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Sweat Testing Cycles of Batteries for Different Electrical Power Applications

MINA ABEDI VARNOSFADERANI[1], DANI STRICKLAND[1], MARTIN RUSE[2], AND ENRIQUE BRANA CASTILLO[3]
[1]Holywell Park, Loughborough University Science and Enterprise Parks, Loughborough L11 3TU, U.K.
[2]Denchi Group, Caithness KW14 7XW, U.K.
[3]Jaguar Land Rover Ltd., Warwick CV34 6TB, U.K.

Corresponding author: Mina Abedi Varnosfaderani (m.abedi-varnosfaderani@lboro.ac.uk)

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ABSTRACT This paper looks at six different applications for a domestically located battery system and determines how these could be translated into different electrical power application "drive" cycles. The applications considered are as follows: 1) A house with four people and a solar panel using the battery to absorb extra energy when the PV panel is producing more power than is absorbed in the house and then releasing this energy afterwards. 2) A house with four people and PV panels on a time of use tariff. 3) A house with four people and no PV on a time of use Tariff – where the battery is charged at low tariff and discharged on high tariff. 4) The battery is operating as part of an aggregated frequency response system performing on the Firm Frequency Response (FFR) market. 5)The battery is operating as part of an aggregated frequency response system performing on the Enhanced Frequency Response (EFR) market. 6) The battery is operating as part of an aggregated system looking at competing in the day ahead market. This paper describes each use cases and developes a representative charge/discharge profile of these applications using MATLAB code and generates waveforms of battery charging and discharging for each use case over a year-long period in monthly intervals. Any time intervals where the battery was inactive were removed from the generation of the cycling patterns. Two statistical analysis methods (Haar transform and a pragmatic method) were used to condense the data into programmable steps for generating battery sweat testing and cycling model. These were then coded and used to generate year-long sweat testing of the different applications for use with degradation and financial analysis to look at business opportunities. This paper looks at the development of the charge and discharge profiles of these applications and defines a set of power application "drive" cycles which are published in excel alongside this paper for use by researchers longing at battery degradation.

INDEX TERMS Batteries, drive cycle, cycling, sweat test, frequency response, battery tariffs.

I. INTRODUCTION

There are well established "drive cycles" associated with electric vehicle battery and system testing. Example of common drive cycles include the Urban driving cycle (UDC ECE-15) [1], [2] and the New European Driving Cycle (NEDC) [3]. These offer standardised cycles that can be used by multiple parties to enable performance comparison. There has been some criticism that these are not sufficient real world and additional cycles have been proposed [1]–[3] which represent other conditions, eg a vehicle travelling on a motorway. These drive cycles give parameters such as speed and condition and can be used to design powertrains with batteries, such that these undertake calculable and repeatable cycling behaviour. An example of such an application is shown in FIGURE 1 which is representative of cycle testing around a representative drive cycle.

The type of cycling in an electric vehicle application is not the same as would be seen in an electricity grid application. Energy storage is only recently becoming popular in the domestic market. Currently listed domestic markets products for new and second life battery systems are shown in Table 1.

A performance comparison between different solutions is not possible at this time because different manufacturers and researchers assume different test based conditions to look at

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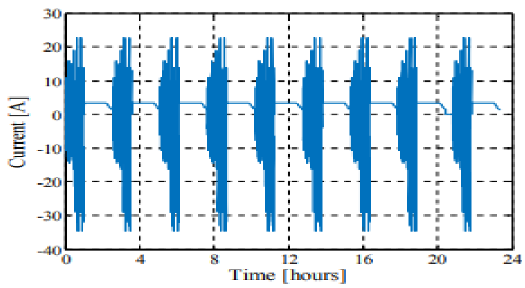


FIGURE 1. One day load current profiling for accelerated aging tests [4] – based on the WLTC drive cycles.

TABLE 1. Different published claimed 2nd life and new systems.

Relectrify – Australia	400W, 1.2kWh
Nissan and Eaton xStorage	up to 6kW
Tesla	13.5 kWh
PowerVault	Up to 7.9 kWh and 20.5 kWh
Sonnen	Up to 16 kWh
BYD	3kWh to 6kWh

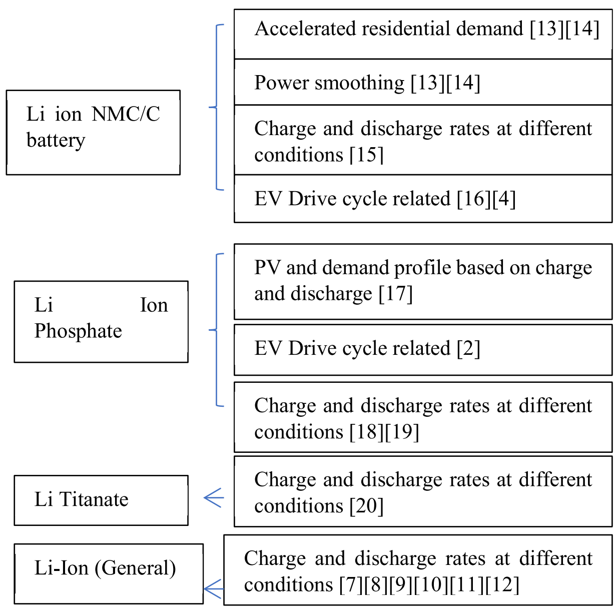


FIGURE 2. Examples of published cycle testing for different battery chemistries.

how these products perform. FIGURE 2 gives an example of previous cycle testing the researchers have undertaken with different battery chemistries – all of which are non-standard with non-detailed data sets.

The majority of the cycles are based on fixed charge and discharge cycles including those from IEC [5] and IEA [6] and don't take into account application specific requirements. Additional testing based on a similar premise has included variation for charge/discharger rate and temperature to allow research into aging mechanisms [7]–[12].

Where an application specific "drive cycle" has been used the underlying data has not been published alongside the paper and therefore it is difficult to replicate the cycle for use with performance testing. This shortfall in relevant application specific "driving" cycling for domestic applications makes it difficult to compare products.

The aim of this paper is to detail some use cases for a domestic battery system and use these to develop a set of "drive cycles" to provide a common sets of curves for batteries to be tested against. The work is based on a 3kW and 4kWh product in a domestic environment for which scaling would be required for size variants. The data is published alongside this paper in excel spreadsheet format for use by other researchers.

The following process has been used to develop the associated data curves;

1. Identifying the characteristics of different applications.
2. Developing a representative charge/discharge profile of these applications.
3. Developing a detailed cycle profile which may be used for sweat testing of the batteries through multiple cycles.

Six cases have been chosen for study;

1. A house with four people and a solar panel using the battery to absorb extra energy when the PV panel is producing more power than is absorbed in the house and then releasing this energy afterwards.
2. A house with four people and PV panels on a time of use tariff where the battery is used to absorb extra energy from the PV panel and release this when the tariff is highest.
3. A house with four people and no PV on a time of use Tariff – where the battery is charged at low tariff and discharged on high tariff.
4. The battery is operating as part of an aggregated static frequency response system performing on the UK Fast Frequency Response (FFR market).
5. The battery is operating as part of an aggregated dynamic frequency response system performing on the UK Enhanced Frequency Response EFR) market.
6. The battery is operating as part of an aggregated system looking at competing in the day ahead market.

It has been decided not to include sophisticated demand side management or fast charging of electric vehicles in these use cases at this time as these are not currently market ready. Similarly, microgrid functionality has not been included for the same reason. Grid scale peak load lopping has also not been included as there is no market mechanism for dealing with this type of energy storage benefit.

There are some additional electricity markets that are open to larger battery systems, but not yet available as an aggregation of smaller domestic units. However, it is thought that these may become a realistic proposition under political pressure. Therefore, the additional auxiliary market mechanisms have been included for study.

This paper deals with each use case in turn and quantifies the charging and discharging that would occur over a year long period. The paper then condenses this profile by removing periods of inactivity and determining an average profile for each month for each use case using two different methods (which tie up with the ability of a load bank to follow a cycle). These are determined for each month of the year. The total year-long data set forms a "drive cycle" for each of the use cases. The study is based on a nominal Powervault kWh & kW battery and scaling would need to be considered for other sizes of battery.

This work is organised around these different applications; Section II looks at case 1 – PV, maximising FIT payments, Section III looks at case 2 – PV, maximising FIT payments and TOU tariff, Section IV looks at case 3 – no PV, but maximising TOU tariff, Section V looks at case 4 – FFR market participation and Section VI looks at case 5 – EFR market participation. Section VII looks at case 6 – Day ahead market participation, Section VIII describes the methodology used to convert the yearlong profile into a set of cycling tests and Section IX concludes the paper.

II. USE CASE 1 – PV AND MAXIMISING FIT PAYMENTS

The Feed-in Tariff (FIT) is an electricity payment scheme for domestic and commercial energy producers that generate their own energy and export it to the grid funded by the UK government and developed to encourage increased used of solar power. The CREST Demand Model [21] is a high-resolution stochastic model of domestic thermal and electricity demand. The model produces one-minute resolution demand data, disaggregated by end-use, using a bottom-up modelling approach based on patterns of active occupancy and daily activity profiles derived from time-use survey data.

The model uses an occupancy model based on the probability of the number of occupants in the house at any given moment. In this work, the max number of residents in a house is set to 4. The model also has some typical solar irradiance-based data which can be used in conjunction with the 3kW model. This example irradiance data is provided from the CREST irradiance database for Loughborough [21]. The data is filtered to a one-minute exponential moving average (with a weighting factor 0.1). The irradiance per month is assumed to be the same for each day of the month.

This work used the solar data along with a years' worth of data generated for a four-person occupancy home over the course of a year with a split between weekday and weekend as appropriate. Use case 1 is about using any excess produced solar power to charge a battery which can then be used to supply household load when the sun isn't shining. This is because the income from exporting excess solar power is lower than the cost to re-import later. FIGURE 3 shows a modelled battery charge and discharge power in spring for a single day (from the year-long study). The full years' worth of this charging and discharging data is available in the files associated with this paper. To ensure that the energy in the battery is managed correctly the software used to generate the battery charging and discharging profile from the input data also ensures that the battery ends the day at the same state of charge as it begins the day to avoid the additional complications that would result from a different starting point each day.

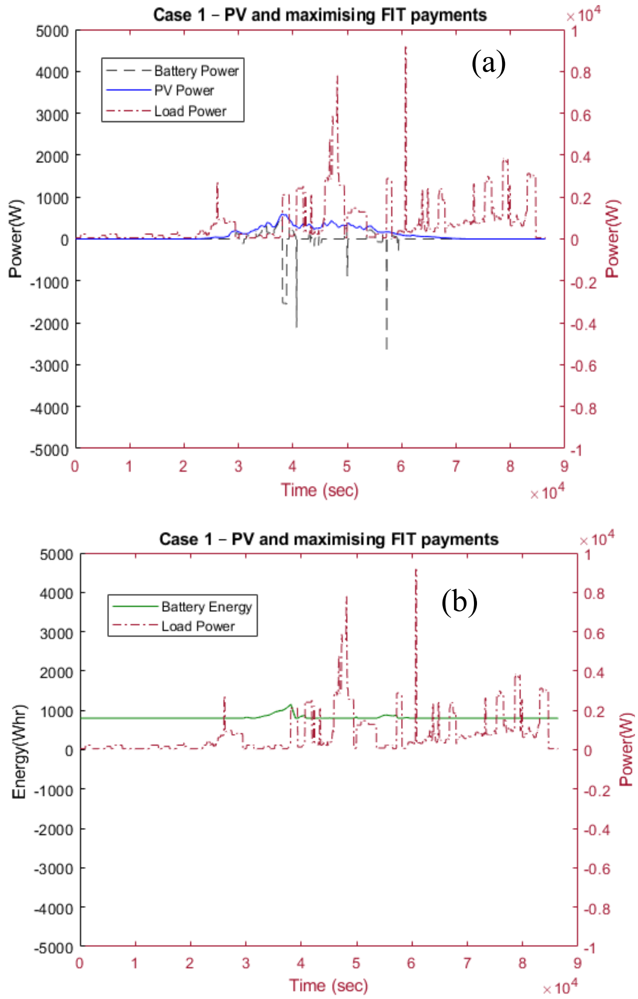


FIGURE 3. Data over a day in spring (April), (a) left Y axis battery power and PV power, right axis load power (b) left Y axis battery energy and right Y axis load power.

TABLE 2. Time of use tariff – price per kWh.

	0:00	06:00	16:00	19:00	23:00 24:00
Monday-Friday	5p	12p	25p	12p	5p
Saturday-Sunday	5p	12p	12p	12p	5p

III. USE CASE 2 – PV, MAXIMISING FIT PAYMENTS AND TOU TARIFF

There are not many time of use (TOU) tariffs currently available in the UK. One such typical tariff has the following characteristics (August 2018) as shown in Table 2.

Looking at these figures shows that it makes sense to discharge the battery between 16:00 and 19:00 on weekdays as much as possible.

The battery charge and discharge power are calculated for a 4-person house with 3kW PV to maximise FIT payment

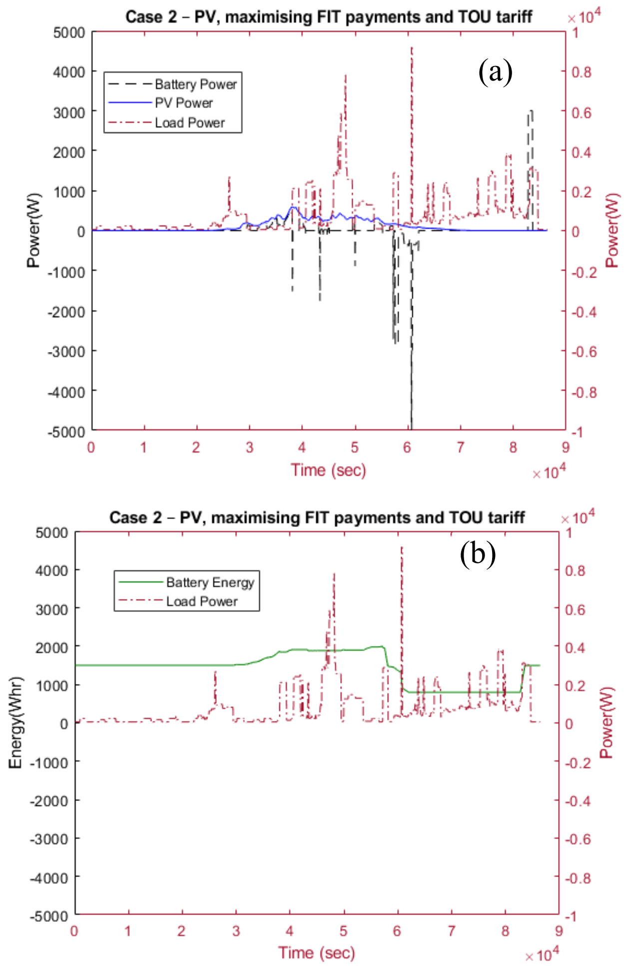


FIGURE 4. Data over a day in spring (April), (a) left Y axis battery power and PV power, right axis load power (b) left Y axis battery energy and right Y axis load power.

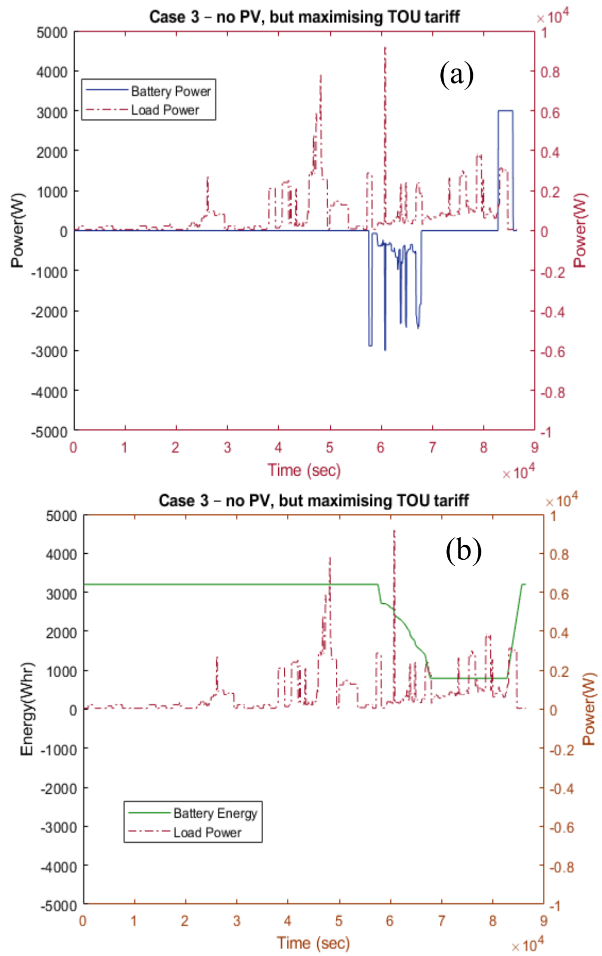


FIGURE 5. Data over a day in spring (April), (a) left Y axis battery power and PV power, right axis load power (b) left Y axis battery energy and right Y axis load power.

as well as benefiting from the TOU tariff. FIGURE 4 shows an example of a battery charge and discharge power in spring for a single day. In this case, the battery is discharged between 16:00 and 19:00. The battery is also charged between 23:00 and 24:00 to return the SOC to the same condition as the start of the day.

IV. USE CASE 3 – NO PV, BUT MAXIMISING TOU TARIFF

Not every householder will have PV panels but may want to use a battery to benefit from TOU tariffs. Therefore, this case looks at using a BESS to benefit from tariff. Table 2 is used as the basis for tariff costs. The difference with case 2 is that the solar irradiance-based data is not included in the battery charge/discharge power calculation. Therefore, in this case, the battery is charged when the tariff is low (23:00 – 24:00) and is discharged when tariff is high in this case 16:00 and 19:00.

An example of Battery charge and discharge power for the TOU tariff only in April for a single day is shown in FIGURE 5. A years' worth of this charging and discharging data is available in the associated files.

V. USE CASE 4 – FFR MARKET PARTICIPATION

Representative frequency data with a one-second resolution has been made available by National Grid [22] over a year. This paper uses the data from the year July 2017- June 2018. The FFR response service is split into two products; static and dynamic frequency response. Static response is where battery operation is triggered by a threshold, whereas dynamic response means the setpoint of the battery is continuously adjusting. As the dynamic response is similar to EFR (Enhanced Frequency Response: this is done in use case 5). In this case, a static response is modelled with a dead band of 50Hz $\pm$ 0.1Hz as shown in FIGURE 6. The battery is operated as follows:

- The battery is used to absorb extra energy when the FFR frequency is higher than the lower limit
- The battery to release energy when the day FFR frequency is lower than the upper limit

FIGURE 7 shows an example of the battery performance in April for a single day. The battery is discharged when the frequency exceeds the lower limit and charged when the frequency is higher than higher limit.

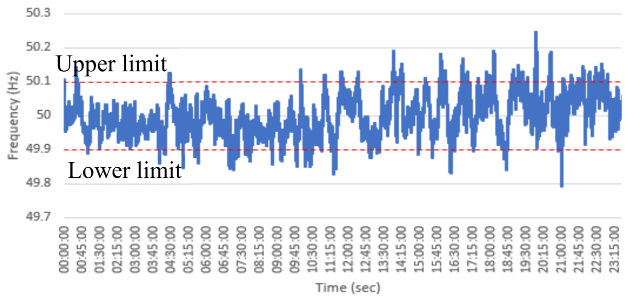


FIGURE 6. FFR frequency boundary limits over a day in winter (January).

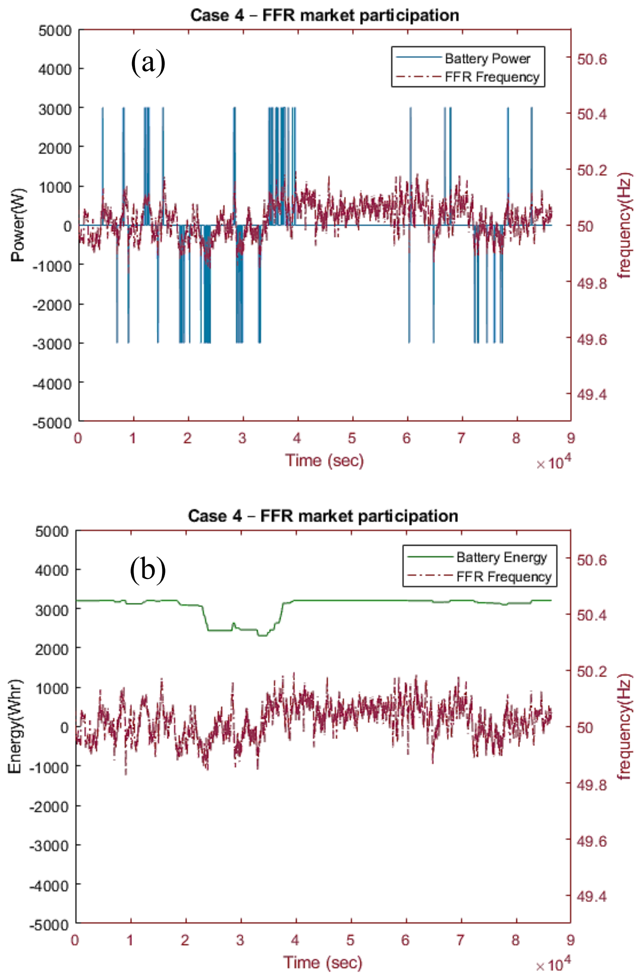


FIGURE 7. Data over a day in Spring (April), (a) left Y axis battery power and right axis frequency, (b) left axis battery energy and right Y axis frequency.

VI. USE CASE 5 – EFR MARKET PARTICIPATION

Enhanced Frequency Response service (EFR) is a trial method to help to control frequency by National Grid. It is similar to dynamic response [23]. Similar type curves have been suggested in other European countries and so it is likely that some form of curve like this will be adopted. This service is only a dynamic service with variable battery output depending on frequency. There are two variants wide and narrow band. However, current metering does not allow for narrow band – so this will not be considered. FIGURE 8

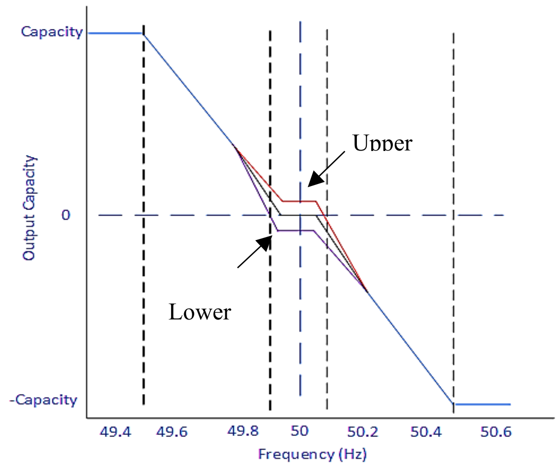


FIGURE 8. National Grid EFR battery storage specifications - Wide specification.

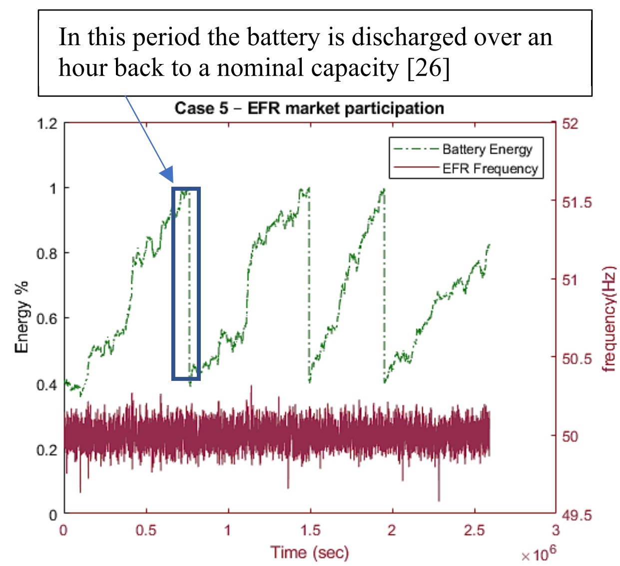


FIGURE 9. Data over a month in spring (April), left Y axis (Battery Energy in %) and right Y axis (EFR Frequency).

shows the technical requirement for the EFR energy storage system with wide frequency band (50Hz $\pm$ 0.05Hz) response [24], [25]. This response envelope provides the battery storage response required for a specific frequency value. Each of these envelopes is represented by a lower and upper limit for battery SOC management. The x-axis is the frequency in which the provided response must remain within the frequency envelope with the nominal frequency of 50Hz. The y-axis is the percentage of deliverable power of the battery storage.

This paper uses the provided envelope relative to the presented battery capacity to model the battery SOC and charge and discharge power pattern.

An example of Battery charge and discharge Energy for EFR market participation in April for a month are shown in FIGURE 9.

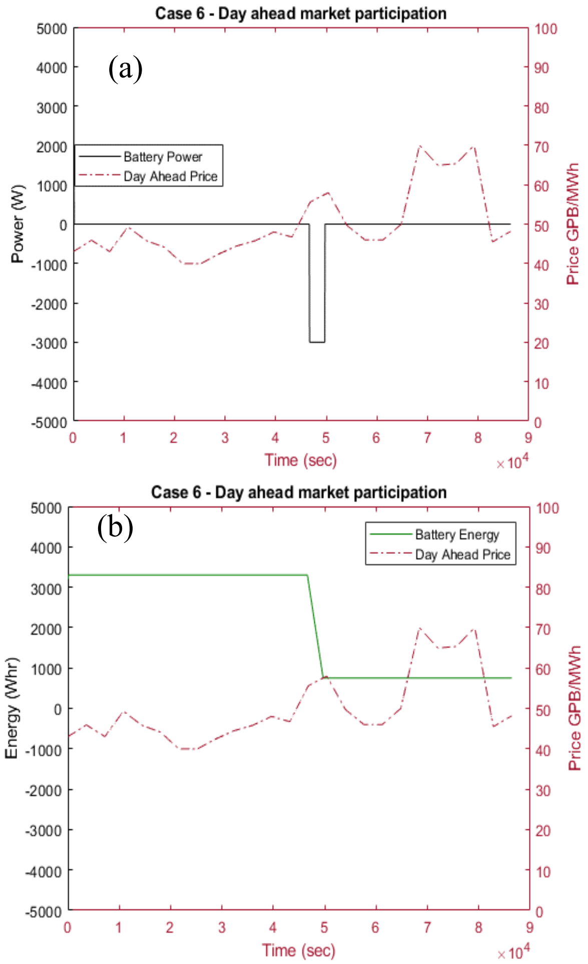


FIGURE 10. Data over a day in spring (April), left Y axis ((a) Battery Power, (b) Battery Energy) and right Y axis (Day ahead market price).

VII. USE CASE 6 – DAY AHEAD MARKET PARTICIPATION

The day ahead auction price is agreed 24 hours ahead in one-hour periods ahead of delivery of electricity. The day ahead block prices are available from "Nord pool group website" [27]. In this case, it is assumed that an aggregator trades the battery to deliver power when the price is above a price limit and consume power when it is below a price limit. The battery is operated as follows:

- The battery is used to absorb extra energy for 1 hour when the day ahead price is lower than the lower limit
- The battery is used to release energy for 1 hour when the day ahead price is higher than the upper limit

The higher limit and lower limit is estimated based on a years' worth of data. FIGURE 10 shows an example of the battery operation for a day in April.

VIII. PRODUCING CYCLE TEST DATA

It is important to be able to take the data generated in the 6 use cases over the course of the year and produce application specific battery systems cycle testing to help get an indication of life span. The process around this is typically;

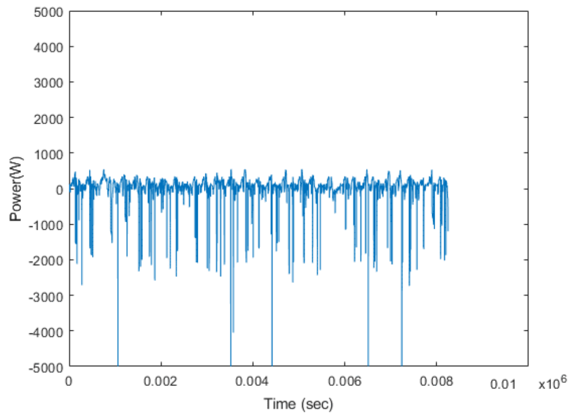


FIGURE 11. Case 1 – PV, maximising FIT participation data over a month in spring (April).

1. Quantify the charge/discharge test profile associated with each application
2. Develop accelerated aging tests around the profile

The process is complicated by the processes around aging and degradation. This section explains how the yearlong data is turned into sweat test curves that represent the typical usage that the batteries could see over a year-long period of their life.

The waveforms for battery charging and discharging for each use case over a month-long period are taken and any battery rest time is removed. FIGURE 11 shows an example of the data for use case 1 in April.

This data was then used to generate statistical data for each month of the year using two different methods. Two different methods were used because not all load bank and power source/ battery testing equipment has the capability to undertake fast switching transients to capture all of the possible micro-cycling that may be occurring. Matlab 2018b was used to generate a Haar Transform of the data – this is similar to a Fourier Transform but generates pulse patterns rather than sine waves as an output. These can be re-combined according to the battery tester specification to re-generate a signal set close to the original waveform. Where a battery tester cannot meet such fast testing – an alternative approach has been used.

FIGURE 12 and FIGURE 13 show a generated Haar Transform coefficient and histogram chart respectively. The Haar transforms offers a more complex method of taking into account the cycling that the battery would go through but is significantly more complex to code.

The charging and discharging curves are partly cyclic but with variation caused by load, PV, frequency etc. These waveforms can be decomposed in a manner very similar to a Fourier Transform to create a set of component parts which when added together give the original waveform. The Haar transform is a wavelet transform and is often used to compress and sample signal and images in electrical engineering. Similar to Fourier transform, Haar transform is a sequence of square-shaped functions which their summation forms the original signal. These sequences can be calculated

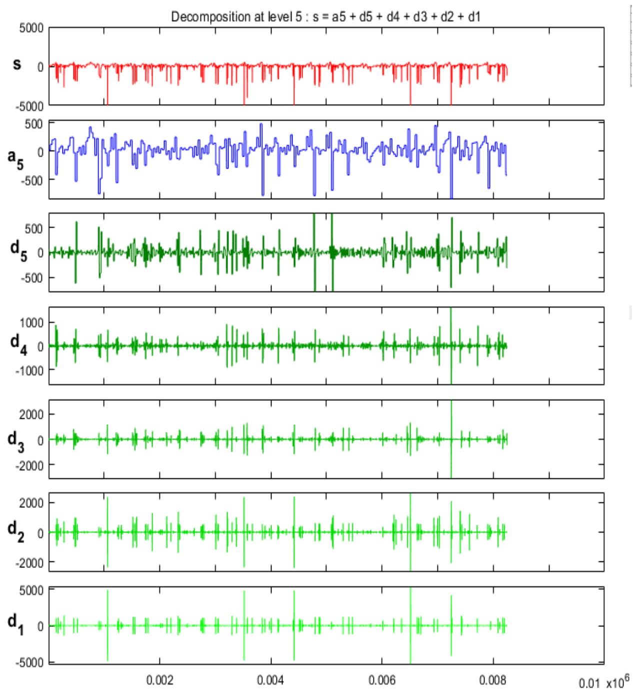


FIGURE 12. Case 1 – PV, maximising FIT participation data over a month in summer (April) x axis is time (sec) and y axis is power (W).

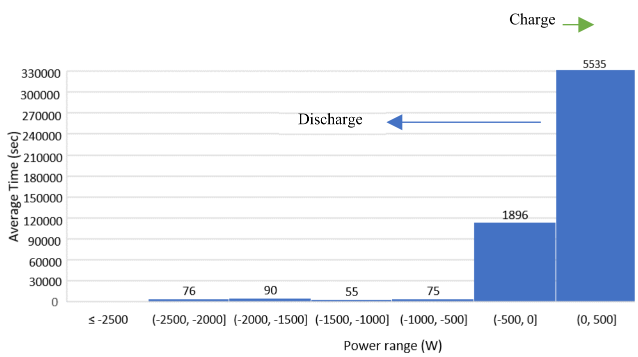


FIGURE 13. Case 1 – PV, maximising FIT participation data over a month in summer (April) x axis is Power range (W) and y axis is Time average (sec).

using Equation 1 and Equation 2.

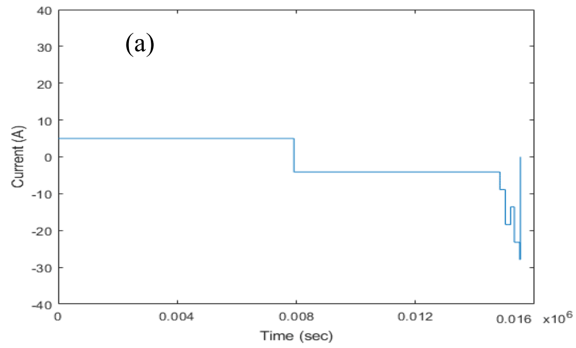
$$\psi_{n,k}(t) = 2^{\frac{n}{2}}\psi\left(2^n t - k\right) \qquad \text{Equation 1}$$

$$y_n = \psi_n x_n \qquad \text{Equation 2}$$

where ψ is Haar function, n and k are integers in Z (in this case n = 5 and $0 \leq k \leq 2^n - 1$), y is Haar transform function of input function x. The MATLAB wavelet toolbox was used to generate square-shaped sequences of the modelled battery charge and discharge.

FIGURE 12 shows an example of the Haar transform of the battery operation for use case1 over April. Where S is the original signal, a_5 and d_1 to d_5 are Haar coefficients. Coefficients d_1 to d_5 mostly contain high-frequency details and abrupt changes in signal. Coefficient a_5 contains an approximation of the signal. This depends on the level that the Haar transform is calculated. A proposed sweat testing and cycling waveform could therefore be based on coefficient d_5 and approximation a_5. However, not all equipment is capable of dealing with this level of sophisticated and fast coding, so an alternative is also suggested.

The other method proposed is to use a more pragmatic approach. In this method, the cycling patterns are statistically analysed, and an "average" daily cycle is composed. This



	Current	Time(min)	Time(sec)
Charge	5.0	132	7920
Discharge	4.1	115.3	6918
Discharge	8.9	3	180
Discharge	18.4	3	180
Discharge	13.6	2.1	126
Discharge	23.2	3	180
Discharge	27.9	0.4	24

(b)

FIGURE 14. Case 1 – PV, maximising FIT participation data over April a) Battery charge and discharge cycle, x axis is Time(min) and y axis is Current (A), b) Battery charge/discharge current + duration.

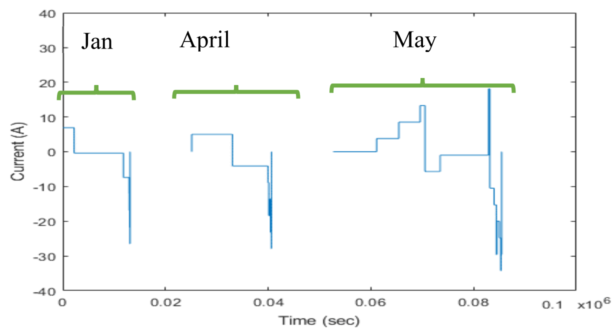


FIGURE 15. Use-case 1 histogram based sweat test monthly waveform shown for three separate months.

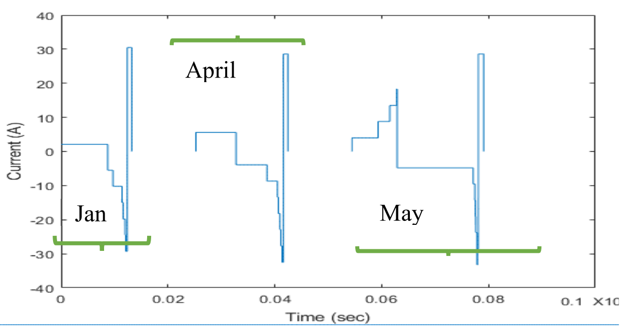


FIGURE 16. Use-case 2 histogram based sweat test monthly waveform shown for three separate months.

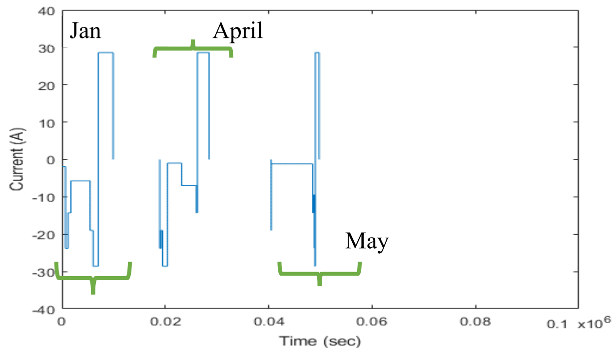


FIGURE 17. Use-case 3 histogram based sweat test monthly waveform shown for three separate months.

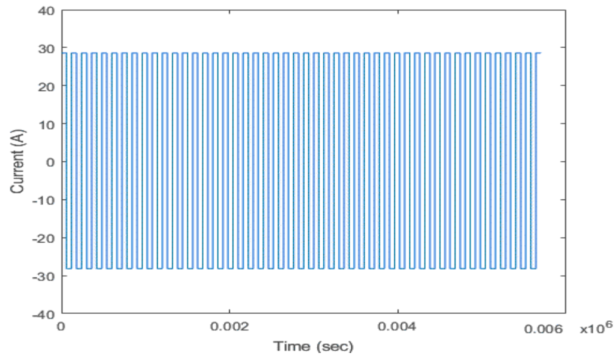


FIGURE 18. Use-case 4 Sweat test over April.

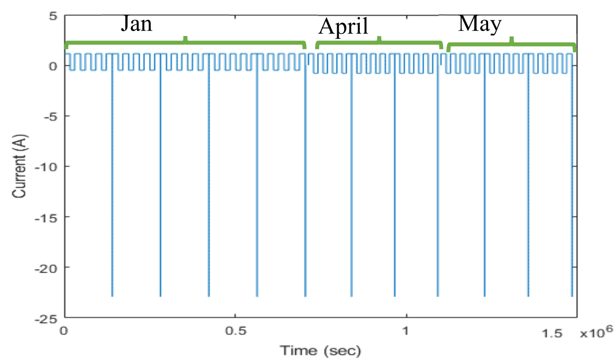


FIGURE 19. Use-case 5 histogram based sweat test monthly waveform shown for three separate months.

is done by analysing the total time the battery is operating at each charge and discharge rate over the month and then averaging this over a day to give the charge and discharging rates and their duration. These are then organised as close to the loading shape as possible to ensure the battery does not exceed any limits. The distribution of battery power variations over time in a month are plotted as a histogram. These are then averaged to create a daily cycle for that month and coded for all the days of the month. FIGURE 13 shows an example of the histogram chart of the battery operation for case1 over month of April.

FIGURE 14 shows an example of the cycling pattern of the battery for case1 over the month of April using the histogram data from the table.

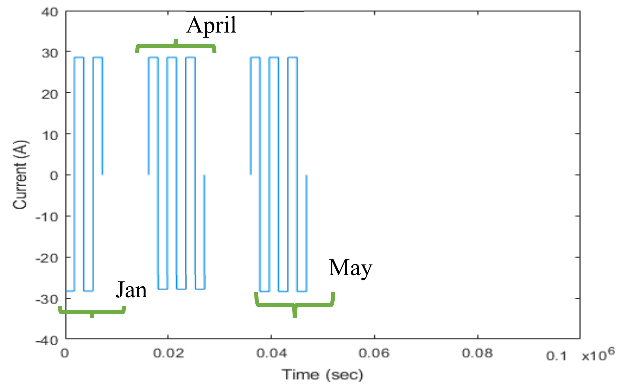


FIGURE 20. Use-case 6 histogram based sweat test monthly waveform shown for three separate months.

TABLE 3. Summary of battery charge and discharge energy over a year.

Use case Scenarios	Total charge over a year (kwh)	Energy Balance
Use case 1 – PV and maximising FIT payments	890	Energy in battery balanced at the end of each day
Use case 2 – PV, maximising FIT payments and TOU tariff	838	Energy in battery balanced at the end of each day
Use case 3 – no PV, but maximising TOU tariff	609	Energy in battery balanced at the end of each day
Use case 4 – FFR market participation	1120	energy is balanced over the course of a year
Use case 5 – EFR market participation	202	energy is balanced over the course of a year
Use case 6 – Day ahead market participation	1404	energy is balanced over the course of a year

FIGURE 15 to FIGURE 20 show examples of the battery sweat test over three different months of January, April and May for each application using this method. This data is representative of a day's worth of charge and discharge and needs to be run for the number of days in each month. In FIGURE 18, the battery is charged and discharged for a duration of 1 min in line with the National Grid data and as the battery is triggered on or off this is at full power.

The discharge current in FIGURE 19 is because the battery ends up in a fully charged state and needs to be discharged back to a nominal SOC regularly for this years' worth of data.

IX. CONCLUSION

Table 3 gives a summary of battery energy throughput of all application scenarios over the year. On the surface the EFR application shows the lowest energy throughput- but this belies the tiny micro-cycling that occurs as part of the dynamic frequency response and impacts aging.

This paper identifies the characteristics of different applications for a domestic battery, develops a representative profile of these six scenarios and develops a ''drive'' cycle test for each application. The battery operation principle of each scenario was explained and some of battery energy/power and cycling waveforms were represented. A full set of curves for use by others with this data is available alongside this paper. It is hoped that these curves will help define a common power application test platform that can be used to quantify performance, allow comparison of different applications for battery types and allow comparison between different system by different manufacturers.

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REFERENCES

[1] H. Helms, M. Pehnt, U. Lambrecht, and A. Liebich, "Electric vehicle and plug-in hybrid energy efficiency and life cycle emissions," in *Proc. 18th Int. Symp. Transp. Air Pollut., Session*, Vol. 3, May 2010, p. 113.

[2] P. Cicconi, D. Landi, A. Morbidoni, and M. Germani, "Feasibility analysis of second life applications for Li-Ion cells used in electric powertrain using environmental indicators," in *Proc. IEEE Int. Energy Conf. Exhib. (ENERGYCON)*, Sep. 2012, pp. 985–990.

[3] T. J. Barlow, S. Latham, I. S. Mccrae, and P. G. Boulter, "A reference book of driving cycles for use in the measurement of road vehicle emissions," Dept. Transp., Cleaner Fuels Vehicles 4, TRL, Wokingham, U.K., Tech. Rep. PPR354, Nov. 2009.

[4] D.-I. Stroe, M. Swierczynski, S. K. Kær, E. M. Laserna, and E. S. Zabala, "Accelerated aging of Lithium-ion batteries based on electric vehicle mission profile," in *Proc. IEEE Energy Convers. Congr. Expo. (ECCE)*, Oct. 2017, pp. 5631–5637.

[5] J. Shim, R. Kostecki, T. Richardson, X. Song, and K. A. Striebel, "Electrochemical analysis for cycle performance and capacity fading of a lithium-ion battery cycled at elevated temperature," *J. Power Sour.*, vol. 112, no. 1, pp. 222–230, 2002.

[6] L. Liao, P. Zuo, Y. Ma, X. Chen, Y. An, Y. Gao, and G. Yin, "Effects of temperature on charge/discharge behaviors of $LiFePO_4$ cathode for Li-ion batteries," *Electrochim. Acta*, vol. 60, pp. 269–273, Jan. 2012.

[7] J. M. Timmermans, A. Nikolian, J. De Hoog, R. Gopalakrishnan, S. Goutam, N. Omar, T. Coosemans, J. Van Mierlo, A. Warnecke, D. U. Sauer, M. Swierczynski, D. I. Stroe, E. Martinez-Laserna, E. Sarasketa-Zabala, J. Gastelurrutia, and N. Nerea, "Batteries 2020—Lithium-ion battery first and second life ageing, validated battery models, lifetime modelling and ageing assessment of thermal parameters," in *Proc. 18th Eur. Conf. Power Electron. Appl., (EPE ECCE Europe)*, Sep. 2016, pp. 1–23.

[8] G. Lacey, G. Putrus, and A. Salim, "The use of second life electric vehicle batteries for grid support," in *Proc. IEEE EuroCon*, Jul. 2013, pp. 1255–1261.

[9] H. Li, M. Alsolami, S. Yang, Y. M. Alsmadi, and J. Wang, "Lifetime test design for second-use electric vehicle batteries in residential applications," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1736–1746, Oct. 2017.

[10] I. Baghdadi, O. Briat, J.-Y. Delétage, P. Gyan, and J.-M. Vinassa, "Lithium battery aging model based on Dakin's degradation approach," *J. Power Sources*, vol. 325, pp. 273–285, Sep. 2016.

[11] W. Liu, C. Delacourt, C. Forgez, and S. Pelissier, "Study of graphite/NCA Li-ion cell degradation during accelerated aging tests—Data analysis of the SIMSTOCK project," in *Proc. IEEE Vehicle Power Propuls. Conf., (VPPC)*, Sep. 2011, pp. 1–6.

[12] A. Eddahech, O. Briat, H. Henry, J.-Y. Delétage, E. Woirgard, and J.-M. Vinassa, "Ageing monitoring of lithium-ion cell during power cycling tests," *Microelectron. Reliab.*, vol. 51, nos. 9–11, pp. 1968–1971, Sep./Nov. 2011.

[13] E. Martinez-Laserna, E. Sarasketa-Zabala, I. V. Sarria, D.-I. Stroe, M. Swierczynski, A. Warnecke, J.-M. Timmermans, S. Goutam, N. Omar, and P. Rodriguez, "Technical viability of battery second life: A study from the ageing perspective," *IEEE Trans. Ind. Appl.*, vol. 54, no. 3, pp. 2703–2713, May/Jun. 2018.

[14] E. Martinez-Laserna, E. Sarasketa-Zabala, D.-I. Stroe, M. Swierczynski, A. Warnecke, J. M. Timmermans, S. Goutam, and P. Rodriguez, "Evaluation of lithium-ion battery second life performance and degradation," in *Proc. IEEE Energy Convers. Congr. Expo. (ECCE)*, Sep. 2016, pp. 1–7.

[15] A. Burke and M. Miller, "Life cycle testing of lithium batteries for fast charging and second-use applications," in *Proc. World Electr. Vehicle Symp. Exhib. (EVS27)*, Nov. 2014, pp. 1–10.

[16] P. J. Hart, P. J. Kollmeyer, L. W. Juang, R. H. Lasseter, and T. M. Jahns, "Modeling of second-life batteries for use in a CERTS microgrid," in *Proc. Power Energy Conf. Illinois (PECI)*, Feb. 2014, pp. 1–8

[17] M. Abdel-Monem, O. Hegazy, N. Omar, K. Trad, P. Van den Bossche, and J. Van Mierlo, "Lithium-ion batteries: Comprehensive technical analysis of second-life batteries for smart grid applications," in *Proc. 19th Eur. Conf. Power Electron. Appl. (EPE ECCE Europe)*, Sep. 2017, p.p. P.1–P.16.

[18] R. Sathre, C. D. Scown, O. Kavvada, and T. P. Hendrickson, "Energy and climate effects of second-life use of electric vehicle batteries in California through 2050," *J. Power Sources*, vol. 288, pp. 82–91, Aug. 2015.

[19] D. Hill, B. Gully, A. Agarwal, A. Nourai, L. Thrun, S. Swartz, M. Koslowske, S. Cummings, J. Butkowski, and B. Moore, "Detection of off gassing from Li-ion batteries," in *Proc. IEEE Energytech*, May 2013, pp. 1–7.

[20] *Secondary Cells and Batteries Containing Alkaline or Non-Acidic Electrolytes. Guide to the Designation of Current in Alkaline Secondary Cell and Battery Standards*, Standard BS EN 61434:1997, IEC 61434:1996, 1996.

[21] *Domestic Electricity Demand Model—Simulation Example*. Accessed: Oct. 1, 2018. [Online]. Available: https://dspace.lboro.ac.uk/dspace-jspui/handle/2134/5786

[22] *Historic Frequency Data | National Grid ESO*. Accessed: Oct. 1, 2018. [Online]. Available: https://www.nationalgrideso.com/balancing-services/frequency-response-services/historic-frequency-data

[23] *Firm Frequency Response | National Grid*. Accessed: Oct. 1, 2018. [Online]. Available: https://www.nationalgrideso.com/balancing-services/frequency-response-services/firm-frequency-response-ffr

[24] A. Cooke, D. Strickland, and K. Forkasiewicz, "Energy storage for enhanced frequency response services," in *Proc. 52nd Int. Universities Power Eng. Conf. (UPEC)*, Aug. 2017, pp. 1–6.

[25] *Historic Frequency Data | National Grid ESO*. Accessed: Oct. 1, 2018. [Online]. Available: https://www.nationalgrideso.com/balancing-services/frequency-response-services/historic-frequency-data

[26] H. Nute, D. Strickland, M. Abedi-Varnosfaderani, "A study of different loss of life based calculations on batteries operating in enhanced frequency response," in *Proc. 53rd Int. Universities Power Eng. Conf. (UPEC)*, Sep. 2018, pp. 1–6. 10.1109/UPEC.2018.8542094.

[27] N. P. Group. *View Hourly UK Prices*. Accessed: Sep. 29, 2018]. [Online]. Available: https://www.nordpoolgroup.com/Market-data1/GB/Auction-prices/UK/Hourly/?view=table

MINA ABEDI VARNOSFADERANI received the M.Eng. degree in electrical and electronics engineering from the University of Birmingham, and the Ph.D. degree in electrical engineering from Aston University, Birmingham, U.K. She is currently a Research Associate with Loughborough University. Her research interests include hybrid batteries and power sharing systems.

DANI STRICKLAND received the degree from Heriot Watt University and the Ph.D. degree in electrical engineering from Cambridge University, U.K. She has worked for Eon, Sheffield University, Rolls Royce Fuel Cells PLC, and Aston University. She is currently a Senior Lecturer with Loughborough University. Her main research interest includes the application of power electronics to power systems.

MARTIN RUSE received the degree in aeronautical engineering and the MBA degree. He has qualified in VBSS and lean engineering. He has over 20 years' experience in global corporate environment of precision engineering at companies, such as ITT (now Xylem) and Crane, where he was responsible for global sales, operations, and new product development. He spent the last six years of his career providing operational support and consultancy services to technology startups in motorsport, media, and harsh environment electronics. These management roles have covered everything from Research and Development, through development and manufacture, to global system deployments. He is currently with the Denchi Group.

ENRIQUE BRANA CASTILLO received the bachelor's degree in energy engineering from Vigo University, Spain. He was with Powervault as a Test Engineer. He is currently with Jaguar Land Rover as a Battery Test Engineer.