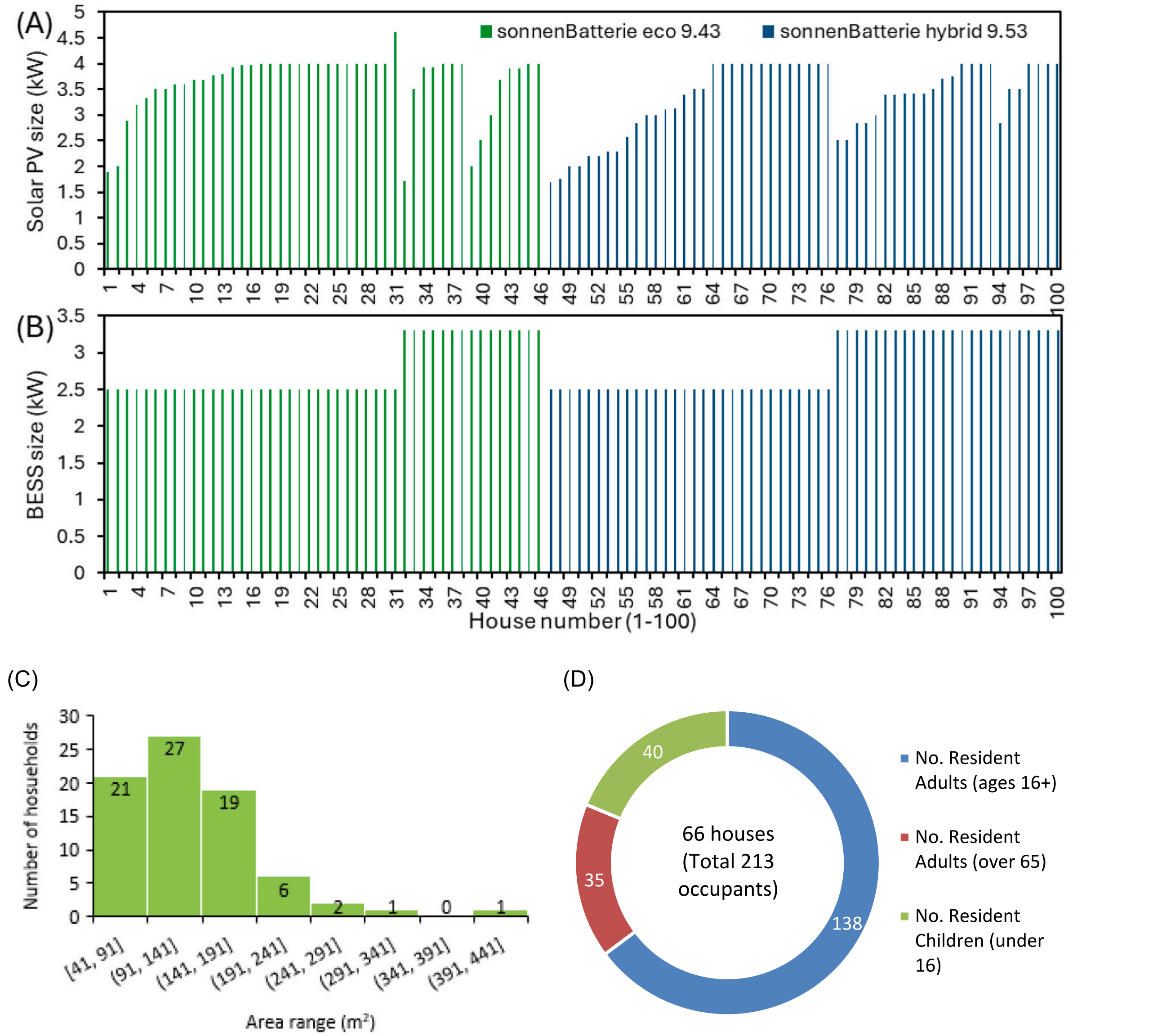

Fig. 2. (A) Solar PV and (B) BESS size in the 100 houses and their battery types; (C) Floor area distribution among 77 houses (23 no data); (D) Number of occupants in 66 Houses (No data for 34 houses); (E) Cumulative number of appliances in 66 houses (there were no data for 34 houses); (F) Heating types in 100 households; (G) Heating fuel used in 100 houses.

3. Results

3.1. Aggregated electricity consumption

The analysis of examining the impact of average temperature on aggregated hourly electricity consumption vs in the studied location of 100 houses in April–August 2020 showed R^2 values for April, May, June, July, and August 2020 were 0.159, 0.201, 0.258, 0.411, and 0.254, respectively (Supplementary Fig. 1). Due to the low correlation, the electricity consumption data were not weather-corrected. Electricity consumption between April and August 2020 decreased significantly, ranging from 1.4% to 10.6% compared to the same period in 2019 (Supplementary Fig. 2). Analysing the aggregated 1-minutely average for 100 houses during the lockdown and subsequent months, the density distribution analysis of electricity consumption revealed a distinct bimodal shape (Supplementary Fig. 2). This bimodal distribution during the lockdown period (April and May 2020) indicated a shift in electricity consumption towards lower and higher consumption bins, suggesting a varied and possibly adaptive response to the unique circumstances imposed by the lockdown. However, the June to August 2020 distribution exhibited a unidirectional shift towards lower consumption bins, maintaining the bimodal characteristic (Supplementary Fig. 2). This shift in distribution during the later months of the study period implies a continued adjustment in electricity consumption patterns, potentially influenced by evolving societal behaviours and changes in restrictions. Notably, although the electricity consumption distribution for July and August 2019 also demonstrated a bimodal pattern, the bimodal distribution became notably more pronounced from June to August 2020.

Electricity consumption analyses on weekdays and weekends during April–August showed that in April and May 2020, weekends had a higher shift towards lower consumption bins than weekdays (Fig. 3A). Average consumption was reduced by 4.70% (weekdays) and 12.26% (weekends) in April, increased by 0.45% (weekdays), and decreased by 6.93% (weekends) in May. However, weekdays and weekends significantly shifted towards lower consumption bins from June to August. In June, the distribution changed from unimodal to bimodal, indicating

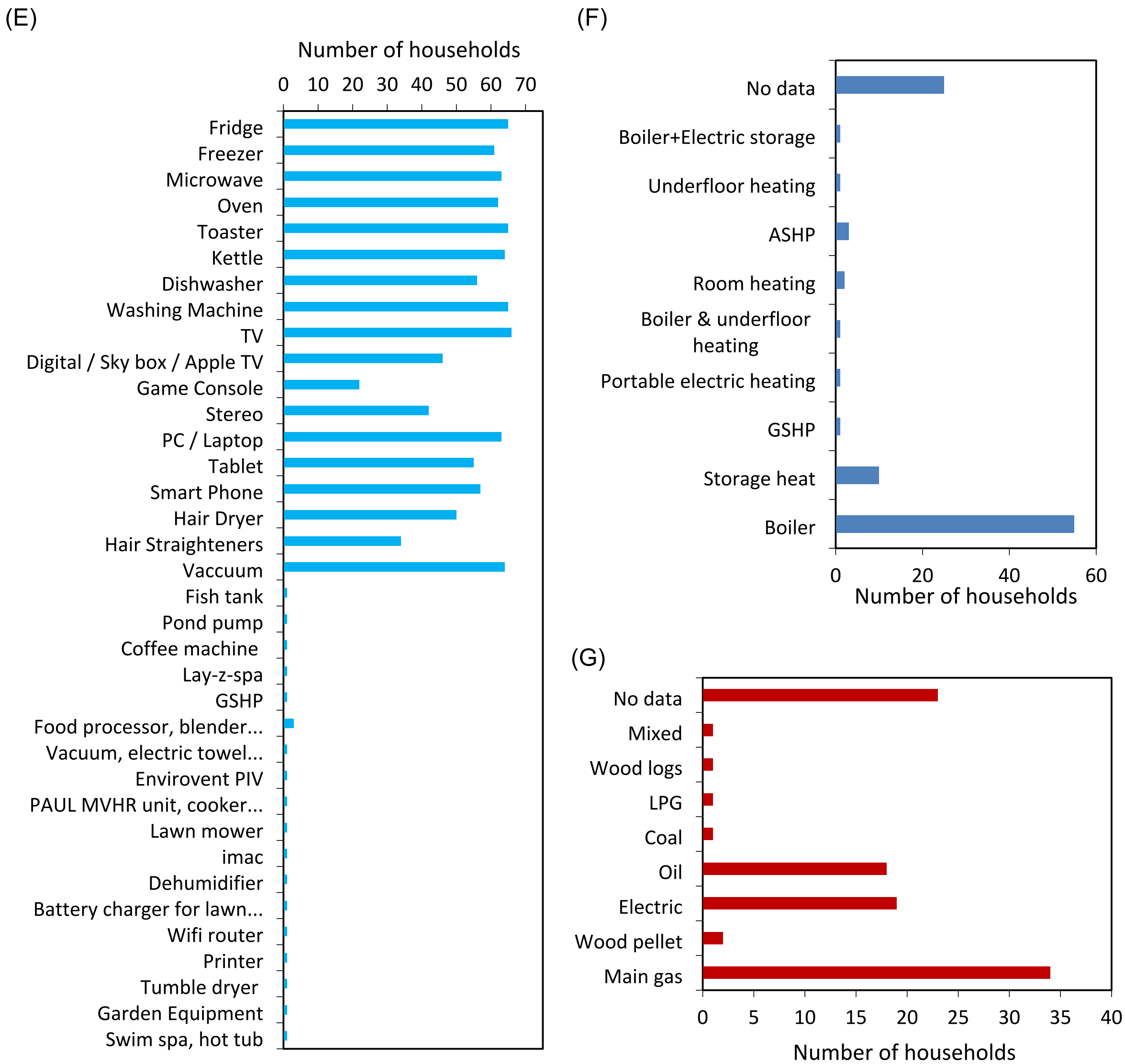

Fig. 2. (*continued*).

two distinct consumption patterns. Moreover, average consumption was reduced by 11.57% (weekdays) and 8.13% (weekends) in June, 3.92% (weekdays) and 7.13% (weekends) in July, and 3.97% (weekdays) and 4.94% (weekends) in August. This observation highlighted the sustained impact of the lockdown and related circumstances on electricity consumption, underscoring a persisting alteration in consumer behaviours and energy usage patterns during the specified period.

A paired *t*-test was performed on data collected from 100 houses, comparing their electricity consumption for April through August in both 2019 and 2020. The null hypothesis was that there would be no statistically significant difference in the mean consumption between the two years. The *p*-values obtained for April through August 2019 and 2020 were all 0.000. In statistical terms, a p-value <0.05 was conventionally considered indicative of statistical significance at a 95% confidence interval. As all the obtained p-values were 0.000, falling well below this threshold, the evidence strongly supported rejecting the null hypothesis. Therefore, with a high confidence level, it showed a statistically significant difference in mean electricity consumption from 2019 to 2020 for each analysed month. These results referred to a notable shift or alteration in electricity consumption patterns among the examined houses during the specified months, highlighting the impact of external factors, such as the COVID-19 pandemic or other influential variables that may have contributed to the observed changes.

We used paired *t*-tests to compare the electricity consumption between weekdays and weekends from April to August 2019 and 2020. The null hypothesis posited that there would be no statistically significant difference in the mean consumption on weekdays and weekends when comparing the years 2019 and 2020. The obtained *p*-values for weekdays and weekends in the analysed months (April to August) for 2019 and 2020 were all 0.000. In statistical terms, a p-value below 0.05 indicated rejecting the null hypothesis at a 95% confidence interval. As all the p-values in our analysis were 0.000, well below the significance threshold, a statistically significant difference existed in mean electricity consumption for both weekdays and weekends when comparing 2019 and 2020 across each month in the specified period (April to August), which signified a notable shift in electricity usage patterns during this timeframe.

Heating fuel was utilised as a critical parameter considering the UK's building stock, leading to the identification of three distinct clusters: gas (34 houses), oil (18 houses), and electricity (19 houses) to classify residences based on heating fuel types. Notably, houses with gas boilers exhibited the most significant changes in 2020 compared to those reliant on oil and electricity (Fig. 3B). A detailed examination of the gas boiler houses revealed a distinct bimodal distribution in April and May 2020, contrasting with the unimodal distribution observed in 2019. This bimodal pattern persisted from April to August 2020. The distribution

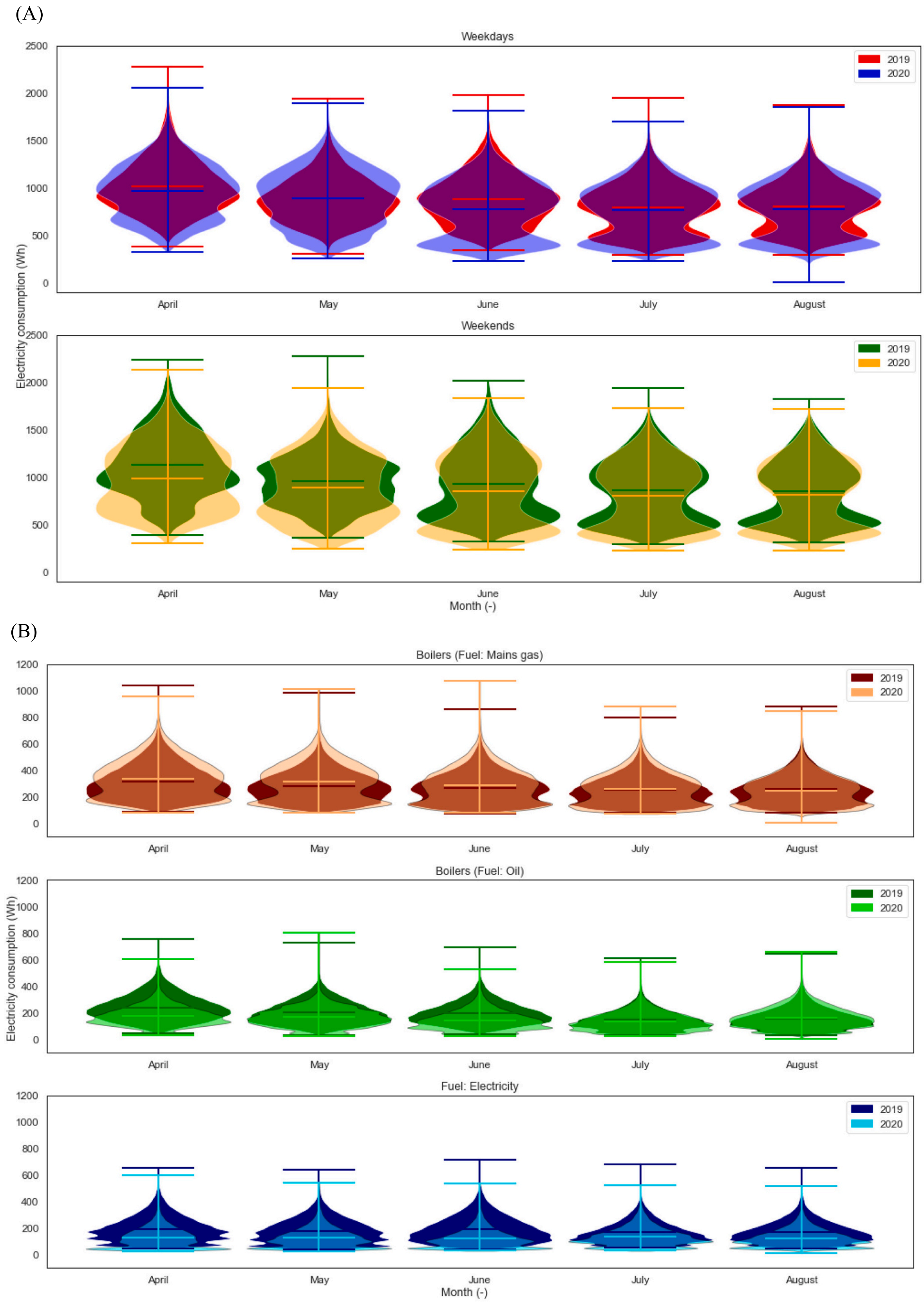

Fig. 3. (A) Aggregated (minutely) electricity consumption distribution of 100 houses for weekdays and weekends in April–August of 2019 and 2020; (B) Aggregated (minutely) electricity consumption distribution for houses with gas, oil, and electricity for heating in April–August of 2019 and 2020. The horizontal line in the middle was the mean of the data, and the top and bottom horizontal lines were the maximum and minimum.

experienced shifts towards both higher and lower consumption bins, with the dominating trend leaning towards higher consumption. Also, the means moved upward compared to 2019, indicating an overall increase in consumption during 2020. Furthermore, our findings showed that houses relying on gas heating experienced a 4–12% rise in average electricity consumption from April to July 2020 compared to the same period in 2019. However, a reversal in trend was observed in August, with average electricity consumption registering a 4–7% decline in 2020 compared to the previous year.

In contrast, residences using oil and electric heating fuels predominantly shifted towards lower consumption distribution in 2020 relative to 2019. For houses with oil-based heating systems, the average electricity demand exhibited reductions ranging from 3 to 29% during April to July and August 2020, compared to the corresponding months in 2019. However, a 4.6% increase in average demand for these houses was observed in August 2020. Houses equipped with electric heating systems demonstrated consistent reductions in electricity demand, ranging from 18 to 37% across April to August 2020 when contrasted with the same months in 2019. This broad analysis provided valuable insights into the diverse and dynamic energy consumption patterns among households with different heating fuel sources during the transformative year 2020.

3.2. Time of use: Aggregated electricity consumption

The analysis of monthly electricity consumption within major heating fuel clusters (gas, oil, and electricity) revealed a notable shift in distribution patterns between 2020 and 2019. The data underwent further categorisation and analysis in five-day intervals to gain in-depth

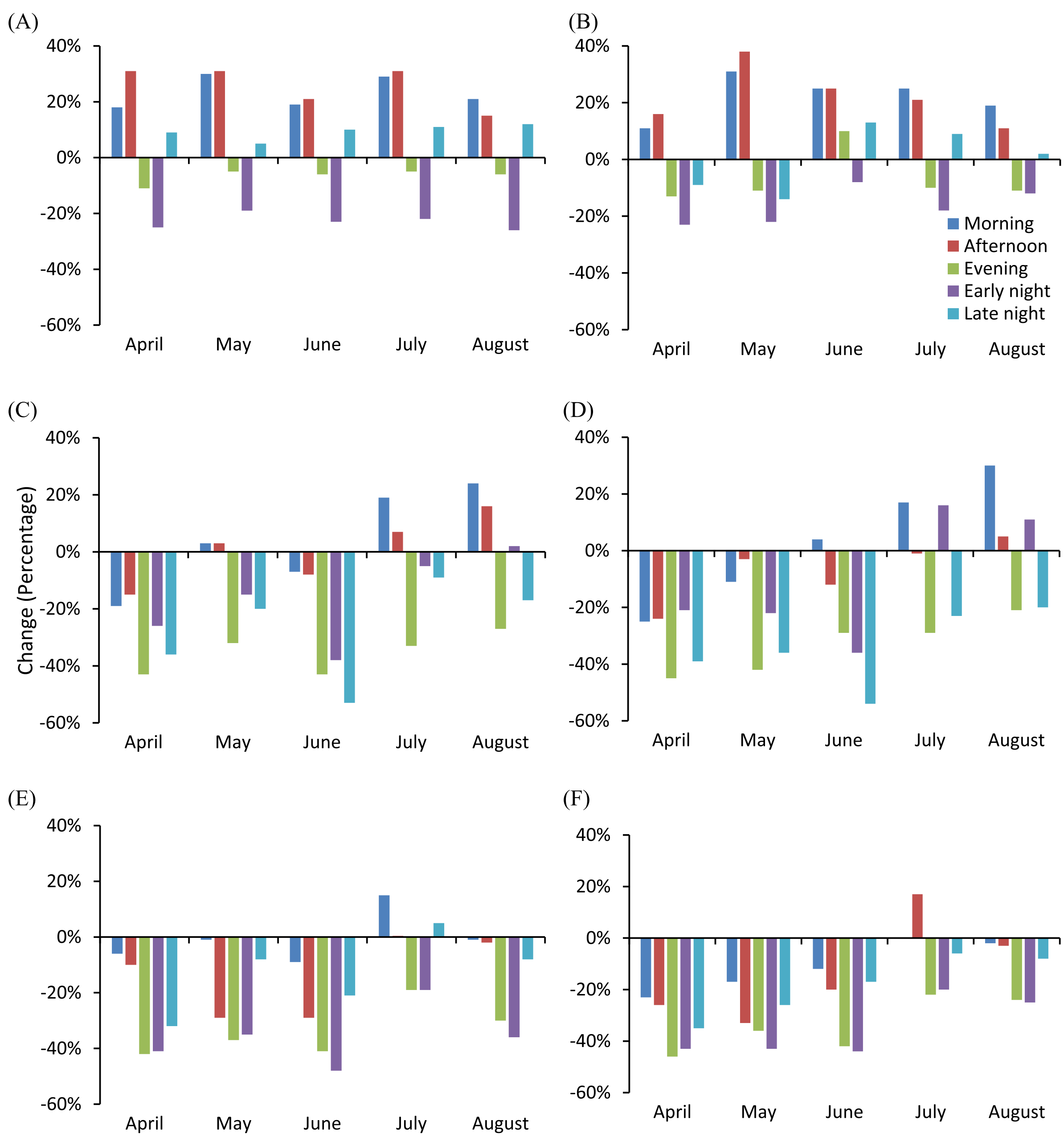

Fig. 4. Change in average 1-minutely electricity consumption in the houses with gas-fuelled heating systems [(A) weekdays and (B) weekends], the houses with oil-fuelled heating systems [(C) weekdays and (D) weekends], and the houses with electric heating systems [(E) weekdays and (F) weekends]in April–August 2020 than 2019.

insights. In the case of 34 houses equipped with gas-fuelled heating systems, a discernible change emerged in the average electricity demand from April to August 2020 compared to 2019 (Supplementary Fig. 3 A and Fig. 4A). On weekdays during this period, the morning and afternoon electricity demand in these houses increased by an average of 10–30% and 15–31%, respectively. Conversely, during the evening and early nights, there was a 5–13% reduction and 19–27%, followed by an upswing of 5–15% in late-night hours and weekends displayed a similar trend, with an elevated demand of 11–31% in the morning and 11–38% in the afternoon. Evening and early-night demand decreased 5–13% (except for a remarkable 10% increase in June 2020) and a subsequent 2–15% rise in late-night hours from April to August 2020 compared to 2019 (Supplementary Fig. 3B and Fig. 4B). Remarkably, there was an overall reduction of 15.2% in average electricity demand in June–April, suggesting a potential influence of the phased easing of lockdown measures initiated in mid-May. This period coincided with the phased reopening of schools, colleges, and nurseries in England starting 01 June 2020 [49]. The observed decline in electricity consumption during morning and afternoon hours in the monitored houses from June to August could be attributed to a shift towards work-from-home, contrasting with the April 2020 lockdown period. This finding highlights the evolving dynamics of energy consumption patterns in response to changing societal circumstances.

In the 18 residences equipped with oil-fuelled heating systems, a nuanced analysis of weekday electricity consumption patterns unveiled intriguing trends. Comparing April and June 2020 to the preceding year, the average electricity demand exhibited a notable reduction ranging from 15% to 43% during weekdays. The most significant decrease, reaching 43%, occurred in the evening hours of April, while June experienced a peak reduction of 53% during the late night. However, a departure from this trend was observed in May, July, and August 2020, when demand increased from 3% to 24% during the morning and afternoon. Subsequently, the demand decreased by 2% to 33% in the evenings to late nights compared to the corresponding periods in 2019. An exception to this general decline was noted on the early nights in August 2020, when demand increased by 2% compared to the previous year (Supplementary Fig. 4A and Fig. 4C).

During weekends, a divergent pattern emerged. In June 2020, the average electricity demand demonstrated a 4% increase in the morning, followed by a decrease in the afternoon (12%) and a substantial drop in the late night (54%) compared to 2019. Conversely, August 2020 witnessed a 17% increase in the morning, a 1% reduction in the afternoon, and a 29% decrease in the evening. We experienced a resurgence in the early night with a 16% increase, followed by a 23% reduction in the late night compared to the same period in 2019. For a more granular understanding, a closer examination of minute-level electricity demand in August 2020 revealed intricate fluctuations. There was an upsurge in the morning and afternoon, followed by a decline in the evening and a subsequent rise in the early night, culminating in a reduction during late nights (Supplementary Fig. 4B and Fig. 4D). These detailed insights illuminated the dynamic nature of electricity consumption patterns in households with oil-fuelled heating systems, showcasing the impact of seasonal and temporal variations on energy usage during the specified timeframes.

In the 19 residences equipped with electric heating systems, notable fluctuations in average electricity demand were observed across various months in 2020 compared to the corresponding periods in 2019. During April 2020, the average electricity demand reduced from 6% to 42%, with the most substantial decrease occurring in the evening. Similarly, the reduction ranged from 1% to 37% in May, again with the highest decrease observed in the evening. In June, the average electricity demand decreased from 9% to 48%, with the most pronounced reduction recorded in the early night. In August, the decline ranged from 1% to 36%, with the highest decrease observed in the early night. In contrast, July 2020 witnessed an upswing in average electricity demand, registering an increase of 15% in the morning and 0.4% in the afternoon, followed by reductions of 5% to 19% in the evening and late-night compared to 2019 (Supplementary Fig. 5 A and Fig. 4E).

Analysing weekend patterns in April 2020, average electricity demand demonstrated a decrease ranging from 26% to 46% in the evening, 17% to 43% in the early night in May, 12% to 44% in the early night in June, and 2% to 25% in the early night in August, all in comparison to the respective weekends in 2019. In July 2020, average electricity demand increased by 0.2% in the morning and 17% in the afternoon, followed by reductions of 6% to 22% in the evening and late-night compared to July 2019 (Supplementary Fig. 5B and Fig. 4F). These findings underscore the dynamic impact of temporal and seasonal variations on residential electricity consumption patterns, particularly in homes utilising electric heating systems.

Considering that the months (April to August) under study did not coincide with the peak heating season, initial expectations leaned towards anticipating more noticeable changes in homes relying on electric heating. A thorough examination of the construction period of heating fuel types yielded only partial evidence to support this assumption. Among the 100 houses analysed, 71 were equipped with gas, oil, and electricity-based heating systems. Supplementary Fig. 6 A illustrates that 65% of the houses with gas-based heating were constructed before 1980, while 90% and 50% of oil- and electricity-based heating homes shared this characteristic. However, a nuanced pattern emerged when cross-referencing heating fuel use with the age-wise occupancy of the houses (Supplementary Fig. 6B). Specifically, 21 houses with gas-based heating systems accommodated 55 adults and 17 children (with no occupancy data for 13 houses). However, 12 houses with oil-based heating systems housed 36 adults and seven children (with no data available for six houses). In comparison, 16 houses with electricity-based heating systems accommodated 34 adults and ten children (with no occupancy data for three houses). During the lockdown period, it became apparent that the higher average demand in houses relying on gas for heating, as opposed to oil and electricity, might be attributed to more adults working and children engaging in remote schooling within these specific households. This demographic factor likely contributed to the observed variations in energy consumption among the different heating system categories.

3.3. Grid and Solar PV electricity consumption

The overall solar PV generation experienced significant fluctuations throughout April, May, June, July, and August 2020 compared to the preceding year. Notably, the average Solar PV generation exhibited an impressive increase of 11.3% and 9.6% in April and May 2020, respectively, surpassing 2019 (Fig. 5A). However, a subsequent 12–20% decline was observed in Solar PV generation from June to August 2020. Conversely, examining mean battery activities (charge, discharge, and grid export) from April to August 2020 revealed minimal variations compared to 2019 (Supplementary Fig. 7), which remained consistent even as aggregated electricity consumption experienced a significant reduction (Supplementary Fig. 1). Two specific types of instantaneous consumption were examined within the homes under study: grid and solar PV electricity. In the case of solar PV self-consumption, there was a significant surge in mean electricity consumption during the lockdown months of April and May 2020, recording increases of 7.6% and 6.9%, respectively, compared to 2019 (Fig. 5A). The increase coincided with an elevation in solar radiation during the same period (Fig. 5B). Following the easing of lockdown measures, the mean consumption exhibited minimal increases (ranging from 0.3% to 0.8%). An intriguing observation was the shift towards higher consumption bins during the lockdown months, explicitly maintaining an unimodal distribution.

In contrast, grid electricity consumption depicted an average demand reduction of 2% to 25% (Fig. 5C). The most substantial reduction occurred in April (25%) and May (24%) 2020, starkly contrasting to the corresponding months 2019. June witnessed a 20% reduction, followed by a 2% increase in July and a 2.5% decrease in August 2020. Notably,

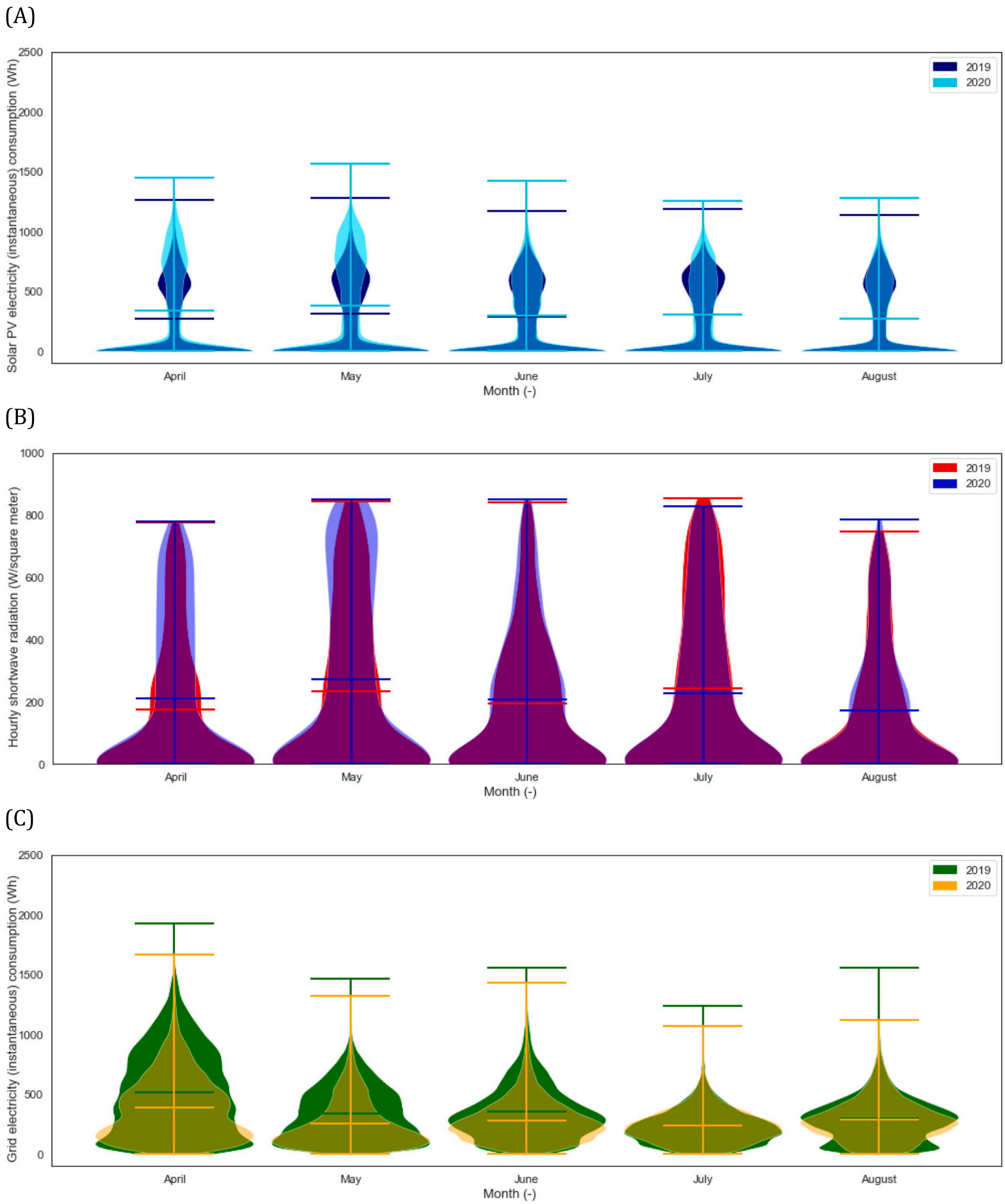

Fig. 5. (A)Minutely aggregated Solar PV electricity consumption, (B) Hourly average solar radiation comparison, and (C) Minutely grid electricity consumption comparison between April–August 2019 and 2020.

the electricity demand shifted towards lower consumption bins, resulting in a bimodal distribution in April and a return to an unimodal distribution in May 2020. These nuanced patterns suggest a complex interplay of factors influencing energy consumption dynamics during the studied period.

3.4. Time of use: Solar PV and grid electricity

Between April and August 2020, there was a notable surge in Solar PV electricity consumption during weekday morning hours, witnessing an increase ranging from 39% to 56%, and on weekends, experiencing a broader range of 25% to 84% (Supplementary Fig. 8 and Fig. 6). Additionally, in the afternoons during the lockdown period, there was a substantial rise in electricity demand, ranging from 12.6% to 13.5% on weekdays and 2% to 5% on weekends. In the evenings, however, there was a reduction in demand during April to August 2020 compared to the same period in 2019.

Demand decreased during the mornings of April and May 2020, ranging from 21% to 34% on weekdays and 30% to 53% on weekends, compared to 2019 (Supplementary Fig. 10 and Fig. 6) while examining the grid electricity consumption within the studied homes. In the afternoons, there was a 5% increase in demand on weekdays but a substantial 53% decrease on weekends in April 2020, relative to 2019. However, demand decreased by 7% on weekdays and 4% on weekends in May. During the evenings, early nights, and late nights, the grid electricity demand experienced a reduction ranging from 7% to 30% on weekdays and 7% to 48% on weekends throughout the first lockdown in 2020 compared to 2019. The disparity in grid electricity demand notably diminished in June 2020 post-lockdown. Moreover, the electricity demand on different days, weekdays and weekends in July and August 2020 closely resembled the patterns observed in 2019. The analysis showcased the dynamic shifts in electricity consumption patterns, particularly in the context of solar PV energy and grid demand, during the unprecedented events of the 2020 lockdown.

3.5. Seasonal-trend decomposition analysis

The analysis of aggregated electricity consumption and its temporal distribution throughout the day revealed a significant influence of the COVID-19 lockdown on both solar PV generation and grid electricity consumption. Seasonal-trend decomposition using Loess (STL) analysis was implemented to investigate the seasonal electricity usage trends. The temporal evolution of electricity demand was focused on distinguishing between Solar PV-generated electricity and grid-supplied electricity. In 2019, there was a distinctive pattern in Solar PV electricity demand. There was an initial surge in demand during weeks 1 and 2, followed by a decline in week three, only to see a resurgence in demand during week 04 April 2019 (Fig. 7). The following year, May 2020, displayed a change from the trends in 2019. While the demand decreased in the first week, a notable increase was observed in the subsequent three weeks compared to 2019. This shift in consumption patterns during the initial stages of the lockdown might have demonstrated a dynamic response to the modified societal and economic conditions. As the lockdown persisted, the divergence in seasonal trends between 2019 and 2020 became less pronounced, particularly from June through August 2020. Therefore, this analysis suggested a stabilisation or adaptation in electricity consumption behaviours during the later stages of the lockdown. The minimal difference in seasonal trends indicated a potential acclimatisation to the 'new normal' as people and industries adjusted their activities and energy consumption patterns to the ongoing restrictions. The STL analysis allowed us to separate the various components contributing to the seasonal trends. It provided

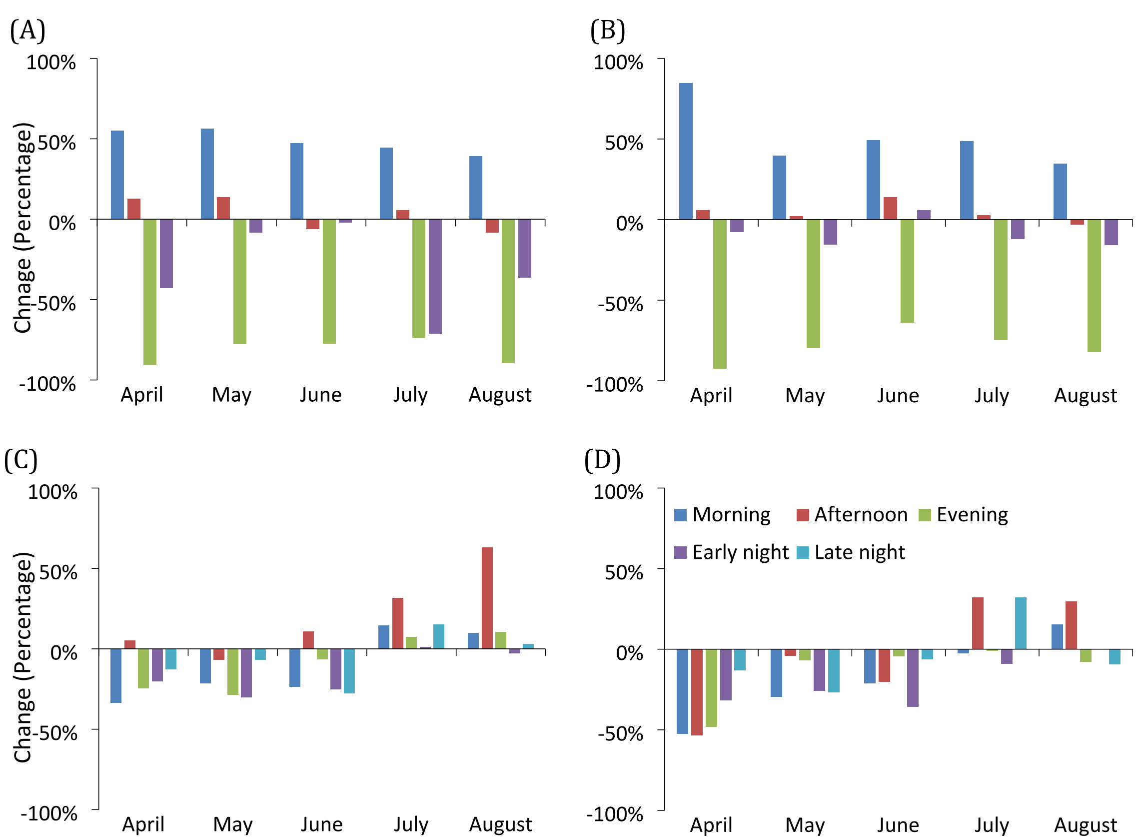

Fig. 6. Minutely average solar PV electricity consumption between April–August 2019 and 2020 during (A) weekdays and (B) weekends. Minutely average grid electricity consumption between April–August 2019 and 2020 during (C) weekdays and (D) weekends. Exceptional Minutely average solar PV electricity consumption during late nights of weekdays and weekends (Supplementary Fig. 9), but the amount of consumption was minuscule.

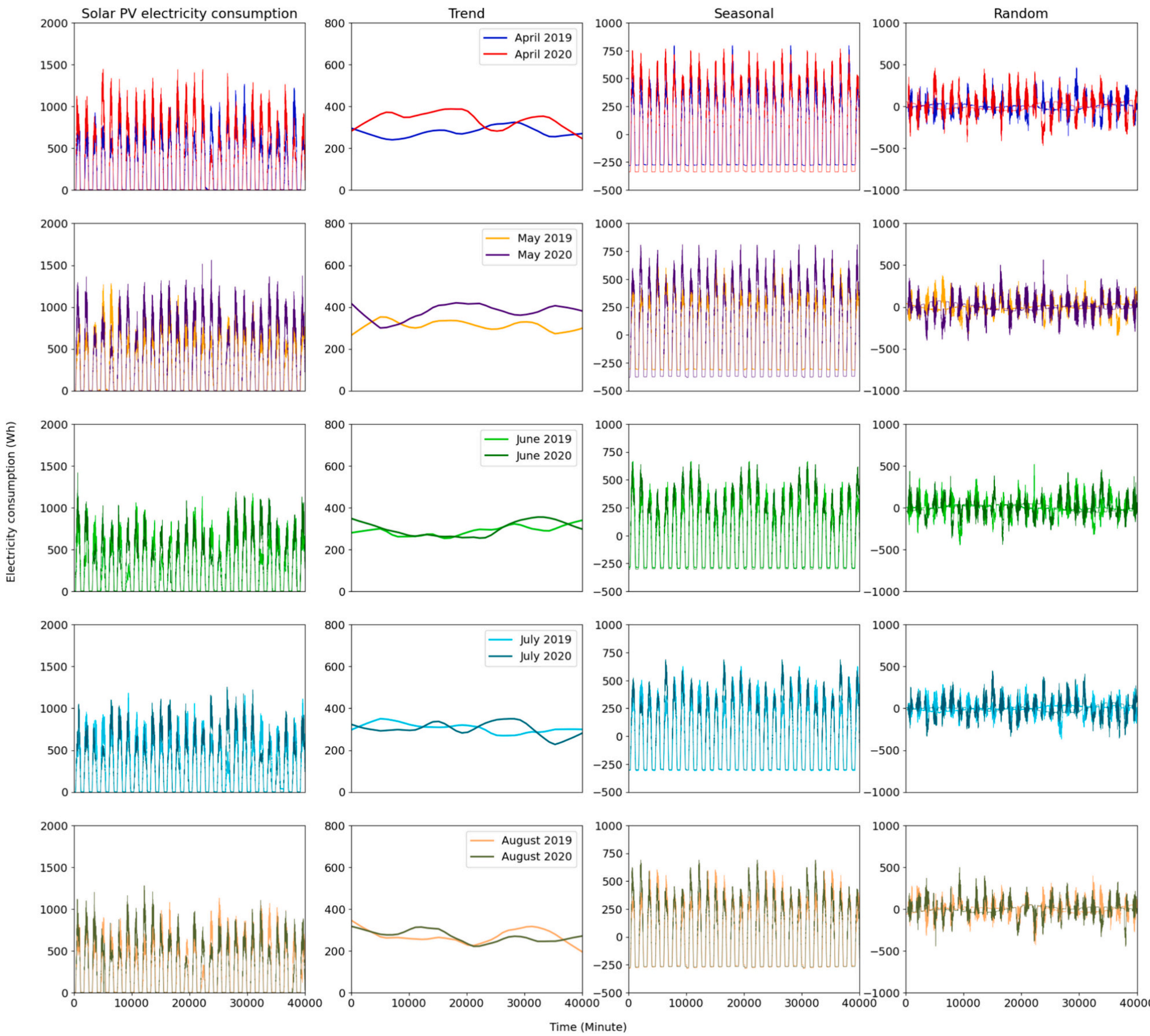

Fig. 7. Seasonal-trend decomposition using Loess (STL) analysis of minutely aggregated solar PV electricity consumption during April–August 2019 and 2020.

insights into how much of the observed variability could be attributed to long-term trends, seasonal fluctuations, and irregular patterns, thus facilitating a better understanding of the intricate dynamics of electricity consumption.

The fluctuations in Solar PV-generated electricity and grid electricity consumption during the lockdown periods underscored the dynamic interplay between external factors and energy usage patterns. These patterns reflected the immediate impact of the lockdown and hinted at the adaptive measures taken by individuals and organisations in response to the changing circumstances. The STL analysis revealed the evolving nature of electricity consumption during the COVID-19 lockdown. From initial disruptions marked by deviations in demand patterns to a subsequent stabilisation and convergence to a 'new normal,' the intricate dynamics of energy consumption became apparent. This nuanced understanding could be vital for policymakers, energy planners, and researchers as they navigate the complexities of post-lockdown energy scenarios and plan for a more resilient and sustainable future.

An intriguing pattern emerged during the lockdown period in the context of grid electricity. In the initial weeks (weeks 1–2) of the lockdown in April 2020, there was an evident reduction in demand compared to the corresponding period in 2019 (Fig. 8). However, this decline in demand was followed by a somewhat unexpected increase in week three, only to decrease again in week four of April 2020. These fluctuations in demand during the early weeks of the lockdown denoted the COVID-19 lockdown's influence on energy consumption patterns.

In May 2020, the demand reduction continued, albeit with a slight increase in weeks 1 and 2. This nuanced shift in demand dynamics hinted at the evolving relationship between energy usage and the changing landscape of work and daily activities during the extended lockdown period. As the lockdown progressed, an interesting observation unfolded during the subsequent months of June to August 2020. The seasonal trends in electricity demand exhibited a minimal impact during this period, which could indicate a certain level of adaptability and stabilisation in the energy consumption patterns as people adjust to the new normal and adapt their lifestyles to the ongoing challenges.

4. Discussions

The initial COVID-19-induced lockdown in the UK on 23 March 2020 had profound implications for residential electricity consumption, as evidenced by granular data analysis from 100 houses in a southwestern UK city. The study revealed a 7–27% increase in daily total electricity consumption during the analysed lockdown weekdays in April and May 2020 compared to 2019. Although total electricity demand decreased

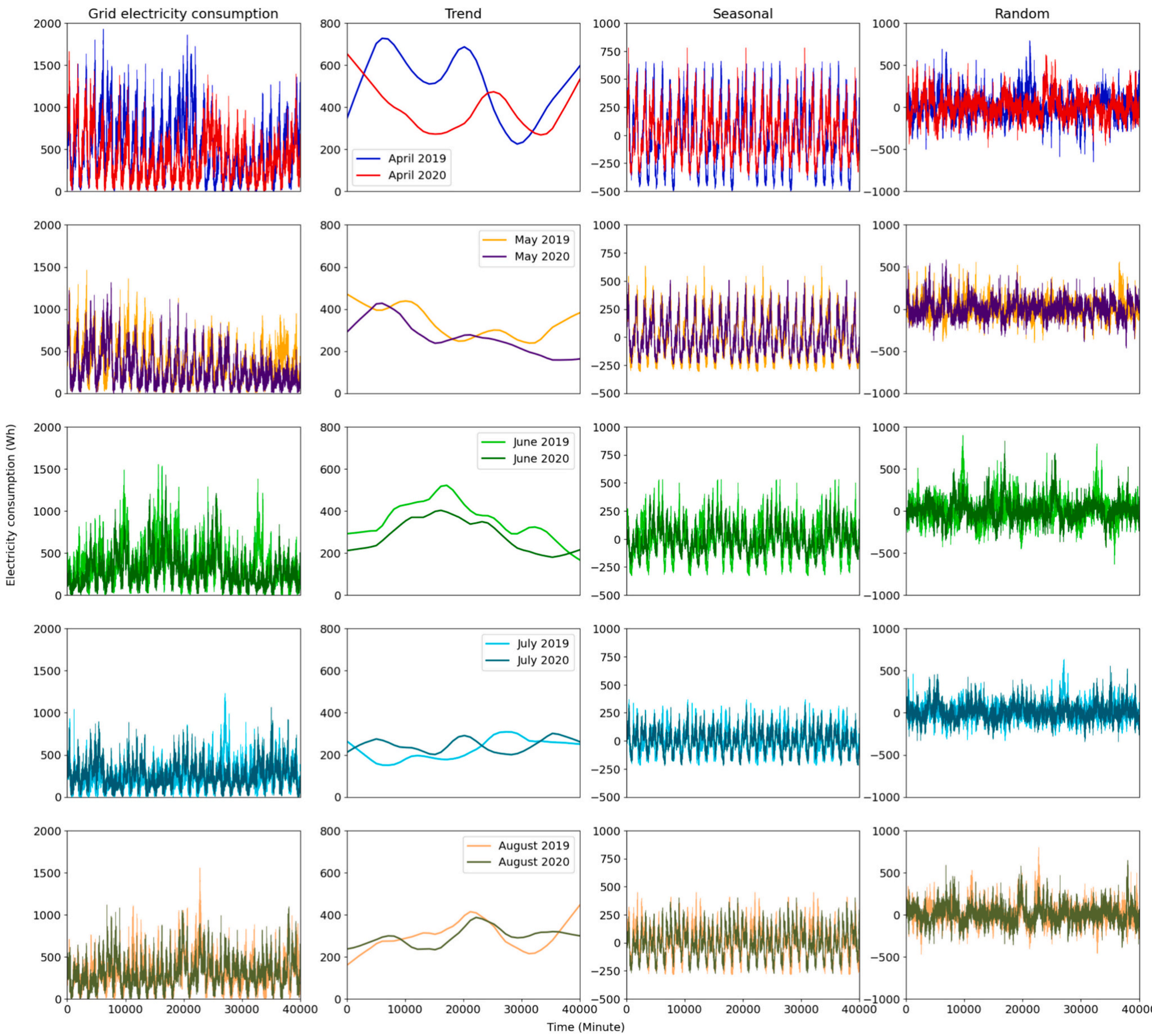

Fig. 8. Seasonal-trend decomposition using Loess (STL) analysis of minutely aggregated grid electricity consumption during April–August 2019 and 2020.

after the phased relaxation of lockdown measures from mid-May onwards, enduring changes in residential electricity consumption patterns persisted from June to August 2020. Despite lifting the lockdown, work-from-home continued as offices and institutions remained closed, contributing to sustained alterations in electricity consumption behaviours. Notably, minutely average electricity consumption exhibited a 6.4% and 1.4% reduction in April and May 2020, respectively, compared to the corresponding months in 2019 within the studied 100 houses. The analysis further illustrated a shift in electricity demand distribution from an unimodal pattern in the summer to a bimodal distribution, particularly evident during weekdays and weekends in April and May.

The lockdown-induced bimodal distribution shift, characterised by distinct clusters of higher and lower electricity consumption bins, hinted at two separate demand patterns likely influenced by the widespread adoption of work-from-home and home-based schooling. Moreover, a discernible shift towards lower energy consumption distribution from April to August 2020 prompted inquiries into the nature of home activities during the lockdown and their subsequent impact on electricity demand. As heating was the dominating demand component of UK homes, an evaluation of house clusters based on heating fuel sources revealed a significant divergence in distribution, notably in houses with gas boilers compared to those with oil and electricity-fuelled heating systems. Even though the study excluded daily heating usage during the summer and autumn, the observed difference in distribution raised essential questions about household energy use practices. Examining the average electricity consumption of the three clusters across five periods of the day unveiled two distinct consumption groups. Houses with gas-fuelled heating systems exhibited a 10–30% and 15–31% increase in electricity consumption during the morning and afternoon, followed by a reduction in demand during the evening and early night. Interestingly, demand increased again late at night in August 2020 compared to the same period in 2019. Conversely, houses with oil and electricity-fuelled heating systems generally demonstrated reduced electricity consumption from April to August 2020, except for specific periods in July and August.

The observed contrasting electricity consumption patterns during and after the lockdown potentially contributed to the emergence of the bimodal distribution in 2020, deviating from the unimodal distribution patterns observed in 2019. Furthermore, the prevalence of adults and children in houses with gas-fuelled heating systems, as opposed to those with oil and electricity-fuelled systems, may have increased electricity demand due to the concurrent demands of work-from-home and schooling from home. While a detailed evaluation of household energy use practices was not feasible with the available granular electricity demand dataset, the study highlighted the significant impact of the COVID-19 pandemic-induced lockdown on residential electricity use in the UK. The differentiated effect on clusters of houses based on heating fuel sources underscores the need for further investigation to unravel the intricacies of residential practices within these households.

An STL analysis was conducted to gain an in-depth analysis of these patterns. This analysis provided insights into the minutiae of solar PV and grid electricity demand trends during the UK's first lockdown. Intriguingly, the 1-minutely data revealed that solar PV and grid electricity demand demonstrated opposing trends, showcasing the impact of localised solar generation on overall demand. As the lockdown gradually eased in mid-May 2020, an interesting trend emerged. The increased adoption of solar PV and the subsequent decrease in grid electricity consumption started to align with patterns observed in 2019. The trend indicated a potential correlation between the relaxation of lockdown measures and a return to more traditional energy consumption patterns.

The change between solar PV and grid electricity demand highlighted the adaptability and responsiveness of energy consumption to external factors such as lockdown measures. The data suggested that as societal restrictions eased, there was a discernible shift towards a more familiar energy consumption landscape, potentially signalling a return to pre-pandemic habits. In conclusion, the analysis of grid electricity demand during the lockdown period revealed a dynamic interplay of factors shaping energy consumption patterns. The data painted a rich tapestry of how societal changes influenced energy use, from the initial reduction in demand to the subsequent fluctuations and eventual alignment with pre-lockdown trends. The STL analysis provided a granular understanding of the intricate relationship between solar PV and grid electricity demand, shedding light on the adaptability of energy consumption in the face of unprecedented challenges.

The surge in residential electricity consumption, particularly during the COVID-19-induced lockdown, had opened a new realm of exploration into the dynamics of energy use and its potential implications for sustainable practices. One notable aspect deserving further investigation was the increased consumption of solar PV-generated electricity, a phenomenon intertwined with the rise in work-from-home. As revealed by the granular analysis of electricity consumption patterns in the southwest UK, the lockdown led to an overall increase in daily total electricity consumption. It triggered lasting changes in residential consumption behaviours. Amidst this shift, the specific uptick in solar PV-generated electricity consumption holds promising implications, especially in fostering sustainable and decentralised energy practices.

Adopting work-from-home or remote work became a prominent feature of the post-lockdown era, with many individuals continuing to work from home even after the formal easing of restrictions. This prolonged reliance on home-based work has contributed to an increased demand for electricity, a portion of which may be supplied by solar PV systems installed in residential properties. Understanding the extent and dynamics of this increase in solar PV-generated electricity consumption might be crucial for several reasons:

- Firstly, it raised inquiries about the efficiency and capacity of existing residential solar PV systems to meet the heightened demand. Assessing the performance of these systems during increased consumption periods, such as daytime work hours, becomes essential. This evaluation ensures that solar PV installations should be optimised to effectively support households engaged in sustained work-from-home energy needs.
- Secondly, the potential impact on tariff systems was a crucial aspect that deserves further exploration. The increased reliance on solar PV-generated electricity for work-from-home might necessitate a re-evaluation of existing tariff structures. Tailoring tariffs to incentivise working from home and encouraging decentralised renewables, such as solar PV, could have far-reaching effects on the sustainability of energy systems. Such policy, in turn, might contribute to a more distributed and resilient energy grid, reducing dependence on centralised power sources and mitigating the environmental impact.
- Thirdly, it could significantly contribute to mitigating the 'Duck Curve.' Effectively managing the surplus solar energy and meeting evening peak demand poses challenges, necessitating solutions like energy storage and demand response. This study showed that prolonged work-from-home and home-based schooling sustained altered consumption behaviours and the surge in solar PV-generated electricity consumption, particularly in the morning and afternoon, which might mitigate the duck curve. In previous studies, different mitigation strategies — such as replacing thermal power stations with CSP stations [34], enhancing power system flexibility [35], optimised dynamic pricing profiles leveraging air-conditioning systems and distributed storage [31], pre-cooling strategies in residential households [36], IOT [38]— were examined. However, this study showed that work-from-home/remote work and decentralised solar PV concurrently might also mitigate the duck curve. As a conceptual illustration in Fig. 9, the remote work would increase occupants' solar PV self-consumption (at home) in the morning and afternoon, reducing the grid demand for office work and allowing the BESS system to store access power generated by the Solar PV to be used in the evening. Although the grid demand reduction in the morning and afternoon would increase the demand difference between the afternoon and evening, the demand reduction in the evening would significantly reduce the jump needed in grid electricity production. Thus, the proposed remote work would enable greater penetration of (decentralised) solar PV energy into the total energy system, particularly in the summer, and lower grid electricity production needed in the evening (Fig. 9). This study's novel outcome reinforced the ongoing debate on work-from-home/remote work/hybrid work in the post-pandemic world, which could become a standard rather than a temporary solution to pandemic or natural disasters [50,51,52].
- Additionally, comprehending the correlation between the heightened consumption of solar PV-generated electricity and work-from-home could guide the formulation of policies advocating sustainable practices. Governments and energy regulatory bodies might evaluate introducing initiatives that facilitate the integration of renewable energy sources into home-based work environments, aligning with the demands of the 'Duck Curve'. Relying more on solar PV for work-from-home presents opportunities and challenges, prompting the need to explore performance optimisation, reassess tariffs, and develop sustainable policies. Also, this could incentivise households to invest in or upgrade solar PV systems, fostering a more sustainable and environmentally conscious approach to work-from-home.

Therefore, the increased consumption of solar PV-generated electricity due to the paradigm shift towards working from home represents an intriguing area for further investigation. This study was vital for optimising the performance of existing solar PV installations and shaping future energy policies and tariff structures. The complex relationship offers an opportunity to develop innovative strategies that support the increasing demand for work-from-home and contribute to a more sustainable and resilient energy landscape.

5. Conclusion

In our study, an examination of aggregated electricity demand revealed a 1.4–10% reduction in consumption. Notably, the case studies were equipped with Battery Energy Storage Systems (BESS), utilising electricity sourced from both solar photovoltaic (PV) panels and the

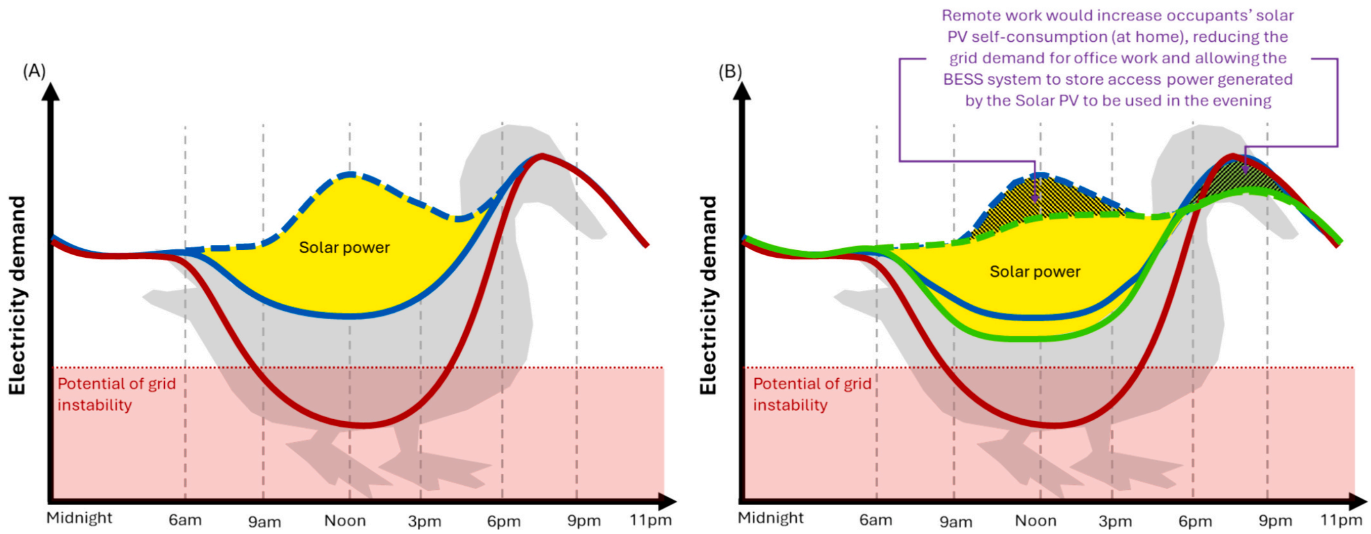

Fig. 9. Conceptual illustration of (A) a Duck Curve, (B) Potential of the solar PV self-consumption (due to remote work) and BESS in mitigating the 'Duck Curve'. Here, the (solid) blue line is the net grid electricity demand, and the (dotted) blue line is the red line is the reduced grid electricity demand due to higher solar PV generation, which might cause grid instability, leading to curtailment and hatched yellow and green area in (B) denoted the Remote work would increase occupants' solar PV self-consumption (at home), reducing the grid demand for office work and allowing the BESS system to store access power generated by the Solar PV to be used in the evening. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

conventional grid. Our findings delineated a notable surge of 7.6–6.9% in solar PV electricity demand, concurrent with a substantial 24–25% downturn in grid electricity consumption during the lockdown period. The noticeable rise in solar PV electricity consumption during morning and afternoon aligned with the extended periods of work-from-home and schooling from home. This trend highlighted solar PV sources' significant role in residential electricity consumption during the lockdown. Adopting work-from-home and home-based education led to a surge in self-consumption of solar PV electricity.

The study revealed that households with solar PV systems contributed surplus electricity to the grid yet experienced a shift towards consuming most energy during morning and afternoon peak usage periods. While this pattern reduced nighttime energy consumption, it resulted in an overall increase in electricity demand during the lockdown. The increased generation of decentralised renewable solar electricity during remote work periods was observed during the lockdown, albeit returning to 2019 levels post-lockdown. Additionally, Seasonal-Trend Decomposition using Loess (STL) analysis provided insights into solar PV and grid electricity demand trends during the lockdown, highlighting the impact of localised solar generation on overall demand. As lockdown measures eased, a reversion to traditional consumption patterns aligned with 2019 trends was observed, indicating a potential correlation between lockdown relaxation and energy usage shifts. These findings emphasise the necessity for further research to comprehend evolving energy dynamics amidst societal disruptions like the COVID-19 pandemic.

Moreover, the impact of heightened self-consumption on the financial returns from grid feed-in necessitates further exploration. Our study raised intriguing questions about shifts in household practices and utilising decentralised renewables. The elevated consumption of solar PV-generated electricity amid the prevalence of work-from-home demands a thorough investigation, given its potential to influence the development of tariff systems that incentivise working from home and the expanded use of decentralised renewables. The complex interaction between residential behaviours and energy consumption patterns during the lockdown period underscored the need for further research to understand better and optimise the integration of renewable energy sources in our evolving societal landscape.

Furthermore, our findings might contribute valuable insights into mitigating the 'Duck Curve' challenge. The observed shift towards increased solar PV consumption during daytime peak hours aligns with the typical dip in electricity demand during daylight hours, potentially addressing the timing misalignment between solar power generation and peak energy demand. Our research suggested encouraging work-from-home practices and optimising solar PV systems to meet heightened daytime consumption could help smooth out the 'Duck Curve,' which could lead to more efficient and sustainable energy grid management, reducing our dependence on centralised power sources and promoting environmentally conscious energy consumption.

In addition to the insights, it's imperative to acknowledge the inherent limitation stemming from the sample size of 100 households in the UK, which may constrain the generalisability of our findings. While our study offers valuable insights into decentralised renewable energy consumption dynamics and its implications for grid management, further research on a larger, countrywide scale is warranted to validate and expand upon our observations. Moreover, developing comprehensive software packages or policy implications based on our findings requires extensive research and development efforts, which fall beyond the scope of our study. Nevertheless, our research lays a solid foundation for future investigations to explore the scalability of our findings and develop practical solutions applicable at a national or even international level. Therefore, future research endeavours could focus on conducting large-scale studies encompassing diverse geographical regions and demographic profiles to enhance the robustness and applicability of our findings. Additionally, efforts to translate our research insights into actionable policies and technologies, such as developing software packages or integration strategies for national control centres operated by transmission system operators (TSOs), hold significant promise for advancing the integration of renewable energy sources into mainstream energy systems.

CRediT authorship contribution statement

Kumar Biswajit Debnath: Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **David P. Jenkins:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Sandhya Patidar:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Andrew D. Peacock:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

David P Jenkins reports financial support was provided by the Engineering and Physical Sciences Research Council. Andrew D Peacock reports financial support was provided by Innovate UK. If there are other authors, they 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

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.123378.

References

[1] BFPG. COVID-19 Timeline. Britith Poreign Policy Group; 2020 [Online]. Available: https://bfpg.co.uk/2020/04/covid-19-timeline/. [Accessed 2020].
[2] JHU. COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU). Johns Hopkins University; 2020. 29 06. [Online]. Available: https://coronavirus.jhu.edu/map.html. [Accessed 29 06 2020].
[3] ONS. Key workers: population and characteristics, 2019. Office for National Statistics; May 2020 [Online]. Available: https://www.gov.uk/government/statistics/key-workers-population-and-characteristics-2019. [Accessed March 2021].
[4] ONS. Coronavirus Job Retention Scheme statistics: July 2020. Office for National Statistics; 16 July 2020 [Online]. Available: https://www.gov.uk/government/statistics/coronavirus-job-retention-scheme-statistics-july-2020/coronavirus-job-retention-scheme-statistics-july-2020. [Accessed March 2021].
[5] ONS. Coronavirus and homeworking in the UK: April 2020. Office for National Statistics; 8 July 2020 [Online]. Available: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/coronavirusandhomeworkingintheuk/april2020. [Accessed March 2021].
[6] IES. On Notice: Estimating the impact on redundancies of the Covid-19 crisis. Institute for Employment Studies; 2020.
[7] Anderson B, James P. Covid-19 lockdown: impacts on GB electricity demand and CO2 emissions. Build Cities 2021;2(1).
[8] National Grid. 4 ways lockdown life affected UK electricity use. 21 07. 2020 [Online]. Available: https://www.nationalgrid.com/uk/stories/grid-at-work-stories/4-ways-lockdown-life-affected-uk-electricity-use.
[9] Santiago I, Moreno-Munoz A, Quintero-Jiménez P, Garcia-Torres F, Gonzalez-Redondo M. Electricity demand during pandemic times: The case of the COVID-19 in Spain. Energy Policy 2021;148:111964.
[10] Bahmanyar A, Estebsari A, Ernst D. The impact of different COVID-19 containment measures on electricity consumption in Europe. Energy Res Soc Sci 2020;68:101683.
[11] Rome R, Hamman J. What does lockdown mean for electricity in Great Britain?. In: National Grid ESO; 2020. 31 03. [Online]. Available: https://www.nationalgrideso.com/news/what-does-lockdown-mean-electricity-great-britain. [Accessed 29 06 2020].
[12] Kirli D, Parzen M, Kiprakis A. Impact of the COVID-19 lockdown on the electricity system of Great Britain: A study on energy demand, generation, pricing and grid stability. Energies 2021;14(3):635.
[13] Krarti M, Aldubyan M. Review analysis of COVID-19 impact on electricity demand for residential buildings. Renew Sustain Energy Rev 2021:110888.
[14] Jenkins DP, Patidar S, McCallum P, Debnath K. Modelling community electricity demand for UK and India. Sustain Cities Soc 2020;55:102054.
[15] Cerqueira PA, da Silva PP. Assessment of the impact of COVID-19 lockdown measures on electricity consumption–Evidence from Portugal and Spain. Energy 2023;282:128849.
[16] Zapata-Webborn E, McKenna E, Pullinger M, Cheshire C, Masters H, Whittaker A, et al. Working from home and electricity consumption: Lessons from the UK's first COVID-19 lockdown. Energ Buildings 2023;297:113428.
[17] Carvalho M, de Mello Delgado D Bandeira, de Lima KM, de Camargo Cancela M, dos Siqueira CA, de Souza DLB. Effects of the COVID-19 pandemic on the Brazilian electricity consumption patterns. Int J Energy Res 2021;45(2):3358–64.
[18] Zhong H, Tan Z, He Y, Xie L, Kang C. Implications of COVID-19 for the electricity industry: A comprehensive review. CSEE J Power Energy Syst 2020;6(3):489–95.
[19] Snow S, Bean R, Glencross M, Horrocks N. Drivers behind residential electricity demand fluctuations due to COVID-19 restrictions. Energies 2020;13(21):5738.
[20] El-Khozondar HJ, El-batta F, El-Khozondar RJ, Nassar Y, Alramlawi M, Alsadi S. Standalone hybrid PV/wind/diesel-electric generator system for a COVID-19 quarantine center. Environ Prog Sustain Energy 2023;42(3):e14049.
[21] CREDS. Ending the daily work commute may not cut energy usage as much as one might hope. Centre for Research into Energy Demand Solutions; 2020. 29 04. [Online]. Available: https://www.creds.ac.uk/ending-the-daily-work-commute-may-not-cut-energy-usage-as-much-as-one-might-hope/. [Accessed 02 07 2020].
[22] HMG. Solar photovoltaics deployment: Monthly deployment of all solar photovoltaic capacity in the United Kingdom. Department for Energy Security and Net Zero; 29 February 2024 [Online]. Available: https://www.gov.uk/government/statistics/solar-photovoltaics-deployment. [Accessed 26 March 2024].
[23] Solar Energy UK. Lighting the way making net zero a reality with solar energy. London: Solar Energy UK; 2021.
[24] Solar Planet. The future of solar energy in the UK. Solar Planet; 01 May 2023 [Online]. Available: https://solarplanet.uk/the-future-of-solar-energy-in-the-uk/. [Accessed 26 March 2024].
[25] House of Commons. Decarbonisation of the power sector: Eleventh Report of Session 2022–23. 2023.
[26] Saxena V, Kumar N, Singh B, Panigrahi BK. A spontaneous control for grid integrated solar photovoltaic energy conversion systems with voltage profile considerations. IEEE Trans Sustain Energy 2021;12(4):2159–68.
[27] Kumar N, Singh B, Panigrahi BK. Voltage sensorless based model predictive control with battery management system: for solar PV powered on-board EV charging. IEEE Trans Transp Elect 2022;9(2):2583–92.
[28] Zafeiropoulou M, Sijakovic N, Zarkovic M, Ristic V, Terzic A, Makrygiorgou D, et al. Development and implementation of a flexibility platform for active system management at both transmission and distribution level in Greece. Appl Sci 2023;13(20):11248.
[29] Pavlatos C, Makris E, Fotis G, Vita V, Mladenov V. Enhancing electrical load prediction using a bidirectional LSTM neural network. Electronics 2023;12(22):4652.
[30] Pavlatos C, Makris E, Fotis G, Vita V, Mladenov V. Utilization of artificial neural networks for precise electrical load prediction. Technologies 2023;11(3):70.
[31] Sheha M, Mohammadi K, Powell K. Solving the duck curve in a smart grid environment using a non-cooperative game theory and dynamic pricing profiles. Energ Conver Manage 2020;220:113102.
[32] Leonard MD, Michaelides EE, Michaelides DN. Substitution of coal power plants with renewable energy sources–Shift of the power demand and energy storage. Energ Conver Manage 2018;164:27–35.
[33] Staple GC. California's Grid Geeks: Flattening the 'duck curve'. GreenBiz; 25 January 2017 [Online]. Available: https://www.greenbiz.com/article/californias-grid-geeks-flattening-duck-curve. [Accessed 18 November 2023].
[34] Wang Q, Chang P, Bai R, Liu W, Dai J, Tang Y. Mitigation strategy for duck curve in high photovoltaic penetration power system using concentrating solar power station. Energies 2019;12(18):3521.
[35] Hou Q, Zhang N, Du E, Miao M, Peng F, Kang C. Probabilistic duck curve in high PV penetration power system: Concept, modeling, and empirical analysis in China. Appl Energy 2019;242:205–15.
[36] Calero I, Canizares CA, Bhattacharya K, Baldick R. Duck-curve mitigation in power grids with high penetration of PV generation. IEEE Trans Smart Grid 2021;13(1):314–29.
[37] Olczak P, Jaśko P, Kryzia D, Matuszewska D, Fyk MI, Dyczko A. Analyses of duck curve phenomena potential in polish PV prosumer households' installations. Energy Rep 2021;7:4609–22.
[38] Kalair AR, Abas N, Seyedmahmoudian M, Rauf S, Stojcevski A, Khan N. Duck curve leveling in renewable energy integrated grids using internet of relays. J Clean Prod 2021;294:126294.
[39] Pandey HW, Kumar R, Mandal RK. Ranking of mitigation strategies for duck curve in Indian active distribution network using MCDM. Int J Syst Assurance Eng Manag 2023;14(4):1255–75.
[40] Watari D, Taniguchi I, Onoye T. Duck Curve Aware Dynamic Pricing and Battery Scheduling Strategy Using Reinforcement Learning. IEEE Trans Smart Grid 2024;15(1):457–71.
[41] Nichols D, Kane D. Centrica PLC: Cornwall LEM residential electricity dataset with solar production and battery storage. UK Data Service; 2021 [Online]. Available: https://reshare.ukdataservice.ac.uk/854578/.
[42] Hafez AA, Nassar YF, Hammdan MI, Alsadi SY. Technical and economic feasibility of utility-scale solar energy conversion systems in Saudi Arabia. Iranian J Sci Technol Trans Elect Eng 2020;44:213–25.
[43] Ali Ahmed A, Alsharif A, Khaleel M, Nassar Y, Oubelaid A, Bajaj M, et al. Integrating renewable energy sources with electric vehicle infrastructure for enhanced renewability. In: in 3rd EAI International Conference on Intelligent Systems and Machine Learning (ICISML-2023), Pune, India; 2024.

[44] Meteoblue. Datasets. Meteoblue; 9 May 2023 [Online]. Available: https://docs.meteoblue.com/en/meteo/data-sources/datasets#era5-era5t. [Accessed 08 August 2023].
[45] ECMWF. ERA5: data documentation. European Centre for Medium-Range Weather Forecasts; 30 October 2023 [Online]. Available: https://confluence.ecmwf.int/display/CKB/ERA5%3A+data+documentation#ERA5:datadocumentation-Accuracyanduncertainty. [Accessed 01 November 2023].
[46] ECMWF. ERA5: uncertainty estimation. European Centre for Medium-Range Weather Forecasts; 05 May 2023 [Online]. Available: https://confluence.ecmwf.int/display/CKB/ERA5%3A+uncertainty+estimation#ERA5:uncertaintyestimation-(6)HowreliableistheERA5uncertaintyestimate?. [Accessed 01 November 2023].
[47] Cleveland RB, Cleveland WS, McRae JE, Terpenning I. STL: A seasonal-trend decomposition. J off Stat 1990;6(1):3–73.
[48] Patidar S, Jenkins DP, Peacock A, McCallum P. A hybrid system of data-driven approaches for simulating residential energy demand profiles. J Build Perform Simulat 2021;14(3):277–302.
[49] GOV.UK. PM confirms schools, colleges and nurseries on track to begin phased reopening. Prime Minister's Office; 24 May 2020 [Online]. Available: https://www.gov.uk/government/news/pm-confirms-schools-colleges-and-nurseries-on-track-to-begin-phased-reopening. [Accessed 18 March 2021].
[50] Smite D, Moe NB, Hildrum J, Gonzalez-Huerta J, Mendez D. Work-from-home is here to stay: Call for flexibility in post-pandemic work policies. J Syst Softw 2023;195:111552.
[51] Allen KS, Grelle D, Lazarus EM, Popp E, Gutierrez SL. Hybrid is here to stay: Critical behaviors for success in the new world of work. Personal Individ Differ 2024;217:112459.
[52] Chan RY, Lin X, Bista K. Is Hybrid and Remote Work Here to Stay? Opportunities and Challenges in the United States and Abroad. In: Chan RY, Lin X, Bista K, editors. Rethinking Hybrid and Remote Work in Higher Education: Global Perspectives, Policies, and Practices after COVID-19. Springer International Publishing; 2023. p. 7–27.