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Development of a profile-based electricity demand response estimation method: An application based on UK hotel chillers

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Abstract
In principle, Demand Side Response (DSR) is increasingly seen as a critical component of a low-carbon electricity network with renewables as main sources of generation. In practice, DSR has been slow to emerge in most electricity markets of developed and developing countries. One of the main reasons for the slow penetration of DSR is the difficulty to assess the flexibility potential of individual sites. This paper develops a new DSR estimation method which uses detailed profiles information based on data on Heating, Ventilation and Air Conditioning (HVAC) chillers in five UK hotels between 2013 and 2017 and applies a combination of clustering analysis and subsequent stochastic sampling using cluster-weighted date-based predictors. Findings show that the profile DSR estimation method features a better balance of error compared with previous methods.

Keywords: Demand side response, electricity demand, flexibility assessment, error estimation, usage profiles

Highlights

- ➔ The profile DSR estimation method features a better balance of error compared with previous methods.
- ➔ Clustering of detailed usage data to create profiles is a viable approach for improving DSR estimation.
- ➔ Profiles can provide greater account of estimation uncertainty compared to existing deterministic methods.

1 Introduction

In principle, Demand Side Response (DSR) is increasingly seen as a critical component of a low-carbon electricity network with renewables as main sources of generation. In practice, DSR has been slow to emerge in most electricity markets of developed and developing countries. One of the main reasons for the slow penetration of DSR is the difficulty to assess the flexibility potential of individual sites. A comparison of existing site-level DSR estimation methods showed that these have high output errors, high costs and are also deterministic in nature, and therefore unable to provide any measure of certainty in their outputs (Curtis et al., 2018). Accordingly, obtaining any accuracy in understanding the nature and scale of the output uncertainty for existing methods would require retroactively evaluating estimation results against actual data once the new site has gone live. Yet this is inefficient as a solution for improving the viability and market penetration of DSR solutions. This paper develops a new estimation method that aims to address limitations in existing estimation methods. The profile DSR estimation method, or 'profile method', established in this paper uses detailed usage information (from sub-meters for example) of electrical assets to create a set of load profiles to represent common usage patterns. These profiles can then be used to determine the likely usage levels for similar assets at sites where detailed usage data are not available.

Once the DSR estimation profiles have been created, this method aims to provide as benefits: (i) only requiring very basic information to perform a DSR potential assessment for a new site (namely the site's business category and maximum kW ratings for potential DSR assets), (ii) being immediately implementable (with the usage profiles being applied automatically once the basic information is entered), and (iii) providing the user with the ability to manage and understand the estimation uncertainty.

By seeking to develop a new estimation method through creating and then applying load profiles, this paper builds upon existing published approaches for analysing electricity demand. At a macro level, for example, load profiles are already used by the electricity industry to understand country level demand for electricity (Heffron et al., 2020). To enable demand forecasting, Elexon (the UK's electricity settlement service) has created temperature based regression models in eight expected usage profile classes for domestic and non-domestic sites that lack half hourly metering (Elexon, 2013). These Elexon profiles are generated by using data captured from up to 2,500 half hourly meters which are installed across sites throughout the UK.

In contrast, Räsänen et al. (2010) demonstrated the value of improved monitoring for load profile assignment over use of site characteristics and annual usage alone. By use of clustering techniques for 3,989 sites in Finland, the approach was shown to improve (increased index of agreement: 0.478 to 0.627) demand forecasting across 230 sites in comparison to site characteristic profiling. The granularity of load profile has also been considered at finer scales such as by room type (non-domestic, Liddiard (2014)) and by end-use activity (domestic, Widén et al. (2009)), with varying degree of accuracy reported in estimation capability.

Despite the extensive use of load profiles in the energy industry, their value to assess a site's DSR potential has received little attention. The closest relevant research arises in the context of estimating country level DSR potential. Non-domestic DSR capability was estimated for the UK using industry level profiles (offices, retail, etc.) with breakdown by end-use categories - e.g. catering, IT, heating and lighting (Element Energy, 2012). Yet these profiles were limited as end-usage levels were calculated using sector level values of percentage use with an assumed constant rate of usage across the day. Sector level half-hourly data provided high level consideration of daily profiles with seasonal adjustments. The lack of available sub-metered data was a major limitation to estimating end-use profiles in most cases and for sectors such as *hotel and catering*, *communications*, and *transport* even site level half hourly electricity data were limited.

In this paper, previously published research into load profiling for the energy industry will be used to help develop a method for DSR estimation of individual sites with greater consideration of site variance in potential response. Variability in demand will be used as a measure of uncertainty in ability of a site to respond, with monitored usage profiles of similar sites providing the prior knowledge of load profile distributions. The approach is evaluated using sub-metered data from a set of similar hotel sites.

After this introduction, the paper outlines the main steps for developing profiles (Section 2); presents findings (Section 3); and discusses the implications of this work (section 4).

2 Method

The development of the profile method for estimating DSR potential is undertaken using a combination of clustering analysis and subsequent stochastic sampling using cluster-weighted date-based predictors. The profiles created from monitored assets provides representative daily usage patterns of an asset that can be used for estimating turn down potential at sites identified as similar. Usage profiles of assets such as chillers, however, will be dependent on factors such as building design, meteorological conditions, and occupancy levels and occupant preferences. The development of usage profiles must, therefore, consider the variance resulting from these factors.

All variance is not necessarily of value in estimating DSR potential, as aggregated assets for DSR companies provides some assurance over small scale difference. In the first instance, large scale structural characteristics in demand profiles have been effective in profile creation, with specific reference to the use of unsupervised methods such as clustering (Zhou et al., 2013).

Figure 1 outlines the process undertaken for development of the profiles, which starts with obtaining the primary information input of sub-metered usage data for the same types of electrical assets as used in selected categories of businesses. The example asset used in this study being Heating, Ventilation and Air Conditioning (HVAC) chiller assets at hotels. The data are normalised to a percentage of the intended DSR asset's maximum load for the sites and assets identified as similar. The normalised sub-metered data are then clustered into comparable groups of daily usage patterns. Each group is then formed into a profile that represents the upper, median, and lower usage boundaries of the group's daily patterns. The profiles are then assigned a calendar-based predictor that best represents how the data was clustered (for example, Week-of-Year, Month-of-Year, etc). The profiles are then utilised by applying these to similar assets and business categories to estimate their potential for DSR. These steps are outlined in the following sub-sections with further detail in appendix A.

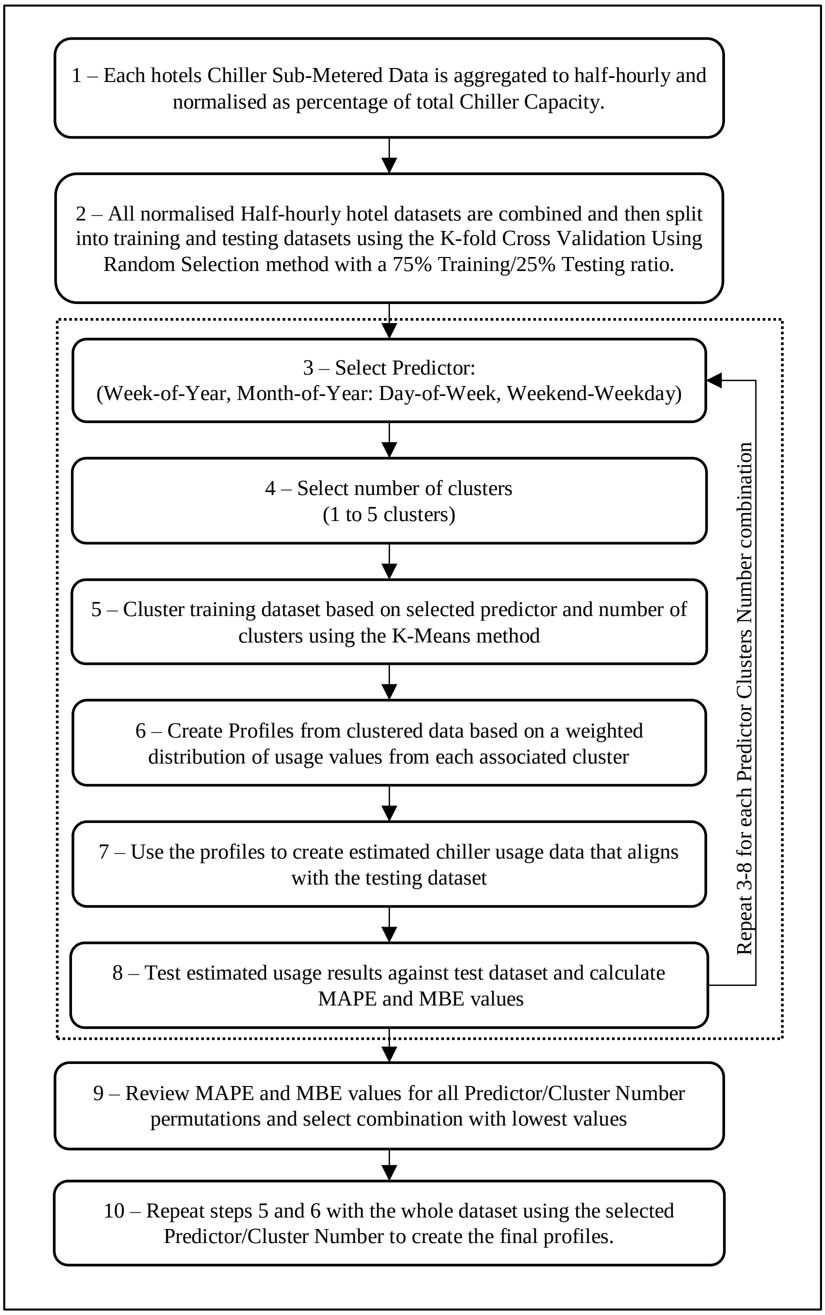

Figure 1: Profile creation process

2.1 Data (step 1)

Data were collected on HVAC chillers in five hotels from January 2013 to June 2017 in partnership with a UK DSR operator. HVAC chillers were being monitored in hotels as part of participating in a DSR Short Term Operating Reserve (STOR) turndown programme. Sub-metering information was required to enable these services and ensure accurate measurement of the assets' performance during DSR events. To meet the National Grid STOR programme's metering requirements, minute interval kW readings (National Grid, 2017) were taken on each Chiller unit in each of the five hotels. Real power (kW) was given as minute interval averages from higher frequency current and voltage readings.

HVAC chillers were deemed suitable for inclusion in DSR as switching them off, or ramping down, for up to an hour was thought to have minimal impact to hotel occupants. Flexibility gets implemented through HVAC as this requires limited changes to sensing, computation and communications infrastructure (El Geneidy & Howard, 2020). They offer a large centralised asset that is straight forward to enable for DSR (i.e. can be switched on/off quickly either manually or by an automated system).

Table 1 summarises the information about the chillers in each hotel. The number of days that usage records of each chiller are available for is varied as a result of different monitoring and agreement issues for each site.

Table 1: Details of anonymised sub-metered hotel chillers used for profile creation. **PR** - maximum power rating (kW); **Number of Days** - total day count with recorded usage data.

Meter ID	Hotel ID	Description	PR kW	Number of Days
H1_C1	H1	Chiller 1	111	1115
H1_C2	H1	Chiller 2	111	1115
H1_C3	H1	Chiller 3	111	1115
H2_C1	H2	Main Chiller	132	952
H3_C1	H3	Main Chiller	135	365
H4_C1	H4	Main Chiller	290	973
H5_C1	H5	Main Chiller	86	607

Missing data points at minute resolution were identified on 18 days, equating to 0.16% of all readings. For the purpose of aligning the data with DSR estimation methods, 1-minute resolution data is averaged across 30-minute periods that align to each UK half-hourly settlement period (for example 00:00 to 00:29, 00:30 to 00:59). Most of the missing data were attributed to a small (no greater than 0.31%) number of half hour periods. This high concentration of missing data in a few select periods resulted in null values for all the 368 half hour periods with missing readings.

2.2 Training and testing dataset selection (step 2)

To evaluate the ability of these profiles to estimate demand, the data were split in to two categories - training vs. testing data. Three approaches to creating training and test data were reviewed 'Out-Of-Sample' (OOS), `K-fold Cross Validation Using Sites' (KFCs), and 'K-fold Cross Validation Using Random Selection' (KFCr). The KFCr method was chosen with a ratio of 75% training to 25% testing (split by day) to reduce the impact of outliers – a noted concern of the other methods reviewed.

2.3 Determine optimal predictor and cluster number (step 3 to 9)

To create the profiles a clustering approach is utilised. In order to use the clusters in DSR estimation, it is necessary to be able to identify which cluster (or clusters) to use, when and where. The premise of this study is that features such as asset type (e.g. chiller) and site category (e.g. hotel) will have already been used to determine whether the estimation profiles can be used for the new site. They cannot, therefore, be used in determining what cluster to use as all would be thought to be appropriate. However, the profiles are based on time-series data with expected seasonal and `day-type' variance and therefore four date-based predictors were selected (see appendix A).

In addition to predictor selection, the number of clusters used also plays a critical factor in the resulting outcomes. As this DSR profile-based estimation method is intended to be flexible for different types of assets it has been developed to provide flexibility to select different predictor and cluster number values as fits best with each dataset. To facilitate this, the process iterates through all combinations of each predictor against a range of cluster sizes as per steps 4 to 8. The results of each iteration are evaluated and then compared in step 9 to identify the optimum values to use for the current dataset. For the Hotel Chiller data used in this paper the 4 predictors were iterated against clusters of 1 to 5, therefore creating 20 iterations for evaluation. The selection approach for these input values is explained in appendix A.

3 Results from developing the profile method

One set of generated chiller load profiles is presented as *pars pro toto* to highlight both intraday and inter-day variance (section 3.1) and how the profiles help evaluate uncertainty during DSR estimation (section 3.2). The implication of how uncertainty in

DSR estimation is handled by the profile method is subsequently evaluated by comparison with four pre-existing DSR methods.

3.1 Review of generated profiles

Figure 2 shows the chiller statistical profiles generated using the Month-of-Year predictor. The daily average load is plotted in addition to the range in daily load curves for each month-of-year profile for the purpose of trend analysis. Four months (December, April, July, October) are shown as indicative of behaviour in all months and showing variation across the seasons. The median is used as an initial indicator in screening of a site's DSR potential (i.e. before site survey, where initial estimates are refined). Three major features of the generated hotel chiller profiles are discussed below: (i) unusual load spikes, (ii) variation across months, and (iii) variations across days.

Load spikes occur in the upper confidence interval lines at 06:30-07:00 (half hour period 14) from November to April, and 18:00-18:30 (half hour period 38) from December to February. These spikes were attributed to the management of one asset (H3 hotel chiller) that entailed: (1) a period (87 days) of night (00:00-06:30hrs) switch-off, followed by load peaking (40.7 to 57.8%) in the first half hour after switch-on (06:30-07:00hrs), and (2) a similar period (63 days) of afternoon (16:00-18:00 hrs) switch-off followed by a load peak (30.3 to 49.6%) at switch-on. Figure 2 (December) illustrates this behaviour and shows the loss of information (in terms of sequencing) in confidence interval curves by plotting actual half-hourly asset load (Monday 23/12/2013) onto the existing December load profile. These usage spikes can be attributed to the chiller having to bring the system cooling fluid back to within a pre-set temperature range; seen as a rebound effect (Palensky & Dietrich, 2011).

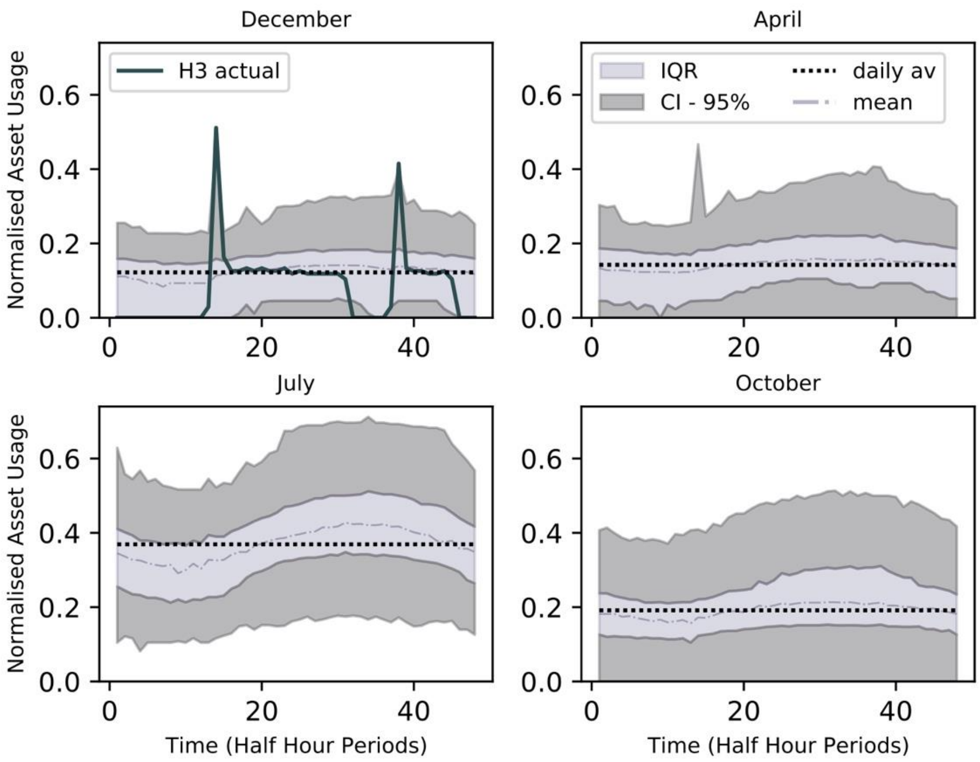

Figure 2: Monthly distributions of half-hour hotel chiller usage - presented as a proportion of the asset maximum capacity. All subfigures showing the 95% confidence interval [CI -95], the inter-quartile range [IQR], the mean half-hourly usage [mean] and daily average [daily av] for December (indicative of November, January and February), April (indicative of March), July (indicative of May, June, August and September), and October (similar profile to May-September but with peak usage dropping below 0.5 of asset capacity). For December an actual single day (23/12/13) usage for one asset is overlaid showing loss of sequencing information in the entire distribution range.

Daily average values by month-of-year highlight seasonal influences on chiller operation, Figure 3. Minimum usage found in winter, the maximum in summer and the rate of change in the spring shoulder months varying (March increase of 2.9% compared to a 46.6% increase in May) compared to a steady decrease in the Autumn (September: 25.4%, October: 26.1%, November: 27.2%). Figure 4 highlights the strong correlation (R^2 of 0.92) of average UK temperature against average chiller usage levels within each month.

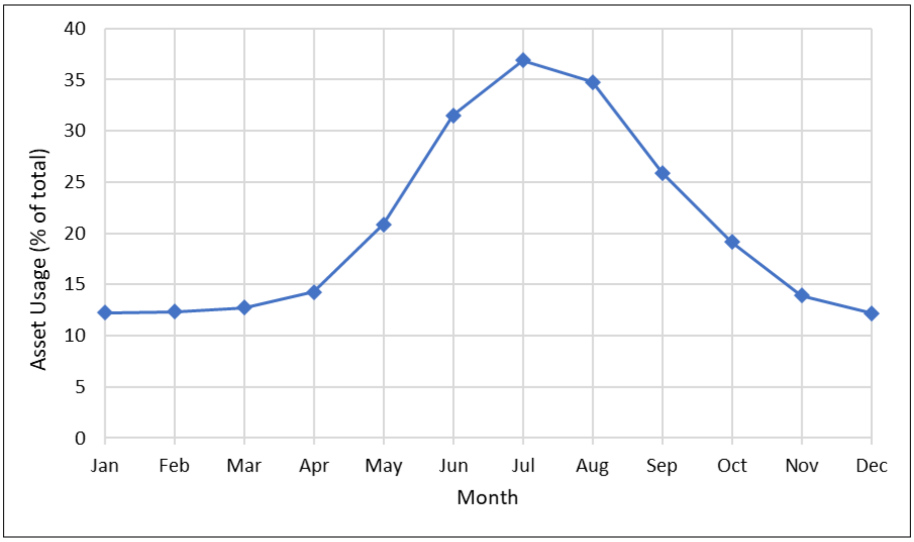

Figure 3: Daily average of HVAC chiller usage profile values per month

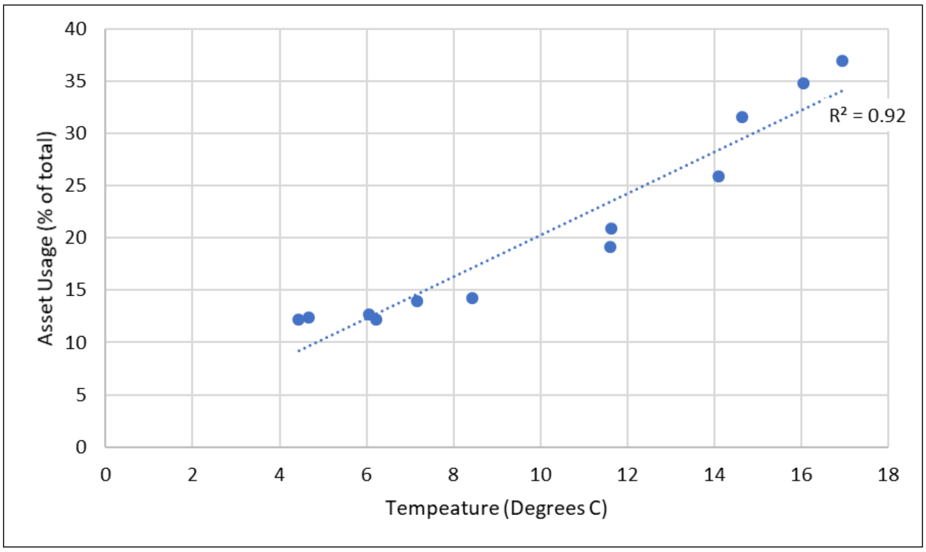

Figure 4: Correlation of daily average of HVAC chiller usage profile values against monthly average UK temperatures between 2013 and 2017. Temperature Source: (UK Met Office, 2017)

The variance within month-of-year demand, both within day and across all days, is important in relation to DSR estimation as it represents risk in asset availability for participation in a DSR event. Figure 5 reveals something of the stability in daily profile of particular assets across the year, despite variance in time of day for the minima and maxima of usage (MinU and MaxU of Figure 5) and seasonality of asset usage (LowT and HighT, Figure 5). These different factors are important for understanding demand response potential in relation to the pre-post transition states of asset usage in the day (lower graph Figure 5) and the associated range in available demand response across days, months, and seasons (upper graph of Figure 5). Combined, these asset `behaviours' represent variation in the median monthly usage associated with different monitored assets of this study as well as a stability in timing of opportunity for DSR for the asset type.

The percentage of time across all twelve (month-of-year) profiles (using the median) that the asset loads are above the daily average value. All asset load profiles (median, month of year) are consistently lower than the daily average from 00:00 to 08:00 (half hourly period 17) and higher than average from 10:30 to 22:00 (half hourly periods 22 to 45). The lowest (highest) average usage occurs within the range of 03:00-05:00 (14:00-18:30) across the year and the highest average usage time is within the range of 14:00 to 18:30 (half hourly periods 29 to 38). Difference between the monthly minimum and maximum asset-percentage usage are greatest (>20%) for the four months (June to September) with highest percentage load.

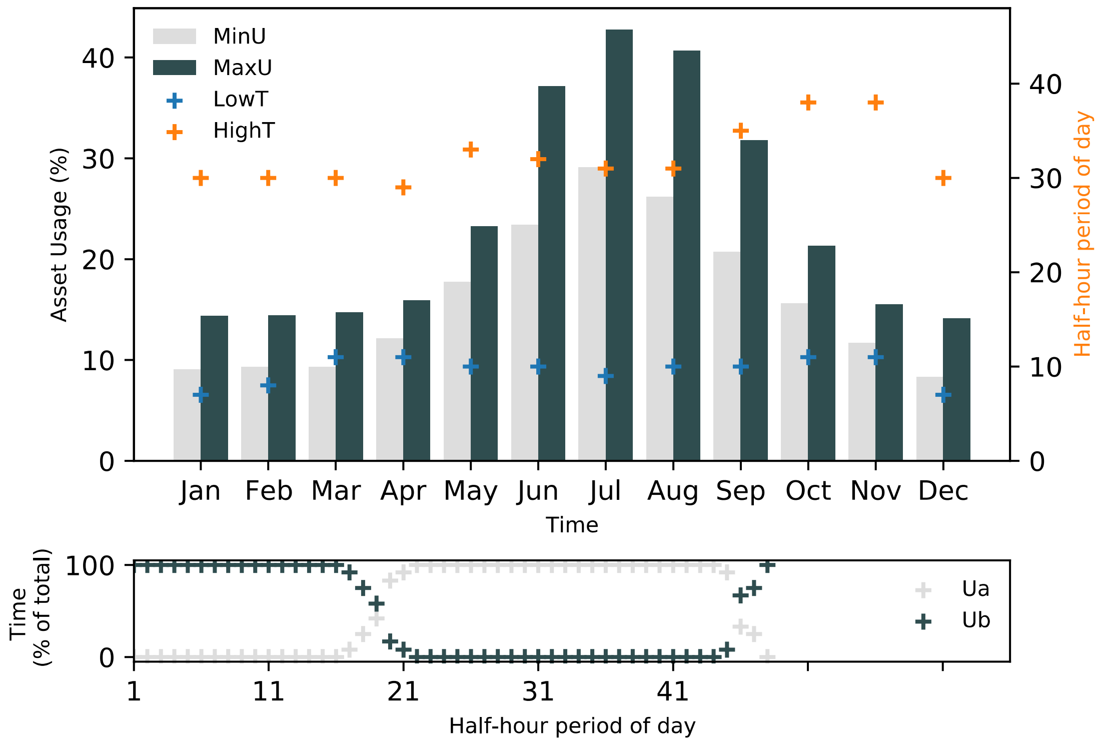

Figure 5: Indication of stability, variance and seasonality in asset availability for demand-response. The top graph shows the minimum (MinU) and maximum (MaxU) median of asset usage for each month as a percentage of asset maximum capacity. The time of day (half-hour period) for the occurrence of lowest (LowT) and highest (HighT) usage are also marked out – right hand ordinate. The lower graph shows the percentage of time (for all 12 monthly profiles) where usage is below (Ub) or above (Ua) the daily median usage

3.2 Reducing DSR estimation uncertainty

The purpose of developing the new profile DSR estimation method is to reduce, or at least give a more considered assessment of confidence in, the uncertainty during initial desktop assessment of the DSR potential of a new site. The ability to assess uncertainty at the time of estimation, by reference to the profile distribution helps overcome the limitations of deterministic estimation associated with methods reviewed in Curtis et al. (2018). Uncertainty for the existing methods can only be addressed by retroactively evaluating the DSR potential estimates once asset usage data is made available after site enrolment to a DSR programme. In this section the uncertainty levels of the profiles generated for the HVAC chillers will be examined to assess how they can be utilised during DSR estimation.

Figure 6 provides a box plot of the usage levels from the profiles presented in Figure 2. The difference between the 95% confidence interval and the inter-quartile range for usage levels by month-of-year predictor. December to March have lowest variance (mean of 28.7% across 95% ci. range) alongside lowest usage, whilst May and September have highest variance (mean of 51.5% across 95% ci. Range). June, July, August, October and November also have relatively high variance in usage (mean 45.1%, ci 95%). The shoulder months for the heating and cooling seasons as well as peak periods of asset usage (summer) carry the greatest uncertainty in DSR estimation. Coinciding with periods of highest load (average and peak) lower risk can be associated with similar levels of DSR capacity as in the months of lowest load and variance. Using the lower (2.5%) confidence bound would minimise the risk to the DSR operator in terms of ability to meet contracted quota. Depending on the asset control options during turndown, the impact to the client may also be minimised (i.e. rarely full switch-off required of asset over DSR period).

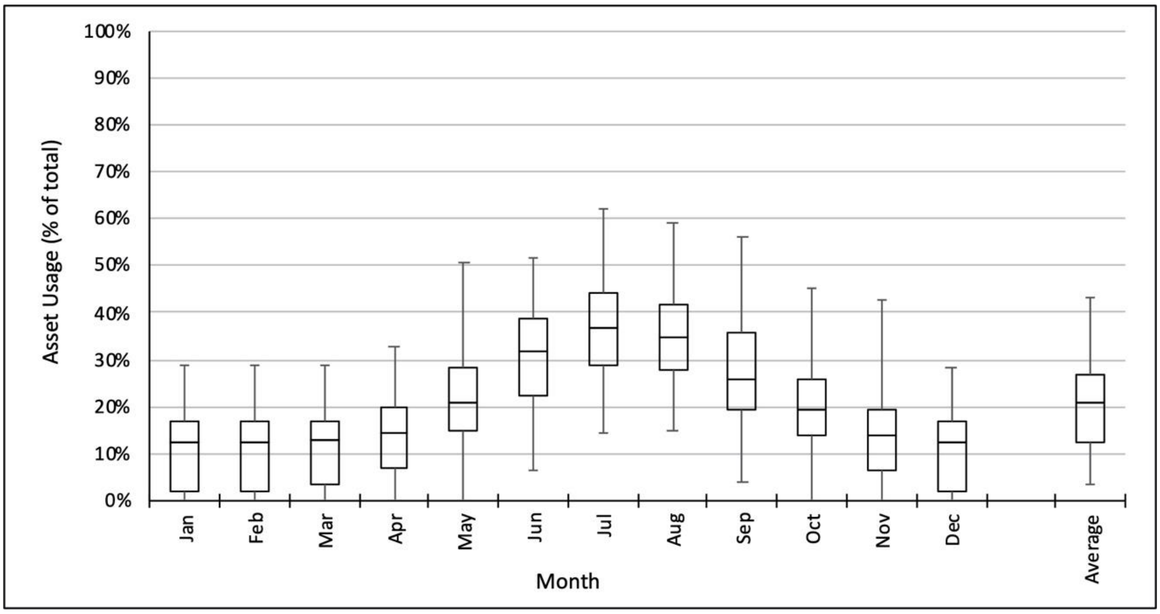

Figure 6: Boxplot of hotel HVAC chiller percentage usage for median and interquartile range with whiskers at 95% confidence interval

Taking the lower 2.5% confidence bound would imply losing out on the majority of the site's DSR potential. As, however, the profile method is proposed here to be used during the early assessment stages for new sites, the confidence bound, rather, informs whether the site being considered presents good potential for DSR. The load profile range provides a risk estimate in terms of further pursuing a site for DSR engagement.

The variances between the uncertainty levels can also be used to ascertain the likelihood of an estimate being different to the median usage levels. To illustrate this, Table 2 shows the results from applying the profile method to estimate the DSR potential of a site with a 200kW chiller. As an example, the January median usage percentage is 12.5%. Therefore, the chiller is expected to use an average of 25kW throughout the month of January. Load profiles vary across the day but as timing of DSR opportunity is not prescribed, daily averages have been used here. This use of daily median presents an in-day risk that is not considered further here.

The percentage difference between the kW values at each usage level is calculated as shown in Table 2. This analysis can be used to understand which months will have a higher impact if the selected level of usage is not met. For example, in July the median level estimate shows the chiller usage will be 74kW, yet the lower quartile level shows there is up to a 25% chance that it could be as low as 58kW, which is -22% less than the usage estimate. The lower confidence interval level instead shows that there is up to a 22.5% chance of usage being as low as 29kW, which is -61% less than the median estimate. In comparison the January median usage is 24kW, which drops to 4kW at the lower quartile and then 0kW at the lower confidence interval, comprising a -85% and -100% difference respectively.

Understanding the difference in kW usage per level enables users of the profile method to have a risk acceptance policy. For example, the user could impose a risk tolerance based on the relative difference between the median and lower quartile (the smaller the difference the less risk in opting for the median). If the risk tolerance was set to a difference of 50%, based on Table 2, this would result in using the median usage level for months May to October, and the lower quartile usage level for the remaining months.

Table 2: Percentage differences between usage levels (kW) using the *profile method* with a 200 kW chiller. Clear rows provide kW load at given confidence bound (cb) and grey rows provide percentage difference (Δ) between the median and confidence bounds

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Load (kW) 97.5% (upper) cb	57	58	57	66	102	104	124	118	112	90	86	57
Δ (%) 97.5% cb	57%	57%	56%	57%	59%	39%	41%	41%	54%	58%	67%	57%
Load (kW) 75% cb	34	34	34	40	57	77	89	83	72	52	38	33
Δ (%) 75% cb	38%	38%	34%	39%	36%	23%	20%	20%	38%	35%	38%	36%
Load (kW) at 50% (median) cb	**24**	**25**	**25**	**28**	**42**	**63**	**74**	**70**	**52**	**38**	**28**	**24**
Δ (%) 25% cb	85%	85%	75%	52%	29%	30%	22%	19%	26%	29%	53%	82%
Load (kW) 25% cb	4	4	6	14	30	44	58	56	38	27	13	4
Δ (%) 2.5% cb	100%	100%	100%	100%	100%	80%	61%	57%	86%	100%	100%	100%
Load (kW) 2.5% (lower) cb	0	0	0	0	0	12	29	30	7	0	0	0

3.3 Profile method evaluation

This section examines how the profile method compares to four (M1 to M4) existing DSR estimation methods examined in Curtis et al. (2018). The results of this comparison are evaluated by comparison of MAPE and MBE outcomes and comparison against actual usage data.

The main benefit of the profile method (hereinafter M5) is the ability to evaluate usage against a measure of uncertainty (confidence limits). For development of M5 we combine additional datasets to the 4 years of asset data from H1 and H4 used previously in developing methods M1-M4 Curtis et al. (2018). For the purpose of comparing M5's confidence limits with methods M1-M4, only the four year-two hotel (H1,H4) data were used. MAPE and MBE results based on the error in month-of-year predictors for the 95% confidence interval, as well as median and inter-quartile range are presented in Figure 7 alongside the four existing methods. The hotel site being estimated was removed from the profile creation process to enable an estimate for an unknown hotel.

When compared with M1 to M4, the median profile of M5 had the second lowest MAPE (46.5%), behind M3 (38.8%). The positive MBE value for the M5-median profile (1.1%) indicates that using the median usage level will likely result in a small amount of over estimation; in contrast to the existing methods (except M1-V1) that underestimate. The impact of using confidence intervals in M5 is one of increasing MAPE with increasing over estimation for higher confidence limits (increasing, positive, MBE) and under estimation for lower confidence limits (decreasing, negative, MBE). The MBE and MAPE values reflect the risk in relation to missed DSR potential (negative MBE) and potentially missing contracted DSR targets (positive MBE).

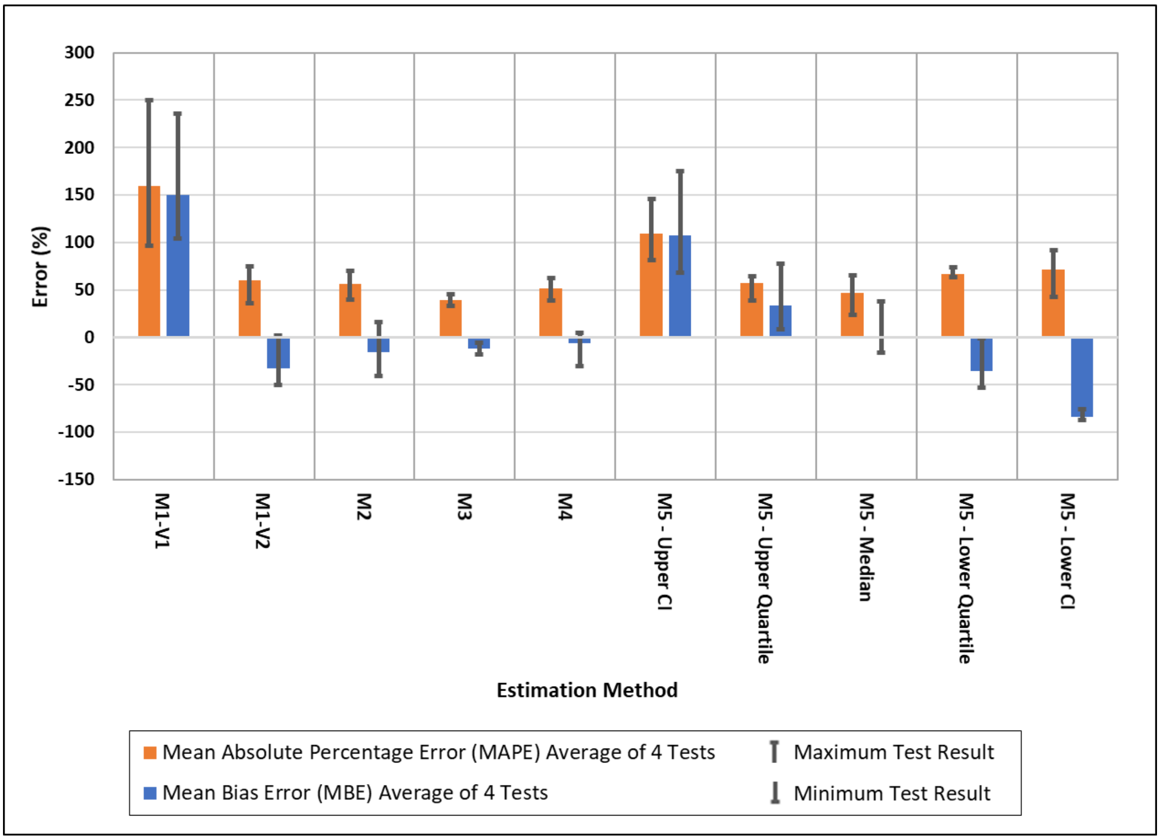

Figure 7: Mean absolute percentage error (MAPE) and mean bias error (MBE) of existing (M1-M4) and new (M5) DSR estimation methods when compared to 4 years of data from 2 hotels. Existing methods: M1-V1 (using set percentage of asset usage); M1-V2 (baseload calculation with set percentage of asset usage); M2 (baseline comparison using cluster analysis); M3 (regression analysis utilising historical DSR event outcomes); M4 (building energy modelling); M5 (profile method).

Direct comparison of the estimation methods against actual usage has been undertaken using the H1 Hotel's 2013 results, as shown in Figure 8. There is an overall trend of underestimating (negative MBE), except for M1-V1, with annual trend captured in most cases. The periods of low asset use and previously identified periods of low variance show greatest alignment between actual usage and estimation. Where the variance in profile method was noted as high, there is a larger error associated with estimation. This is particularly pronounced for July; approximately a third lower than actual usage.

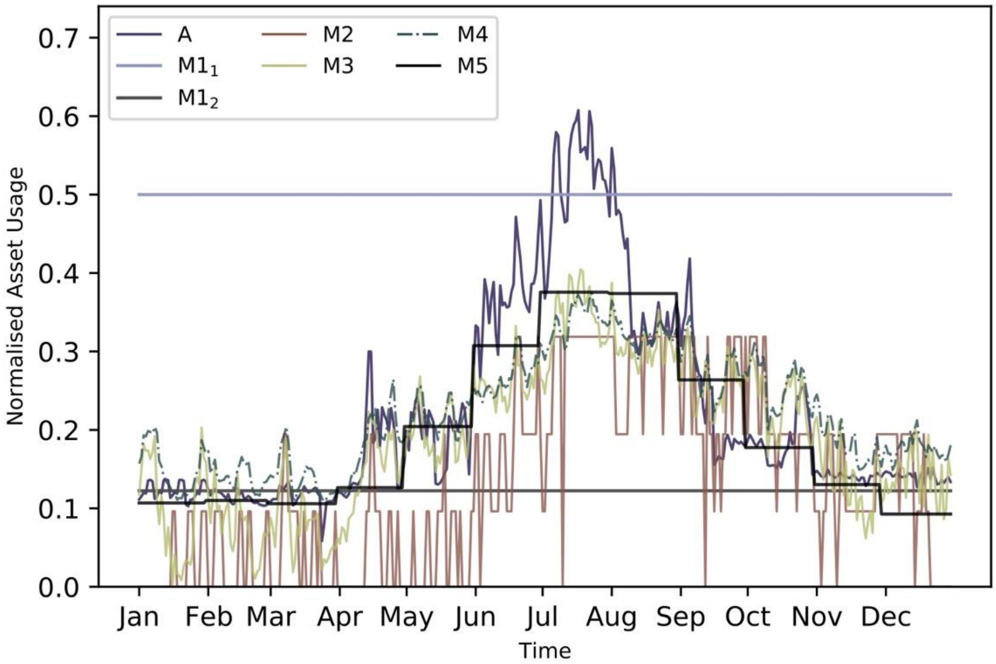

Figure 8: Comparison of actual normalised asset usage (A) from the H1 hotel 2013 HVAC chiller dataset against estimation methods averaged by day. Usage normalised by asset maximum capacity. M1$_1$ (M1-V1 MAPE = 193%, MBE = 122%); M1$_2$ (M1-V2 MAPE = 35%, MBE = -46%); M2 (MAPE = 57%, MBE=-41%); M3 (MAPE = 33%, MBE = -15%); M4 (MAPE = 58%, MBE = -1%); M5 (MAPE = 24%, MBE = -12%)

M1-V1 is based on assuming a fixed 50% usage level of the assessed asset's maximum kW rating. Although a simple estimation approach it has the highest MAPE (193%) and MBE (122%), over estimating load in all months except June and July, see Figure 8. M1-V2 is a variation of M1-V1 and performs a pre-calculation step by first determining the site's baseload usage, which is calculated at a 5% percentile of overall electricity usage levels for a year. A percentage (default 10%) of the baseload is then deemed to be used by the DSR asset. This approach reduced the MAPE to 35%, the third lowest error level of the methods for H1 Hotel in 2013. The baseline approach results in a consistent estimation level, which results in a -46% MBE due to underpredictions during the summer months. However, as the estimation closely aligns to the non-summer months, M1-V1 has a significantly lower MAPE error than M1-V2.

M2 used clustering to identify when the chiller was operating based on the site's overall electricity usage records. As this method assumed that the lowest usage cluster represents the chiller not operating, the estimation levels (see Figure 8) show a distinctive on-off cycling due to certain days deemed to have no usage. This method underestimated usage (-41% MBE) and produced the third highest MAPE of 57%.

M3 uses regression analysis of past DSR event outcomes in conjunction with outside air temperature to predict the expected level of chiller usage over a year. This method had the second lowest MAPE of 33% for the H1 Hotel in 2013 and an overall underestimation bias based on an MBE of -15%.

M4 used a Building Energy Model to simulate the expected kW usage level of the chiller for the site. The energy model used the same outdoor air temperature dataset as M3 and the estimations from these two methods also follow a similar trend from May to October. Outside of these months the simulation estimate is generally higher than the actual usage levels, which results in this method receiving the second highest MAPE of 58% with an MBE of -1%. It should be noted this is both a time and information intensive approach.

The M5 profile method outlined in this paper provided the lowest error level for the H1 Hotel in 2013, with a MAPE of 27% and a MBE of -12% when using the median values from the HVAC chiller profiles. If the profile optimisation process had instead selected the day-of-week predictor, for example, then this would have resulted in greater variations within month; as observed in other estimation methods.

It is noted that the underprediction in June, and more notably July, reflects a comparatively warmer period than other years in the data set. As all estimation methods considered are averaging over time and all assets, these case specific peaks in demand are not represented in prediction models, particularly in relation to using the median profile for M5. We note, however, the observed peaks in actual demand are not necessarily indicative of capacity for demand response (i.e. high-environmental stress limiting ability to switch off/turn down a HVAC chiller at this time).

4 Conclusion

This paper developed and evaluated a new DSR estimation method with capability for evaluating uncertainty in the resulting outputs. The method requires detailed usage information (e.g. from sub-meters) of electrical assets to be used in DSR programmes in order to develop load profile distributions that can be applied for similar asset DSR estimation. The nature of the approach enables an updating of prior knowledge informing the load profile distributions as more sites/assets of the same type are brought into a DSR programme.

In the development and evaluation of the profile method, a ‘rebound’ effect was shown to cause spiking of usage during winter in the morning and evening at one of the hotels of our study (H3). Associating these features with sequencing and modes of asset operation (i.e. overnight switch-off, existing demand shifting programmes) would not be possible within the profiles alone. A question of ability to flex time of switch-on needs to be addressed alongside asset response capacity. Identifying modes of asset operation is important additional information for assessing potential sites for DSR.

The data showed the assets (chillers) to have similar diurnal load profiles across the year with a common seasonal influence in the median usage as well as variance. Despite greater potential asset demand response in summer months, the variance (and so uncertainty in estimation) also increased. These features have several implications for DSR. Where DSR programmes have inflexible reduction commitments like STOR (e.g. only allowing a single daily kW reduction amount), the daily and seasonal variations impact DSR potential. The seasonal variation will also impact the amount of load reduction, depending on how inflexible the DSR programme is (e.g. single annual fixed amount vs. multiple tendered for periods). Where DSR programmes involve higher levels of flexibility, like frequency response, then usage profiles could be used to improve the DSR estimation potential, by varying the reduction targets across the day and month.

Using the median load curve from the profile method demonstrated comparable (or better MAPE) asset load estimation to existing methods. However, the profile method can also evaluate uncertainty in assessment through alternative load curves representing different confidence limits. The implications of the capability for assessing uncertainty in the DSR estimation arises in the ability of the user to determine an acceptable risk strategy, informed by anticipated percentage variances between the profile usage levels. The confidence limits provide a formal approach to evaluate risk of under and over estimation due to uncertainties in operational loads that give an ability to adjust DSR estimates according to user risk preferences.

The profile method has been developed and evaluated using hotel chiller usage data only where seasonal and diurnal cycles are typical. The differing patterns of load and variance (and the associated error in estimation) for different asset types and end-user categories are not understood.

Declaration of Competing Interest
None

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5 Appendix A

A description of steps 3 to 10 in profile creation method Figure 1.

Step 3 - Select predictor

Four date-based (using time-series data) predictor options used for evaluation are: week-of-year (1 – 52); month-of-year (1-12); day-of-week (Monday to Sunday); and weekday-weekend (Weekday or Weekend). Within these predictors the asset usage (percentage of capacity) is used as the measure on which the clusters are identified.

Step 4 - Select number of clusters

To determine a suitable range an initial test of 1-10 clusters showed a plateauing of difference after 3 clusters. A selection range of 1 to 5 was chosen for evaluation.

Step 5 – Perform clustering

For the purpose of load pattern grouping, Chicco (2012) identified the k-means method of clustering as appropriate, and Panapakidis et al. (2014) showed k-means to have the lowest error in comparison to minimum variance criterion, fuzzy c-means, and self-organising maps. For these reasons, k-means clustering was adopted to group (cluster) the daily usage records in the training dataset; with average intra-cluster distance determining the optimal cluster centroids.

Step 6 - Create profiles

The cluster trained dataset is then assessed to identify and count all daily usage records for each date-based predictor. Using these counts, the percentage split of cluster usage for each predictor is calculated. For example, a January profile predictor (from Month-of-year) value might have a cluster split of 60% of daily records for cluster 1, 30% of daily records for cluster 2, and 10% of daily records for cluster 3. For each profile predictor an array of half-hourly usage records is created, using the previous percentage-of-clusters array to determine a weighted random selection of values from each applicable cluster.

The profile predictor's half-hourly usage record arrays are then converted into the final usage profiles by identifying the median, upper and lower quartile, and the 95% confidence limits are identified at each half-hour. These are used to facilitate trend analysis. Half hourly values at each confidence interval are independent such that sequencing of load is not captured. The profiles only show the trend that the next value is likely to be in a similar value range. This is suitable for DSR estimation of a new site over a year as the load profiles can provide an indication of overall potential.

Sampling in each cluster is intended to capture variation in daily profiles that do not follow a single probability level of the given date-based predictor - as seen in real daily profiles (demonstrated in the December profile of new Figure 2). It is the statistical variation across all clusters, rather than within clusters, that is being captured. We therefore sample across clusters to generate the daily statistical profiles for use in analysis of DSR potential across the year, with a choice of 3,000 samples in the presented work determined by measuring the impact of sample size (ranging from 100 to 10,000) on MAPE. A stability in MAPE was observed from 3,000 samples onward and so used to minimise computational constraints.

Step 7 – Use profiles to create usage estimates

The profiles are then used to estimate a usage value for each actual half-hour in the testing dataset based on the median profile value (e.g. if a test dataset has an actual usage of 50% at 12:00 on 2nd January then the profile for January is used to select the corresponding estimated usage value for this time).

Step 8 – Evaluate estimates against test dataset

The half hourly estimated usage values are then evaluated against the actual usage in the test dataset using the Mean Absolute Percentage Error (MAPE) and Mean Bias Error (MBE) metrics.

Step 9 – Review evaluation results

The MAPE and MBE metrics are compared for all interactions of predictor and cluster size to determine the optimal values to use for the current dataset profile creation. For the Hotel Chiller dataset, it was determined that Month-of-Year predictor and a cluster size of 3 provided the lowest MAPE and MBE.

Step 10 – Create final profiles using optimal values

To generate the final profiles as shown in Figure 2, steps 5 and 6 are repeated using the complete dataset with the Month-of-Year predictor and cluster size of 3 input values.

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