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Article

Impact of the COVID-19 Lockdown on the Electricity System of Great Britain: a Study on Energy Demand, Generation, Pricing and Grid Stability

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Abstract: The outbreak of SARS-COV-2 disease 2019 (COVID-19) abruptly changed the patterns in electricity consumption, challenging the system operations of forecasting and balancing supply and demand. This is due to the mitigation measures that include lockdown and Work from Home (WFH), which decreased the aggregated demand and remarkably altered its profile. Here, we characterise these changes with various quantitative markers and compare it with pre-COVID-19 business-as-usual data using Great Britain (GB) as a case study. The ripple effects on the generation portfolio, system frequency, forecasting accuracy and imbalance pricing are also analysed. An energy data extraction and pre-processing pipeline that can be used in a variety of similar studies is also presented. Analysis of the GB demand data during the March 2020 lockdown indicates that a shift to WFH will result to a net benefit for flexible stakeholders, such as consumer on variable tariffs. Furthermore, the analysis illustrates a need for faster and more frequent balancing actions, as a result of the increased share of renewable energy in the generation mix. This new equilibrium of energy demand and supply will require a redesign of the existing balancing mechanisms as well as the longer-term power system planning strategies.

Keywords: electricity system, COVID-19, electricity demand, energy, demand, behaviour, lockdown, electricity pricing

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1. Introduction

The outbreak of coronavirus disease 2019 (COVID-19) lead to a lockdown on Wednesday, 23rd of March in the United Kingdom (UK) . The government instructed that people should leave their homes only for purchasing necessities and exercising. People were only allowed to go to work if working from home (WFH) was not possible. Failing to follow the new lockdown measures would lead to fines. [1]. These measures lead to a disruptive change in the electricity demand and influenced the wider energy sector. Energy companies in the UK warned about potential blackouts [2]. The analysis of this high impact and low probability event is significant as any adverse effects on the electricity sector due to future pandemics or lockdowns could be forecast using the insights of this analysis.

Studies such as [3] investigate ways to improve the power system resilience for high impact, low probability events under future climate and extreme weather conditions . However, the impact of a pandemic such as the one experienced with COVID-19 is still unclear. The changes and trends in energy due to the pandemic are identified for demand [4,5], generation, grid stability [5] and various power markets [6,7]. Most of the aforementioned analysis quantify changes by determining absolute or percentage change between pre and post-COVID periods.

As noted in [4], all analysis should be addressed with caution, since comparing different timeframes in power systems is a challenge due to various distorting factors that play a role such as weather, human behaviour, economic climate, etc.

As result this study seeks to analyse the changes in demand, generation, grid stability and market prices in a quantitative manner where changes are striking, and choosing a qualitative approach where the difference is ambiguous.

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2. Methodology

In order to analyse the impact of the COVID-19 lockdown on the electricity market, a systematic approach is used which involved creating an efficient pipeline to extract the target data, pre-process, analyse and visualise. In this section, the methodology used in the pipeline is explained. The instructions for future use are detailed using a flow diagram. The actual Python code employed can be accessed at the GitHub repository[1] [8].

Both pure Python (i.e. py) and interactive Python notebook (i.e. ipynb) formats are made available.

2.1. Function of the Data Pipeline Code

As this study involves a comparative analysis, various actions, such as cleaning the data and calculating the percentage differences, had to be repeated for different data sets like frequency and demand. In order to minimise the time spent from the import of the data to the analysis and visualisation stages, a data pipeline on Python is programmed to fetch the data directly using the application programming interface (API) of the provider - see [8].

This process is also commonly referred to as scripting, extracting and scraping the data. This pipeline is used for analysing the system frequency, demand, generation and other types of data and all results are presented in Section 3. It performs the following steps listed below.

1. Import the data from the source webpage using the API user key
2. Identify the keywords and group the data
3. Create weekly data frames (according to the Monday-to-Sunday convention (i.e. ISO 8601))
4. Check for zeros, invalid or duplicate data
5. Label and discard the columns that are not of interest
6. Adjust the date and time format (e.g. change from half-hourly settlement period convention (where 01:00 is denoted by 2) to time)
7. Save the adjusted data in CSV format with an automated title (*DataLabel*`_Week_starting_`*StartDate*`.csv`)
8. Calculate statistical and other quantitative descriptors such as mean, peak-to-mean ratio, etc.
9. Produce comparative visualisations of the data

2.2. Other uses of the Data Pipeline

In most of our analysis cases, the data source is the Balancing Mechanism Reporting Service (BMRS) [9]. The website [10] provides open-source data that is used for the balancing and settling the GB electricity system.

The data provided (e.g. system demand, frequency, generation by fuel type, etc.) is used for reaching trading decisions and analysing the dynamics of market volumes and pricing. Hence, we believe that this pipeline may be useful for both academic and industrial researchers who are interested in electricity market dynamics, regulation, trading and forecasting as it enables easy data extraction, pre-processing and visualisation. The flowchart in Figure 1, displays the steps required to replicate the results.

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[1] https://github.com/desenk/Electricity-Data-Pipeline

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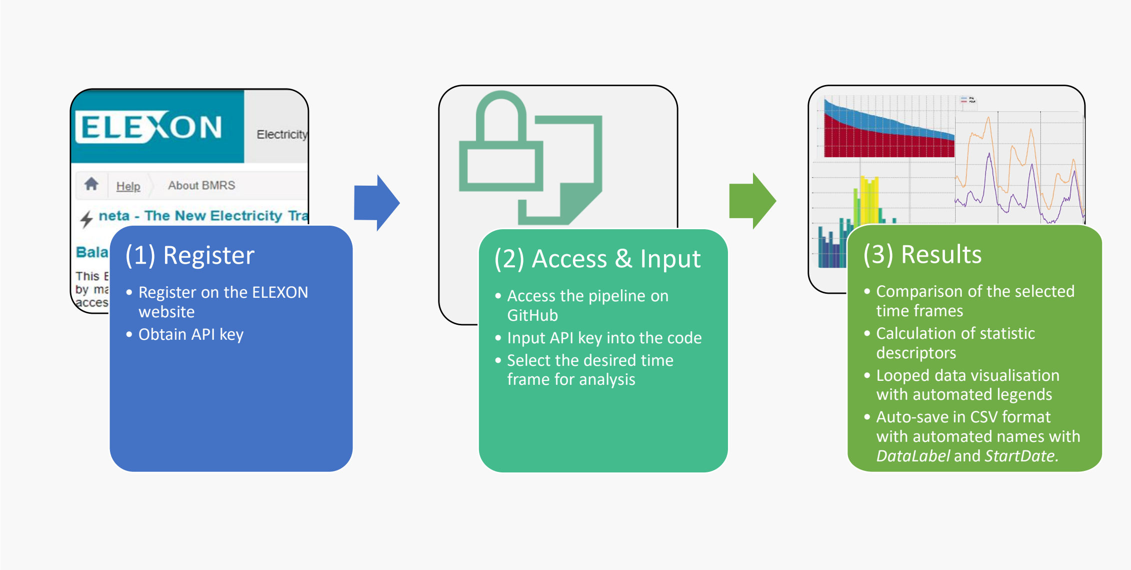

Figure 1. The flowchart displaying the steps for employing the data pipeline which are registering, accessing the code repository and producing the results in order.

As shown in Figure 1, there are 2 prior steps to reaching the results stage where the quantitative data descriptors are calculated and the results are visualised in a comparative manner. The first step is to obtain an API key by registering on the Elexon website [10] - a more detail guidance on this is provided by Elexon [9]. Then, the pipeline can be accessed from the GitHub website [8] and the API key obtained by the user should be input. The default time frames are set to the pre and post-COVID-19 weeks used for this analysis which are weeks commencing on 2nd and 23rd of March 2020. However, these can be adjusted to the timeframe of interest. In addition to the system demand, this pipeline can be used for all other data types provided by Elexon which are listed in [9]. The code can also be modified to refer to any other website to execute a direct data extraction using API.

3. Results

In order to effectively present the impact of the COVID-19 lockdown on the GB electricity system, four main categories are identified and analysed: (1) the changes in demand profile and volume, (2) generation portfolio; renewable and conventional generation shares, (3) forecasting and grid stability indicators, and lastly (4) market prices, including day-ahead wholesale market, system imbalance and variable prices for the distributed consumers. Furthermore, the grid stability subsection inspects imbalance volume, system frequency and the loss of load probability.

3.1. Demand Profile

This subsection analyses and quantifies the changes in the electricity consumption caused by the COVID-19 mitigation actions such as the lockdown. On the 23rd of March 2020, the UK Government recommended work from home (WFH) and closed public spaces such as pubs, restaurants and sport facilities [11]. The impact on the electricity demand is shown by the purple profile and compared to a pre-COVID-19 week in Figure 2. The figure illustrates that the overall demand decreased as majority of the commercial users (e.g. factories, businesses, etc.) shut down. Besides the demand reduction, the lock-down also influenced the consumption pattern which results in a changed load profile shape.

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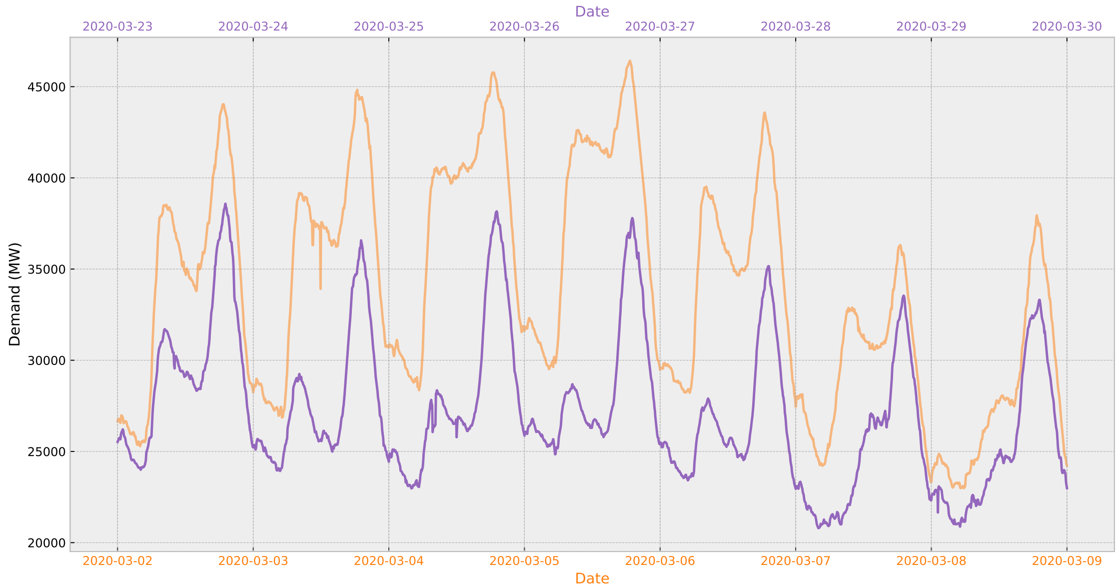

Figure 2. Aggregated system demand before (w/c 02/03/20) and after (w/c 23/03/20) the COVID-19 actions. Changes are observed in demand magnitude and profile with decreased demand after the lockdown.

As displayed in Figure 3, load duration curves show the base and peak demand by visualising the relationship between sorted demand (i.e. ranked descending) and exceedence. Whilst the base demand decreases 10%, the peak and mean demand drastically drop by 20% and 24% respectively, following the start of the lockdown. The changes in the demand profile for peak, mean and base load are shown in Table 1. The decrease in the energy demand can also be observed as the area of the red plot (i.e. post-COVID-19) is smaller than the blue plot (i.e. post-COVID-19). If the demand were constant, that would result in a flat load duration curve. In Figure 3, the post-lockdown plot (in red) is flatter than the previous one. This is also supported by the higher decrease in peak values in comparison to the base. This indicates a significant change in the demand profile and that it is flatter than the pre-action one. Flattening the demand curve means the prime time peaks such as the morning pick-up and the evening demand surge are now less pronounced. Such peaks increase the difficulty of matching demand and supply, puts the grid under stress and also increases the stress on thermal generation and storage to meet the demand. The ripple effects include congestion and high imbalance and transmission charges.

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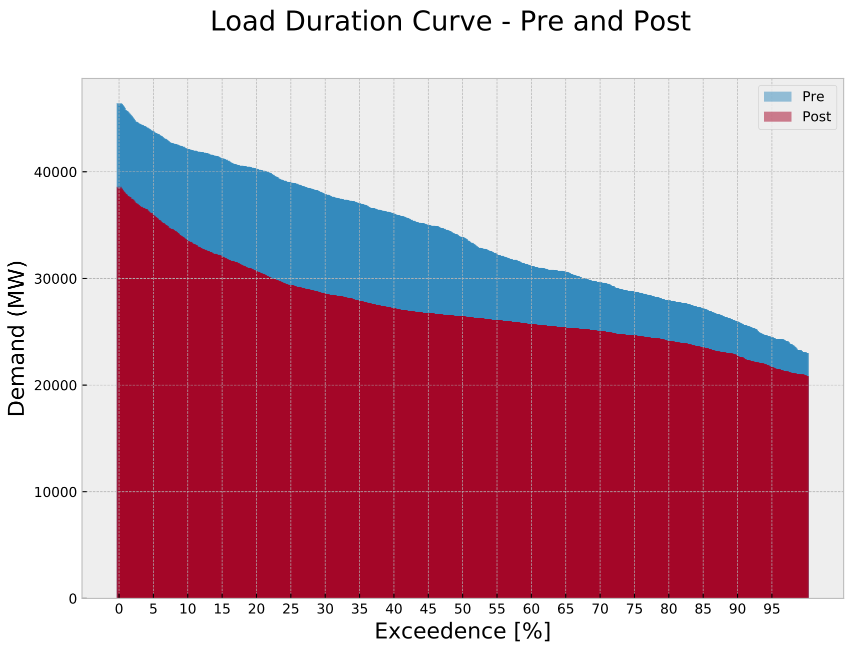

Figure 3. Load duration curve for pre- and post-COVID-19 actions (w/c 02/03/20 and 23/03/20) showing the decrease in the post-action scenario with the highest decrease in peak and lowest in the base load.

Table 1. Changes in demand profile using the data from the load duration curves.

Profile	Peak Load (MW)	%	Mean Load (MW)	%	Base Load (MW)	%
Pre	46425		33868		22982	
Post	38585	-20.31%	27294	-24.08%	20795	-9.5%

To assess how frequently each demand value occured, Figure 4 displays the pre and post demand histograms where the post-action demand is shifted to the left, indicating lower loads. The peak for the post-action demand shows that the range of most occurring demand values is now narrower, meaning there is less variation. Otherwise, the pre-action demand shows a more disperse and even occurrence profile which looks slightly bi-modal. The bi-modality, meaning that two occurrence centres exist. The concentration and higher rate of occurance around 26000 MW also reflect that the demand profile is flatter.

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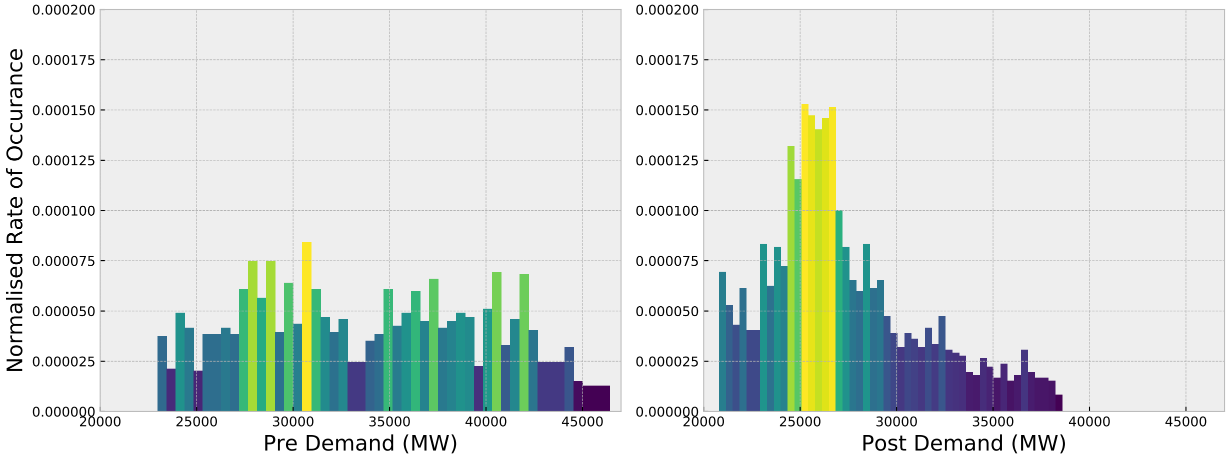

Figure 4. Comparison of pre- and post-COVID-19 demand histograms with normalised occurrences. The range of colours from yellow to dark blue correspond to the highest and lowest values. The post-COVID shape is smoother and occurrence concentrates only once around 26 MW. The plot on the left represents w/c 02/03/20 and the one on the right represents w/c 23/03/20.

Figure 5 uses a ratio of the standard deviation over the mean in order to quantify the variation in the consumption profile. It suggests an overall lower variation in the post-COVID-10 profile with a largest variation in the morning with respect to the mean. The evening variation coefficient is also remarkably lower. The overall standard deviation of the post-lockdown week is a third of the pre-lockdown week. Hence, it also connotes to the discussion of the flatter demand profile. Figure 5 also reflect an hour delay in the morning peak (i.e. 8 to 9 a.m.) and a changed evening profile. Regarding the evening demand surge, it should also be noted the Figure 2 also the post evening peaks are steeper in comparison as the morning peaks become less pronounced. For instance, on average the pre demand used to have a 7500 MW increase over 4 hours to the evening peak whereas the post-action demand escalates by 9500 MW in 5 hours. Despite the longer increase time, the relative increase is higher.

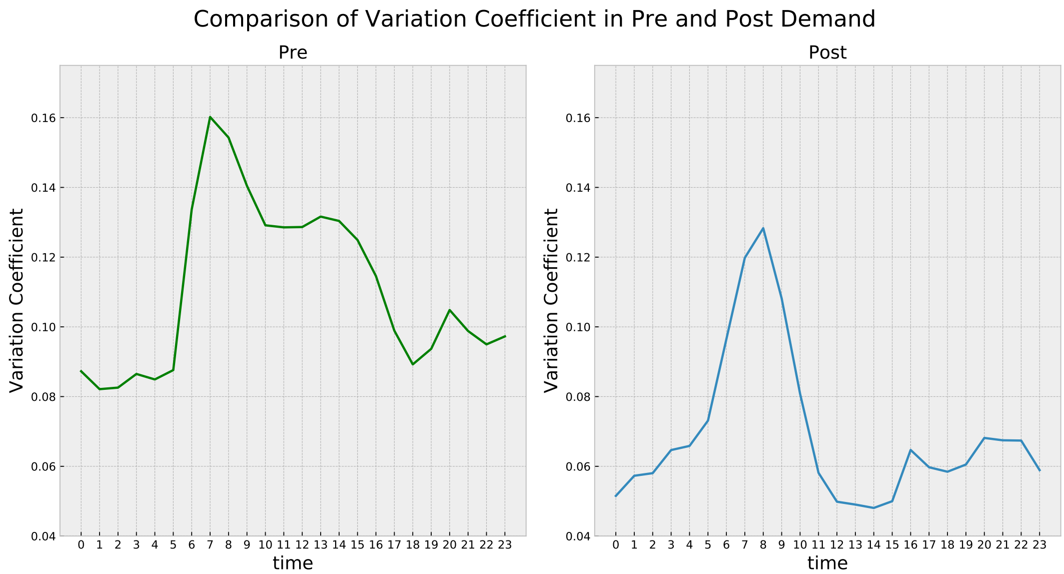

Figure 5. Comparison of variation coefficient to visualise the changes in system demand. The magnitude of the variation coefficient decreases in the post-case, the morning peak is delayed by an hour and the variation in the evening peak is less pronounced. The plot on the left represents w/c 02/03/20 and the one on the right represents w/c 23/03/20.

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It could be speculated that this is due to the human behaviour change as the common 9 a.m. to 5 p.m. working routine may not apply to all WFH. Hence, the delay in the morning peak may suggest a later wake-up time and earlier pick-up in the evening may connote to earlier increase in heating demand, cooking and similar.

3.2. Generation Portfolio

This subsection focuses on how the changes in demand pattern and magnitude affected the generation portfolio. In particular, the lower demand lead to a higher share of variable renewable energy (VRE), namely wind and solar, and consequently impacted the conventional generation portfolio in the power system.

3.2.1. Increase in renewable energy contribution

The share of generation from VRE sources increased following the COVID-19 mitigation actions and consecutive changes in the electricity demand. The hypothesis for this originates from the causality principles in electricity markets which is further supported by an example. Firstly, generators in European electricity markets are scheduled in merit order, which means that the generators with the lowest marginal costs are supplying the power demand. The causality is that the VRE generators have marginal costs close to zero. Therefore, the VREs are usually scheduled before other generation technologies [12]. As the VRE infrastructure already exists, is preferred in the merit order and the VRE output is not restricted by the pandemic circumstances, it is justifiably hypothesised that the changes in the demand profile and magnitude resulted in the increase of the VRE contribution.

Secondly, to support this hypothesis it must be noted that, besides the total generation or load, the VRE share also depends on the weather conditions which impact the VRE output in every point in time. Changing weather conditions make it hard to compare pre and post-COVID-19 data sets as it is not possible to decouple the effect of weather conditions and the VRE generation. This is because the aggregated VRE output from various locations is used for this study. Therefore, Figure 6 illustrates a qualitative example which keeps the VRE generated output stable (i.e. unaffected by varying weather conditions), representing constant solar and wind conditions for a high and low demand case, respectively. The scale for demand and generation in Figure 6, represents approximately real observed data from GB. In the example, the demand reduction of 25 %, which was recognised in the first week after the lock-down, lead to an absolute VRE share growth of 8 %.

As a result of Figure 6 and the preference of scheduling VRE before conventional generators, the average demand reduction lead to higher VRE shares in long-term. If the data from Figure 6 is representative for more periods, it further indicates that the VRE share could increase in the range of 5-10 % in the GB system due to the lower demand profile.

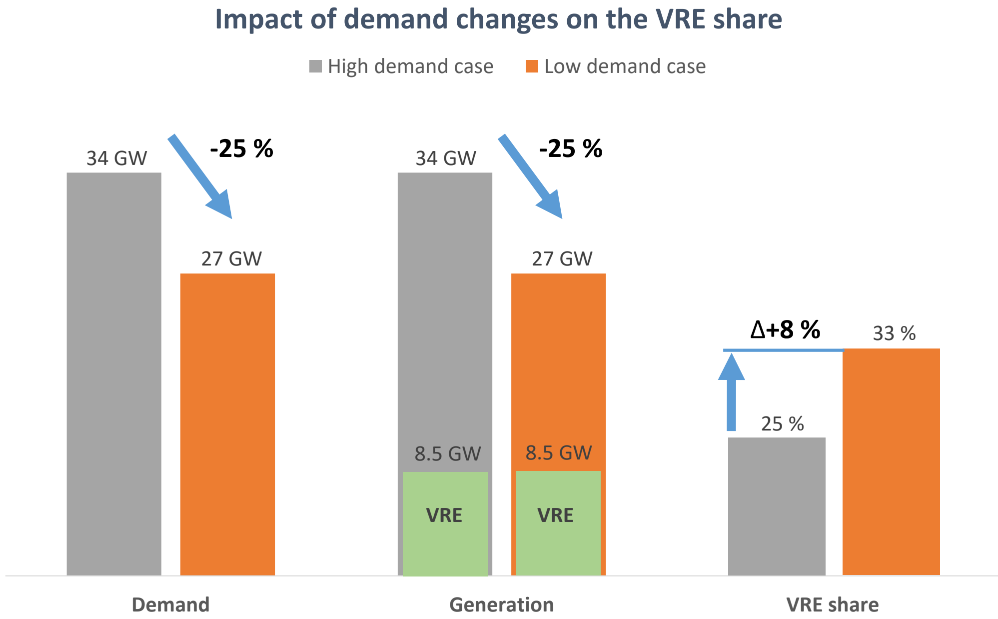

Figure 6. An illustrative example of the impact of demand changes on the VRE share for typical UK VRE conditions. The VRE share grows under the assumption of constant VRE output before and after the demand changes. Most magnitudes and ratio of changes equal approximately the UK case. Only the VRE share for the low-demand case is set constant and not showing the real magnitude in order to point out the impact of a lockdown under constant VRE conditions.

3.2.2. Impact on the conventional generation portfolio

The conventional generation portfolio, including all generation assets with marginal cost above solar and wind technologies, are expected to decrease in operation time compared to the situation without lock-down. The reason is beside the lower total demand, the higher share of VRE assets on the market which are dispatched first because of the merit order. The decrease of operation time will particularly effect higher marginal cost generators, so that nuclear and hydro plants are less effected. However, the higher share of VRE assets cause additionally a need for more flexibility in the power system - such as provided from the natural gas plants [13]. If inflexible plants are not willing to reduce their generation at high VRE times, the more often negative prices will occur [14,15]. Therefore, a flexible gas or biomass plant could be preferred over a less flexible coal plant.

As result, the total generation portfolio is likely to reduce carbon emissions by the increase of the VRE share and the push out of inflexible coal plants.

3.3. Forecasting and Grid Stability

The aspects related to forecasting and grid stability are discussed in this section. These include factors such as the deviations in system frequency, imbalance volume and load forecast error of the system operator. Additionally, it investigates the loss of load probability as indicators of the reserve scarcity and increased stress in the grid.

3.3.1. Deviations in System Frequency

The system frequency varies continuously and reflects the real-time discrepancies between system demand and total generation. Frequency increases when there is too much generation or too little demand on the system and vice versa. Similar to other system operators, National Grid has a legal obligation to maintain system frequency within 49.5 and 50.5 Hertz [10]. This requires the system operators to accurately forecast demand and schedule generation accordingly whilst keeping

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a fast-response reserve or a demand action available for any unforeseen changes. Nonetheless, the changes in frequency are also related to the system inertia. Introduction of most VRE generators such as solar panels and some types of storage such as batteries resulted in a decreased system inertia and consequently a less stable system frequency [16]. Demand-side response (DSR) and other balancing services can be activated to ensure operation within the permitted range of frequency [17]. Currently, there is research assessing whether the wind and solar power plants could deploy synthetic inertia in order to compensate for this problem associated with VRE generation [18–20].

An abrupt change in the demand, like the one due to the lockdown, is expected to negatively affect the frequency. In this case, the frequency is expected to rise as the decrease in demand would result in a surplus of generation. When analysed in its barest form, no significant discrepancies are observed for a pre and post COVID week. The mean and minimum and maximum frequency values also conclude an insignificant difference below 0.2 % difference - see Table 2. Despite the fact that both the minimum and maximum frequency values for the post-action week are higher than the pre-action week, the analysis is not sufficient to state a remarkable frequency variation due to the lock-down or perhaps more likely that it shows that the frequency was maintained well by the National Grid.

Table 2. Comparison of descriptors to quantify the changes in the system frequency pre- and post-COVID-19 mitigation actions. The increase in the post-action minimum and maximum frequency is highlight by the red text colour.

Data	Mean	Min	Max
Pre (Hz)	49.998804	49.736000	50.207000
Post (Hz)	49.998657	49.775000	50.267000

Hence, a normalised occurrence study is carried out to assess the distribution of system frequency in Figure 7. The distribution for the post-action data has more defined peak around 50 Hz and its distribution width from 49.9 to 50.1 Hz is narrower. This suggests that the frequency was maintained within a stricter window than the pre-action week. The concentration of occurrence is below 50 Hz pre-lockdown whilst values above the nominal values are recorded more frequently after the lock-down (where the range of colours from yellow to dark blue in Figure 7 represents the highest to lowest occurrence respectively). Hence, this displays a shift in the system frequency distribution, pointing out the increase in high frequency records.

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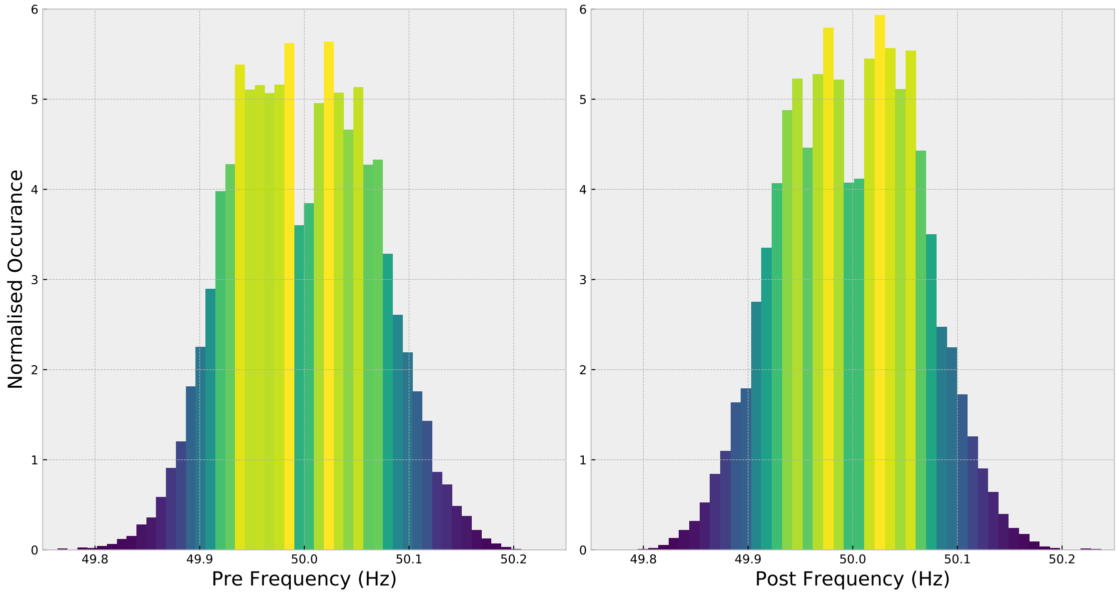

Figure 7. Comparison of pre and post-action system frequency histograms. The plot on the left represents w/c 02/03/20 and the one on the right represents w/c 23/03/20. The post-action frequency distribution is concentrated more in the range of 49.9 to 50.1 Hz.

One reason for this may be the decreased load profile, resulting a generation surplus, thus increasing the frequency - as discussed in Section 3.1. A peak-to-mean analysis is performed on both pre- and post-action data to compare the degree of variation. The frequency data is indexed by the time of the day. The most significant observation is regarding the high peak-to-mean ratio calculated for 8 p.m. for the post-COVID-19 week. This may be because of the unforeseen changes in the shape of the consumption profile - this is discussed in Section 3.1.

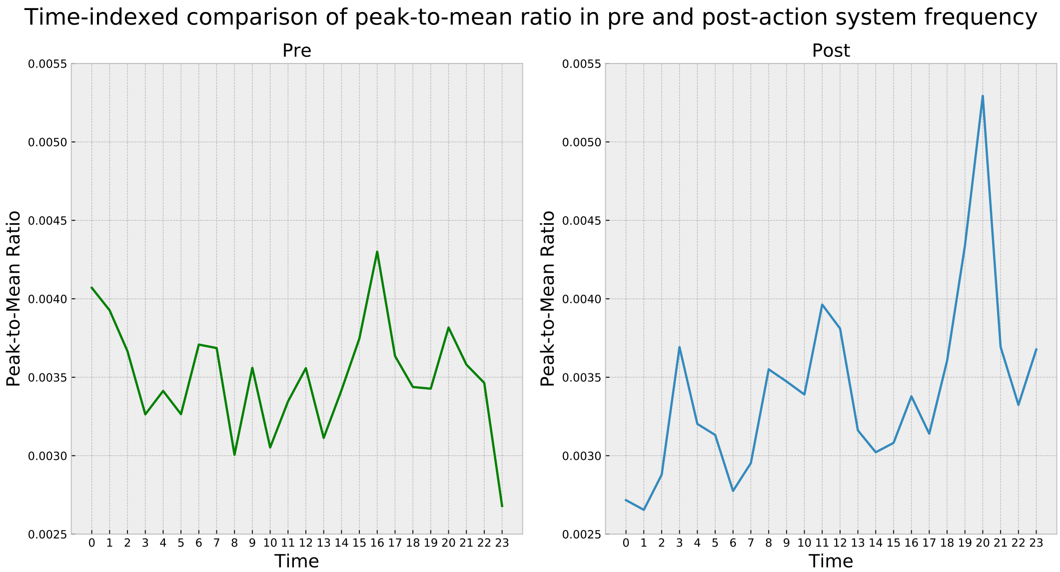

Figure 8. Comparison of hour-indexed peak-to-mean ratios for system frequency, showing an increase in 8pm high frequency occurrence post-lockdown. The plot on the left represents w/c 02/03/20 and the one on the right represents 23/03/20.

3.3.2. Load Forecast Error

The effect of COVID-19 on the short-term load forecasts are analysed in the GB power system. In contrast to mid- and long-term forecast, which make predictions months and years prior to the event,

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the short-term load forecast have a shorter outlook which range from one hour to weeks before the settlement period [21,22]. Short-term load forecasting plays an important role in scheduling the power plants efficiently in electricity market, as it is essential for economic dispatch and unit commitment [23]. As a result, an improved forecast accuracy leads to a more reliable and affordable power system [21].

Two different short-term load forecast are analysed in this study, the day-ahead total load forecast (DAF) and transmission system final load forecast (TSF). The DAF and TSF differ in methodology and forecast length. With regards to the methodology, the DAF represents a forecast for the total load in the power system, which equals the sum of generated power on both, transmission and distribution networks. Whereas, TSF is a load forecast which is equal to the sum of generation present on the transmission network. However, this includes generation from pumped hydro storage and embedded large power plants on the distribution network level. Therefore, TSF is interpreted as the net demand, usually published by the TSO for market clearing, while the DAF represents the estimated actual total load in the power system.

Regarding the forecast length, which is the duration from forecast publication till operation time, it varies for DAF and TSF, see Figure 9. DAF is published only once a day and predicts the next-day average demand in each settlement period, hence, the forecast length vary from 12-36 hours. Similarly, TSF outputs a day-ahead forecasts. However, forecasts for each settlement period is updated until the final TSF which predicts the next average demand in the next settlement period, 1 hour and 15 minutes ahead.

explanation.png

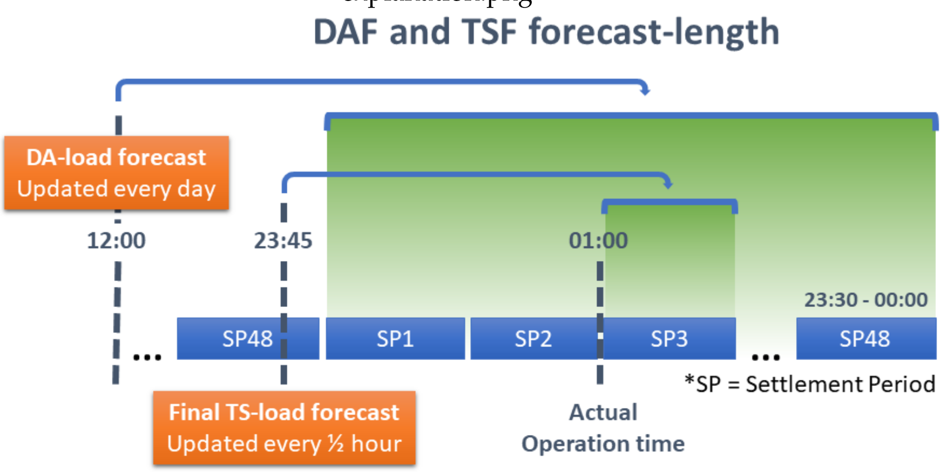
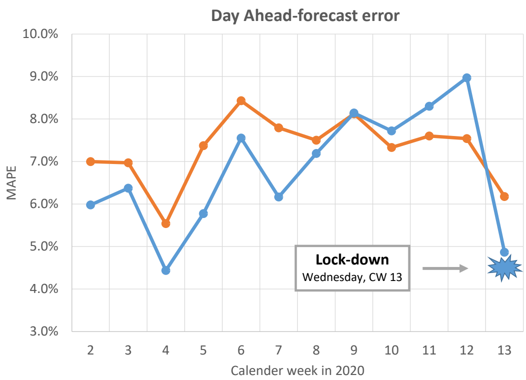


Figure 9. Illustrative forecast lengths for the total Day-Ahead load forecast (DAF) and the final transmission system load forecast (TSF).

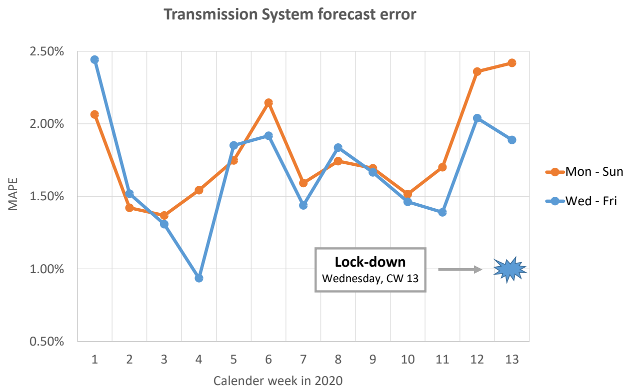
DAF and TSF forecast errors reveal different characteristics due to the lock-down. The DAF forecast is improved while the TSF forecast does not reflect clear changes. This is shown in Figure 10. The forecast error is evaluated by one of the most common performance indicators, namely the mean absolute percentage error (MAPE) [21,23]. MAPE functions well as a forecast performance indicator when employing historical data. Nevertheless, for prediction model selection and estimation it is biased [24]. As only historical data is analysed in this study, this makes MAPE a suitable indicator.

MAPE is defined as a summation of forecast errors, where each error is weighted to the actual load. This is shown in Equation 1 where y represents the actual load, $\hat{y}$ is the load forecast and N is the number of forecasts.

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{y_{i,actual} - \hat{y}_{i,forecast}}{y_{i,actual}} \tag{1}$$



[DAF error.] [TSF



error.]

Figure 10. Weekly aggregated total Day-Ahead load forecast (DAF) and final transmission system load forecast (TSF) error, for the time frame from i) Monday to Sunday and ii) Wednesday to Friday. Note: The Wednesday to Friday frame was used to show the impact of the COVID-lockdown from the workday perspective. A significant improvement for the DAF is observed, while the TSF experience minor changes.

In general, the longer the forecast length is for the same point in time, the higher the forecast error becomes [25].

Therefore, the DAF constitutes a higher forecast error than the TSF. With regards to the lock-down effects, the improved forecast accuracy for the DAF is especially remarkable when distilling the time frame on the weekdays from Wednesday to Friday, which is time frame when the lock-down was initiated. The typical working week differs from the lock-down working week, and the weekend is more similar to the lock-down weekend. Hence, the effect of the lock-down would be overlooked if the analysed time frame was for the whole weak. On the contrary, no such effects are observed for TSF, which implies that the shorter-length forecast is less subjected to the lock-down effect.

The change in the forecast error cannot be solely traced back to the lock-down, since the forecast error is affected by many factors. In [25], a list of components affecting the forecast errors is given. Nevertheless, in particular, the DAF analysis shows a change of magnitude that could indicate that the lock-down improved the day-ahead forecast. One reason could be the smoother, less variable demand profile which was recognised in Section 3.1. Even though the impact of the TSF change cannot be solely linked to lock-down due to minimal visible changes, in combination with the imbalance discoveries in Section 3.3.3, the short-length forecast accuracy evidently decreased.

3.3.3. Imbalance Volume

An imbalance is prevalent in the power system when supply does not match demand. If the imbalance is not tackled, it could lead to an unstable frequency and finally black-outs. It is therefore the System Operators (SO) responsibility to keep the balance in the system [10]. All accepted balancing

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measures in a settlement period are given by the net imbalance volume (NIV), which represents the total sum of positive and negative system management and energy balancing measure in the settlement period. In a perfect market the power plants are scheduled at gate-closure that demand equals supply at any settlement period to ensure a NIV close to zero. However, the energy balance in a settlement period is usually not met, since:

- Demand prediction errors by suppliers
- Generation prediction errors by generators (i.e. not able to tightly control the operation of intermittent units)
- Problems in transmission lines
- Balance must exist at every instant, but market trades in half-hour settlement periods

In section 3.3.2, it was recognised the short-length load forecast accuracy decreased slightly. The consequences of this poorer short-length forecast are amplified in the NIV and cause the NIV to grow significantly compared to all other calendar weeks in 2020, see Figure 11. Which means whatever changed at the lock-down week, increased the amount and volume of balancing measures in the power system.

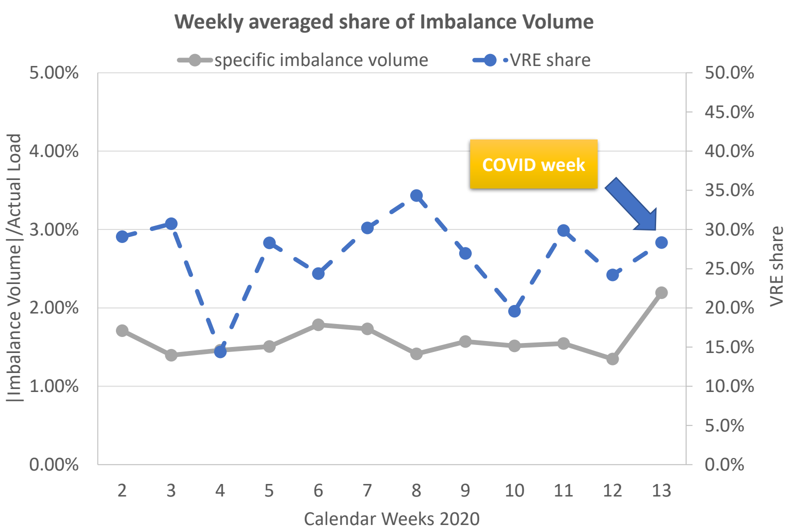

Figure 11. The weekly average share of imbalance volume factorised by the actual total load. Significant imbalance increase at lock-down week. Change of VRE can be excluded as only reason for change.

After the lock-down, the higher share of VRE seems to be the main driver for the increasing imbalance in the power system. In Figure 12, the imbalance volume was weighted to the actual total system demand for a pre- and post-COVID week. On the secondary axes is VRE share plotted. Remarkable is the correlation between weighted imbalance volume and the VRE share after the lock-down. The correlation might be not a permanent condition in future. When analysing data from January to March, a correlation between VRE share and imbalance volume was discovered roughly 20% of the time, though, at approximately 80% of the time there is no clear correlation visible. Nevertheless, a clear correlation between VRE share and imbalance volume is observed after the lock-down, which indicates that the increasing VRE share is the main driver for the higher imbalance volume. The reason for that cannot be precisely untangled as four things can cause an imbalance: generation and demand prediction errors, network constraints, and the balance need at every instance. However, one reason could be that the machine learning approaches used by National Grid to forecast embedded VRE output and load changes together, had problems to adapt [26].

The effect of higher VRE shares explains the slightly poorer performance of the short-length load forecast TSF, as embedded VRE, which consists of 13 GW solar and 6 GW wind capacity in 2018, cause load forecast errors [25,26]. Contrary, the Day-Ahead load forecast improved, so there might be a

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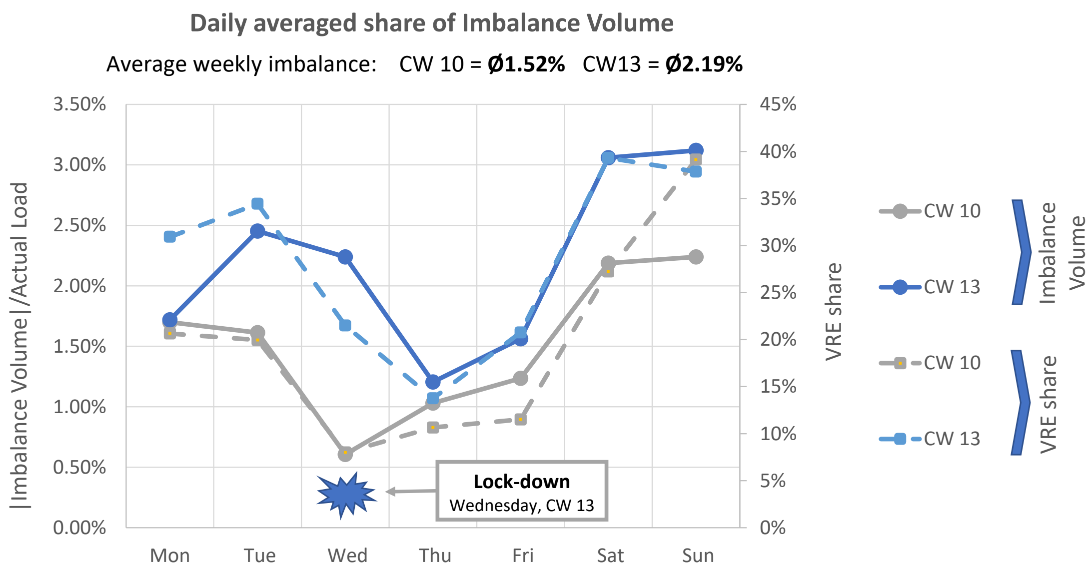

Figure 12. Daily average share of imbalance volume and share of VRE for one pre- and post-COVID week, 02-09 March and 22-28 March, respectively. Correlation after lockdown between VRE share and imbalance volume is remarkable.

trade-off between the benefit of smoother load-profiles and the bad influence of high VRE shares on forecast errors. In summary, it seems that depending on the forecast length, the COVID situation causes improved or worse load forecast performance, see Figure 13. Shorter load forecast-length drop in performance, while longer forecast-length increase in performance.

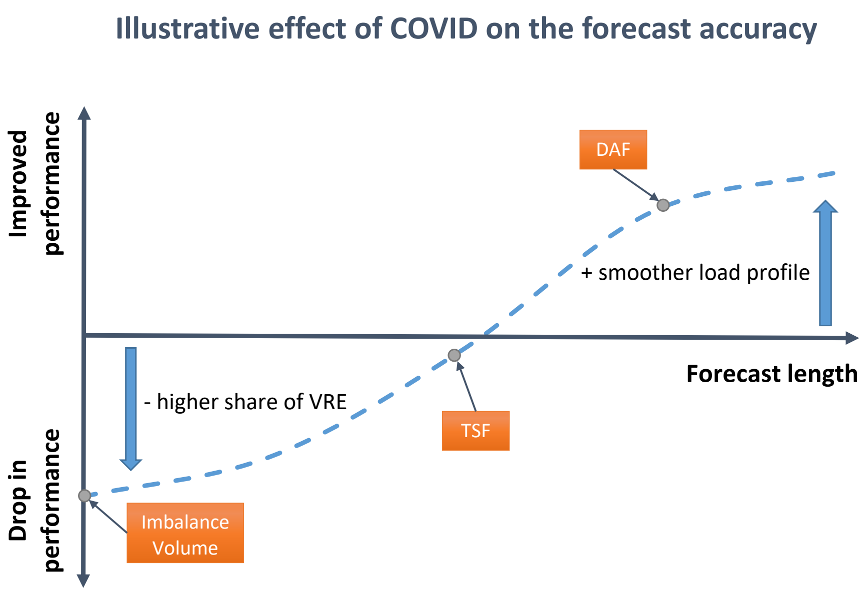

Figure 13. Illustrative effect of COVID on the forecast accuracy compared to pre-COVID weeks. TSF and DAF indicate the transmission system forecast and total Day-Ahead forecast, respectively, as described in section 3.3.2.

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3.3.4. Loss of load probability

Loss of load probability (LOLP) is an indicator for system reliability measured by the system operator for each settlement period [27]. For instance, when National Grid predicts higher probability of loss of load, the balancing mechanism is willing to pay higher prices for balancing at the time of reserve scarcity. The methodology to calculate the LOLP can be found in [28]. The higher prices at high LOLP levels are also known as reserve scarcity prices, which are the product of LOLP and the value of lost load (VoLL). Whereby, the VoLL is determined through the assessment of how much value consumers on average attribute to the security of supply - currently set on £6000/MWh [27].

$$ReserveScarcityPrice = LostofLoadProbability \times ValueofLostLoad \qquad (2)$$

Due to the abrupt changes in the demand profile and eventually the inflexibility of the available generation, National Grid predicted a higher LOLP during the evening of the 25th of March which is the first official day of lock-down. Despite the fact that it was predicted 12 hours in advance, the 1 hour ahead LOLP forecast is 4.5 times higher. This implies that there was a reserve scarcity and/or that the grid was under stress. On the 4th of March, due to reserve scarcity, the system price increased to £2242/MWh in at 17:00 which is the highest recorded value in the last 19 years and almost 20 times higher than the maximum system price in February which was £120/MWh [7].

3.4. The effects on Market Price

3.4.1. Day-ahead wholesale market price

The day-ahead market objective is to define a clearing energy price in which supply meets the demand at any given hour of the day. To do so, a merit order model is used to correctly dispatch power plants by sorting the existing generation units from low to high marginal operating costs. Once the generation meets the demand curve the clearing market price or equilibrium is achieved by minimising the generation cost [29]. Figure 14 shows graphically the process of the merit order model and the location of the clearing price as a result of the intersection of the supply and demand curves. The demand is given as net demand which subtracts the VRE generation from the total demand. This is a common strategy to illustrate the merit-order, since the solar and wind generation plants have marginal cost close to zero, making them always dispatched so far no network or other operational constraints exist [13].

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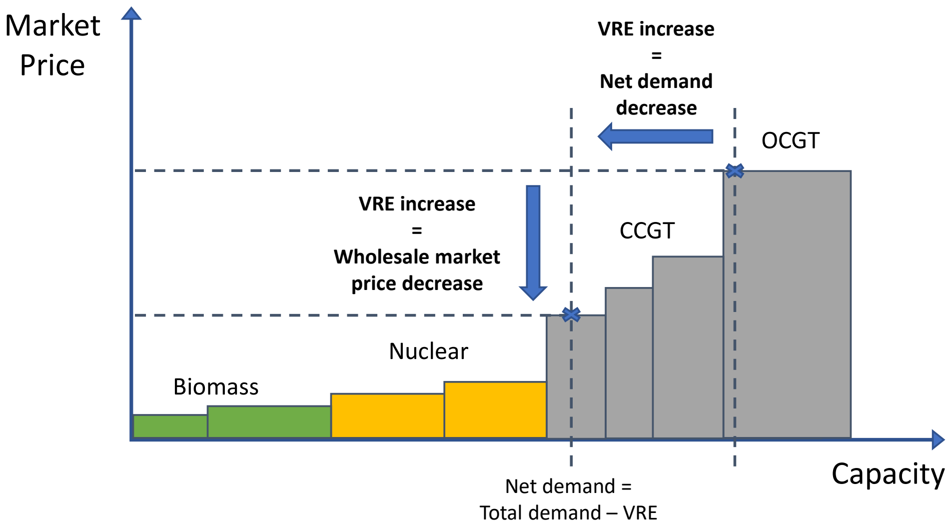

Figure 14. Illustrative effects of the COVID-situation on the wholesale market price. The wholesale market price reduces due to COVID. The higher VRE share after the lock-down lowers the net demand which leads to a wholesale market price reduction.

3.4.2. System imbalance price

The imbalance price is the price set by the system operator for every settlement period to determine imbalance charges on electricity producers (generators) or consumers (suppliers) [27]. Whereby the imbalance charge for a settlement period simply consist of the product of imbalance volume (see section 3.3.3) and imbalance price:

$$\text{Imbalance charge}_{SP} = \text{Imbalance volume}_{SP} \times \text{Imbalance price}_{SP}$$

To understand possibles impacts of the COVID situation on the imbalance price, it dismantled in its components. The imbalance price is the price which must be paid for actions that the system operator choose to resolve the imbalance. However, the reason for the balancing action can vary. It could be either a i) energy balancing or ii) system balancing motivated action in the 30min settlement period [27].

According to [27], the energy balancing action in the "Balancing Mechanism"(BM) make sure that the energy amount of the physical notification is accomplished. This type of balancing action is usually priced by Bid-Offer scheme. The merit-order wise choice of Bid-Offers, meaning cheap actions first, is preferred to reduce the balancing cost. Though, this is not always possible due to technical limitations of generators, demands and networks. An example for a technical limitation of a BM-generator is a non-suitable ramp-up rate, or a limitation for the network, an already congested line which would not allow more generation. Therefore, not only the cheapest BM Bid-Offer prices are selected or resolved by the system operator. In the BM, units are usually priced by the utilisation cost, however, short term operating reserves (STOR) take a special role for the stability and priced by the greater price between i) utilisation price or ii) reserve scarcity price. Whereby, the reserve scarcity price is the product of the Loss of Load Probability (LoLP) and Value of Lost Load (VoLL).

For the purpose of energy balancing, the system operator might additionally purchase non-BM services as "Balancing Service Adjustment Action" [30]. Drivers for such an adjustment action could be a more economical or specific necessary balancing characteristics from non-BM services, such as ancillary services or "other services" according to [17]. These non-BM actions are priced in capacity or energy or both ways and form balancing service adjustment data, consists of adjusted buy and sell prices, which adjust the imbalance price of the previously described BM [17,30].

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The system-balancing actions, otherwise, are only a part of the non-BM actions [17]. They describe balancing actions which keep the energy balance at every instance. For example, a wind power plant might generate the exact energy amount as contracted by the physical notification for the 30 min settlement period, however, its power might fluctuate and mismatch the demand in the settlement period which make system-balancing actions, such as activation's of non-BM STOR units, necessary [17]. The pricing scheme for the system-balancing actions is equal to the energy-balancing scheme for non-BM actions, described in the previous paragraph.

Figure 15, illustrates the weekly averaged imbalance price development in 2020. The imbalance price dropped significantly in the first week of the lock-down, while increased in the following week significantly, hence, showing an unclear trend. As described in the above paragraphs, the imbalance price is a complex construct. Therefore, the impact of the lock-down on the imbalance price can just be qualitatively evaluated.

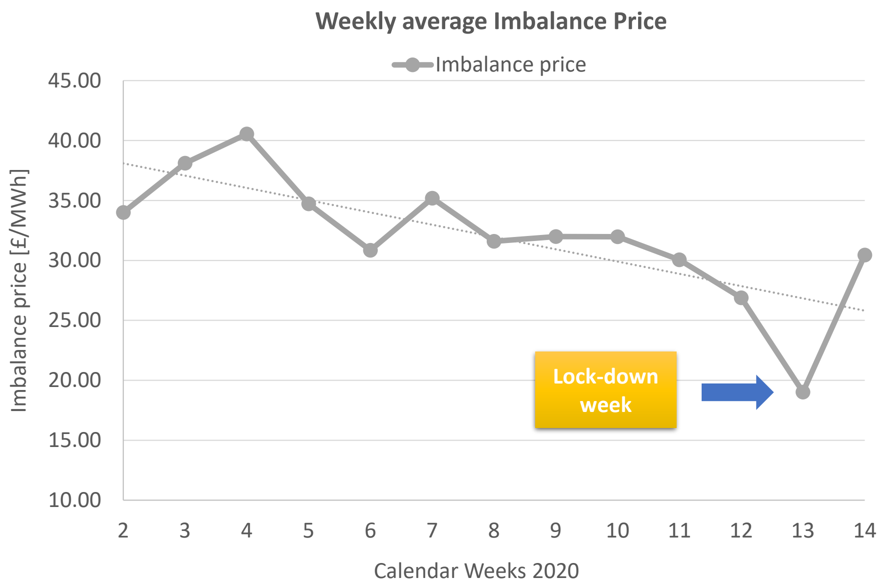

Figure 15. The impact of lower demand on the imbalance price. Ambiguous trend of change. Imbalance price significantly reduces in first lockdown week, but increases in higher magnitude on the following week.

The impacts of the lower demand at the lock-down times could potentially both increase and lower the imbalance price (see Fig. 16). The balancing service options are generally chosen in a merit-order wise way, meaning activating cheap balancing options first, if no system operation limitation exists. Therefore, similar to a the wholesale market price settling, a higher demand would lead to higher prices and cheaper generators could lower the price or vice versa. That the imbalance volume could increase was explored in section 3.3.3, which imply a higher need for balancing services. Moreover, an on average lower demand as discovered in 3.1, would potentially free up more generation units that can provide additional cost-effective balancing services. As result, the imbalance price could increase or decrease. The described effects frame not the whole picture, additionally investigation could be made on the LoLP, the VoLL, the de-rated margin, voltage related services and the network utilisation.

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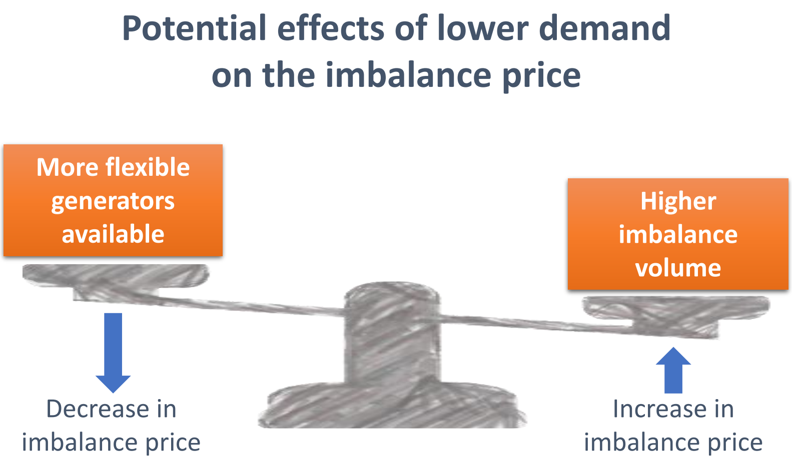

Figure 16. Illustrative example of lower demand impact on the imbalance price. Multiple effects impact the imbalance price in different directions. One effect that reduces the imbalance price is that more flexible conventional plants are available due to the lower demand and higher VRE share. Contrary, the observed higher imbalance volume increases the price since more expensive resources must be used (similar to merit-order).

3.4.3. Variable Pricing for Domestic Consumers

The case for variable pricing for domestic consumers was made by numerous studies [31]. It is a more consumer-centric approach where the domestic consumers are billed using the same half-hourly prices as the commercial ones rather than having a fixed tariff (i.e. a volumetric calculation using a fixed £/kWh rate). There is also the commonly known time-of-use (ToU) pricing where the £/kWh rate varies for different times of the day which usually correlates to higher rates for higher demand periods. For instance, electricity prices from 4 to 7 p.m. would be higher to reflect the evening peak whereas from 1 am to 4 am when the demand is usually low, the prices would be lower. Hence, this method of pricing would also result in demand shifting.

A British energy supplier called Octopus [32] introduced their "Agile" electricity tariff in which is an indexed half-hourly dynamic pricing that tracks the wholesale price of electricity (i.e. the domestic rate paid changes every 30 minutes instead of a fixed monthly rate). On different occasions, this has resulted in negative pricing (i.e. the energy supplier paid its customers to consume electricity). However, this also means that there is usually a steep price from 4pm to 7pm during the evening consumption surge. The following logic in Eq. 3, is used to determine the prime time pricing. It uses the distribution cost coefficient (τ) multiplied by the wholesale cost of electricity (W) and P which is the peak-time premium (which is equal to 12p/kWh during prime time). Then it caps the price to £35p/kWh if the previous outcome is higher than this value. This is because on average the fixed tariff are in the range of 15-20p/kWh and it could be argued exposing domestic consumers to extreme fluctuations in the system would be unfair.

$$min((\tau \times W + P), 35p/kWh) \tag{3}$$

In Figure 17, an example of capping at the maximum price of 35p/kWh is shown on the 4th of March 2020 (i.e. during the pre-COVID-19 week). This day marks the first time a system price was over £2000/MWh since 2001. It peaked at £2242/MWh [7] (See Section 3.3.4 for more information). The week commencing on the 30th of March 2020 is of interest for comparison with the other extreme, namely negative pricing, as it drops to near -3 pence per kilowatt-hour. Similar to the analysis in Section 3.1, the reduction in demand magnitude and changes in profile are correlated to the changes between pre- and post-action pricing profiles in Figure 17.

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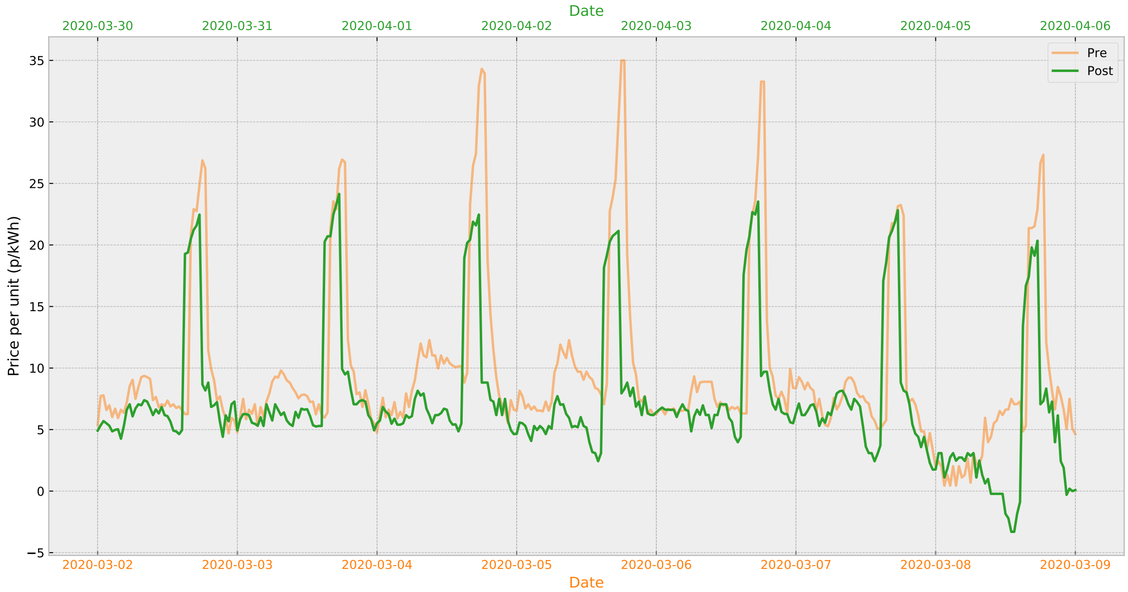

Figure 17. Examples of price capping (5th March 2020 on the lower orange x-axis) and negative pricing (5th April 2020 on the higher green x-axis) during pre- and post-COVID-19 weeks respectively -using the data from [33].

Since the launch of the Agile tariff, there has been 96 occurrences of negative pricing (i.e. price < 0p/kWh). Almost 70% of these events (i.e. 67 out of 96) took place post-COVID-19 actions. Table 3 summarises the pre and post negative pricing events highlighting the highest price the consumers were paid to use electricity and the corresponding dates.

Table 3. Analysis of negative pricing in the Agile tariff -using the data from [33]

Data	**Mean**	**Min**	**Max**	Dates corresponding to max values
Pre (p/kWh)	-1.62	-0.07	-4.85	09-12-2019
Post (p/kWh)	-1.36	-0.02	-3.99	20-04-2020
Overall (p/kWh)	-1.44	-0.02	-4.85	09-12-2019

Octopus also provides variable pricing for selling electricity [32]. The corresponding sell prices are plotted in Figure 18. The highest sell price around 19p/kWh was recorded which corresponds to the day with the highest system price since 2001. The benefit is passed on to the distributed generators. In the case of negative load pricing when the consumers were paid to use electricity on the 5th of May, there would also negative pricing for exporting electricity (i.e. generators pay to export electricity). The pricing for generation is capped at a minimum of 0p/kWh which indicates that the energy was exported for free during that period as shown in Figure 18.

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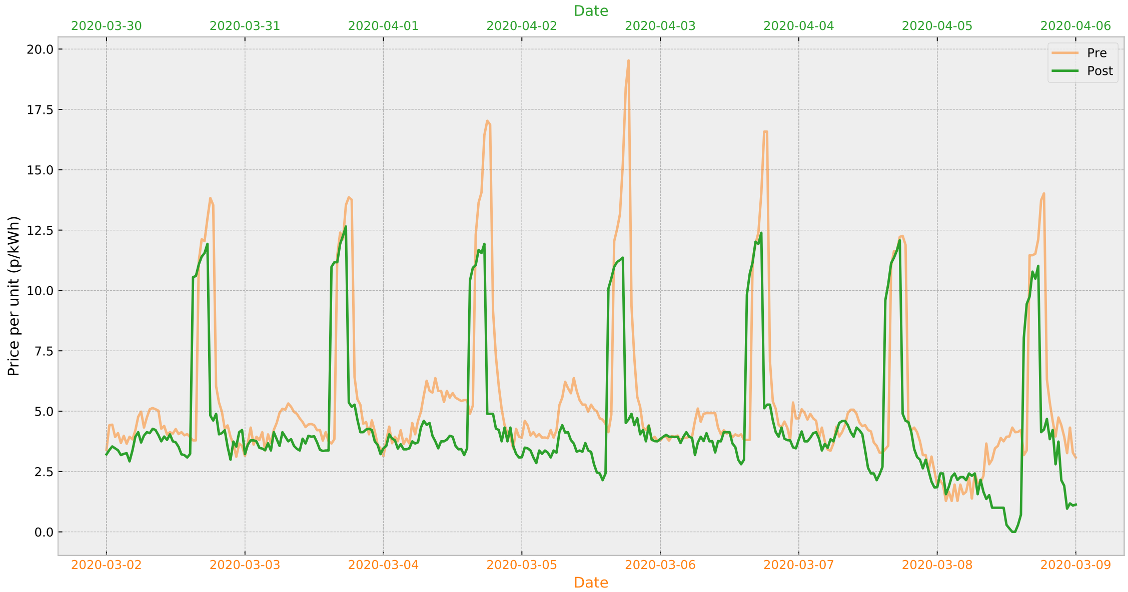

Figure 18. Corresponding Agile outgoing sell prices.-using the data from [33], That shows a high sell price reflecting the reserve scarcity (5th March 2020 on the lower orange x-axis) and a capped price of 0p/kWh (5th April 2020 on the higher green x-axis).

4. Discussion

In Section 3, four main categories of results were presented which are namely: (1) the changes in demand, (2) generation portfolio, (3) forecasting and grid stability, and lastly (4) market prices. In this section, these results are evaluated and their impact on different stakeholders are discussed. Following this, the limitations of the results are addressed along with suggestions for future work.

The key results are summarised in Figure 19. They indicate that the grid is still reliable and stable but operates under stress. More detailed explanation of each point here can be found in Section 3.

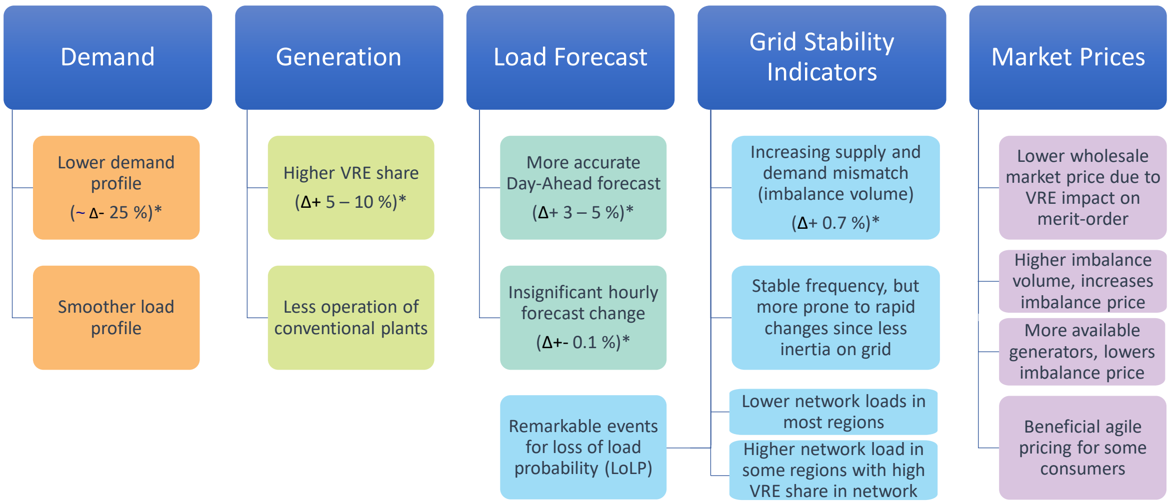

Figure 19. Summarised key results. The asterisk (*) notes that the effect of some factors such as economic climate were not taken into account. More details on whether these changes are representative, can be found in Section 3.

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4.1. Implications for Stakeholders

The new disruptive and lower demand profile has multiple effects on the stakeholders in the electricity system who are the network operators, suppliers, generators, aggregators and DSR providers, and consumers.

The network operators face a lower system demand on average which would result in generally lower loading on the network yet occasionally higher network loads in some cases. Firstly, higher amount of balancing services are expected due to the decreased performance in short-term forecasting (see Section 3.3.2) and hence, the resulting higher volume of imbalances (see Section 3.3.3). Secondly, lower network loads are expected due to the lower average load during the lock-down. Although, at some, particularly high VRE locations, the network load might increase because of the increased power flows (see Section 4.1.1).

In the wholesale market, suppliers interact with generators to form a long-term electrcity supply contracts [27]. The imbalance volume increased due to the lockdown which probably was unforeseen at the time of the contract. The increasing load uncertainty and changes in the load profile may imply that both of these parties are subjected to more imbalance charges. The trend of the total amount of imbalance charges cannot be easily detected, as described in Section 3.4.2. The imbalance price is a complex measure which can increase and decrease due to the lockdown effects. Besides the imbalance, generators and suppliers would suffer from the disruptive demand changes in terms of profitability. The share of fixed cost compared to amount of sales may increase to compensate for the lower volume of electricity demanded. This eventually would lead to higher electricity prices for domestic and industrial consumers. On the contrary, suppliers are expected to benefit from lower wholesale market prices. For instance, as the demand decreased the supplier would need to purchase a smaller volume of energy resulting a lower cost whilst receiving fixed instalments from domestic customers (see Section 3.4.1).

Aggregators and DSR providers are expected to be more often scheduled because of the larger imbalance volume observed after the lockdown. The only requirement for them is to be more competitive than the flexibility offered from the non-scheduled power plants as more plants are expected to be available for such services due to decreased baseline consumption. If so, aggregators and DSR providers woud benefit from the COVID-19 lockdown.

There is virtually no benefit for the distributed consumers with a fix rate supply agreement as the average domestic household demand is expected to increase due to WFH. However, there has been approximately 70 negative pricing events since the lockdown started which suggest that consumers with variable pricing such as the Agile tariff are getting paid to use electricity. Such consumers can also take advantage of reserve scarcity and benefit from exporting when the grid is under stress (see Section 3.4.3 for more details). Regarding the commercial and industrial users, the same would apply which indicates that the user with the most flexible assets/loads would be able to take advantage of the effects of the lockdown on the pricing.

4.1.1. Implications for future systems

The demand and generation findings for the lockdown state of the electricity system can be used as a representation of the next decade according to the International Energy Agency [34]. This would be when the share of VRE, such as from solar and wind, is higher and balancing services are more in demand. Hence, this suggests that the results of this study (see Figure 19) regarding the effect of the lockdown due to the COVID-19 pandemic can be interpreted as an outlook into the future.

As suggested by several indicators, when using the findings of this paper as a future scenario, several assumptions and limitations must be noted. Firstly, the lockdown changed the load profile shape which resulted in a flatter profile that is different than a typical future demand scenario which may assume more efficient home appliances but increase in electric vehicle ownership (i.e. increase in over-night demand). This flatter demand profile, counter-intuitively, lead to better day-ahead load forecast even though the share of VRE increased. Secondly, the current power system is supported

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by inflexible nuclear and gas plants which might change in the future due to the increasing amount of flexibility services such as DSR. Lastly, the current network is comparatively oversized due to the lower load. The same network at higher VRE share could lead to more congestion in a future power system.

One of the most important aspect of planning for a future power system is network congestion that is expected to occur as VRE shares increase. During a lockdown, the network usage is expected to decrease on average but some sections might be loaded more than usual. The lower average demand in GB implies that less energy is transported through the power lines which results in reduced network usage and losses. However, some other network sections could increase in loading as centralised renewable energy sources will transport energy for longer distances. The reason for longer transported energy is the lower electricity consumption closer to the VRE generators. For instance, the large wind generation capacity installed in Scotland provides more energy to the southern parts such as London. As the net consumption in GB decreases, less energy is locally consumed in the north and may lead to higher network loads along the transmission lines when there is generation from wind and/or solar. Therefore, despite the decreased load, some parts of the network are likely to experience higher congestion.

4.2. Outlook & future work

Overall, this analysis implies a significant point for future models of a low probability but high impact event such as the 2019 pandemic. This is that the imbalance increases and stresses the grid if the operator is not prepared. This has the potential to result in a record high system price (such as the £2242/MWh mentioned previously) and/or a more severe problem such as a black-out in the future power system. The findings in Section 3 which are summarised in Figure 19 can be used for modelling the demand, generation, market and grid stability for a future low probability high impact event or the second wave of the lockdown. As shown in Section 3.4.3, the lock-down has led to almost 70 events of negative pricing where the users were rewarded for their consumption. Additionally, following the increase in LOLP (See Section 3.3.4) and reserve scarcity pricing, the distributed generators benefited from some high sell prices during the lock-down. The variable pricing is indexed to the half-hourly rates. This is a consumer-centric pricing method that encourages peak shaving as the consumption during peak times is expensive. Hence, it helps flatten the demand curve. This is a gateway for emergent markets like peer-to-peer trading which involves exchange of electricity amongst distributed consumers, increasing their self-sufficiency. [31] prove that even consumers not participating in DSR actions would benefit from real-time and variable pricing. Using the internet of things (IoT), loads can respond to price signal and adjust their scheduling in order to minimise their electricity cost. This is especially significant when charging electric vehicles as discussed in [35]. On the grid scale, studies such as [36] prove the significance of scheduling algorithms for taking advantage of both arbitrage and other DSR events and highlight the future potential of commercial size battery energy storage systems.

The outcomes of this analysis may be used for predicting the response of the electricity market to another low probability and high impact event in the future.

5. Conclusions

The outbreak of COVID-19 disrupted the patterns in electricity consumption, challenging the system operations of forecasting and balancing the supply and demand. This is due to the mitigation measures that include lockdown and WFH which decreased the aggregated demand by 25% and remarkably flattened its profile. These changes were characterised with various quantitative markers and compare it with pre-COVID-19 business-as-usual data using the case study of Great Britain. Similar observations have been made in different countries such as Australia [37] and Italy [38].

The ripple effects on the generation portfolio with 5-10% higher VRE share and decreased operation of conventional plants. The systems stability indicators suggest that the grid operated well but is under stress The indicators include some remarkable LoLP events and higher overall system frequency. However, contrasting evidence show 3-5% more accurate day-ahead forecasts. The energy market is also greatly affected by this change of consumption pattern. The wholesale market price decreased due to VRE generators raking higher on the merit order. Whilst the imbalance prices are higher due to the higher imbalance volume in the system, this increase is compensated by the increased number of generators due to the decreased demand volume.

An alternative pricing mechanism was also investigated for domestic consumers. With over 70 events of negative pricing, it was shown that the new pricing scheme would have benefited consumers with flexible load such as an EV. Despite the overall drop in the prices due to the decrease in wholesale market price, there were some LoLP events that increased the system price as much as £2242/MWh which is the highest in the last 19 years and almost 20 times higher than the month preceding the lockdown (February 2020).

Echoing four main categories of results presented which are namely: (1) the changes in demand, (2) generation portfolio, (3) forecasting and grid stability, and lastly (4) market prices, Section 4 assessed their impact on different stakeholders such as system operators, suppliers and consumers. Following this, the limitations of the results were addressed along with suggestions for future work.

The proposed open-source energy data extraction and pre-processing pipeline can be used in a variety of similar studies - see Figure 1. It can be useful for both academic and industrial research in electricity markets, trades and forecasts as it simplifies the procedures of data extraction, pre-processing and visualisation.

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