RC25579 (IRE1512-001) December 4, 2015
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IBM Research Report

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ABSTRACT

Historical analysis of electrical energy usage data from over 350 High Temperature and Low Temperature retail refrigeration packs has shown a very high level of variability in pack electrical energy usage. This noisy big data environment makes the task of detecting anomalous pack behaviour energy wastage events, a very difficult one. This paper attempts to address this problem, by presenting a modified process characterization approach that through the meaningful subcategorisation and statistical analysis of a pack's annualized energy usage, can give the practitioner a much better understanding of the relative contributions of baseload, within day variation, and summer seasonal variation sources, present within a pack. It goes on to show that the resultant creation of a screening analytic using only electrical usage data, when applied across a complete estate, can deliver effective pack level anomaly detection, and subsequent cost savings through the timely detection and avoidance of these significant energy wastage events.

Keywords : Refrigeration Packs; Electrical Energy; Screening Analytic;Anomaly Detection

1. BACKGROUND

Because electrical energy used in Refrigeration accounts for between 4% to 6% of the world's energy budget **[Goetzler et al., 2009]**, **[US DOE, 2010]**, gaining a greater understanding of electrical usage within refrigeration systems, and more specifically pack cooling energy supply systems, through data analytics, has the potential to deliver significant savings, within this very energy intensive industry. However because of the compounding effects of the many sources of variability that exist within many large retailer refrigeration asset estates, and a sample of which is presented in Figure 1 below, makes the task of identifying energy wastage opportunities, by manually detecting anomalous behaviour, almost impossible. And so, IBM Research Labs in Dublin, working with the Tesco Regional Energy Management team, which in the past have shown the effectiveness and potential of applying big data analytic approaches to underlying large available refrigeration datasets **[Brady et al, 2015]**, have been applying similar methods to tackle this problem of pack energy variability. This paper presents some of the early work around this refrigeration pack characterization effort, and presents the detail of a pragmatic first pass screening analytic approach that was developed aimed at quickly identifying anomalous pack behaviour in large estates.

Generating aggregation plots for pack electrical usage from sample HT and LT packs, taken over an extended time period, presented in Figure 1, gives a good appreciation of the overall typical levels of energy usage variability present within the refrigeration estate.

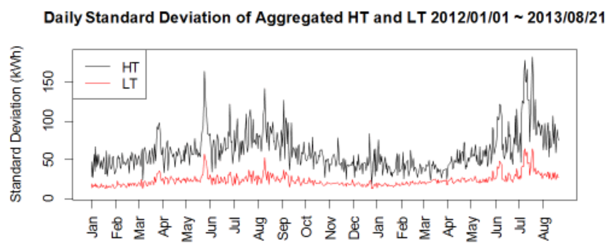


Figure 1 : Pack energy usage variability for estate samples of HT and LT packs over an 18 month period

From Figure 1, one can clearly see the difference in variability observable between HT and LT pack type aggregations, with HT pack type aggregations exhibiting variability 4 to 5 times higher than their LT counterparts. Secondly there is obvious summer seasonality in evidence in both HT and LT pack types, with this phenomenon being more pronounced in the HT pack type. Consequently, it is hoped, that by presenting, and demonstrating the subsequent value of the proposed analytical approach, will offer practitioners a practical means to gain greater understanding of the usage variability within their estate, and additionally to provide a way to automate the anomaly detection process into the future, by using only raw pack electrical usage data.

2. ENERGY USAGE ANALYTICS APPROACH OUTLINE

The use of disaggregation techniques for main meter electrical energy analysis has been used for several years within the Smart Buildings industry [**Mathieu et al., 2011**]. One such approach uses a multi parameter cooling 3PC model [**Kissock et al., 2015]** to model the energy use of a building as a function of outside ambient air temperature, with the model outlined in Figure 2(a) below, and defined in Eq (1), as follows;

$$E_{Bldg} = E_B + CS \cdot (T_{OA} - T_C) \tag{1}$$

where EBldg is the building energy usage, EB is considered the baseload usage, CS is cooling slope, T_C is the temperature change point at which there is a usage response with an increase in outside ambient temperature, and T_{OA} is the ambient temperature

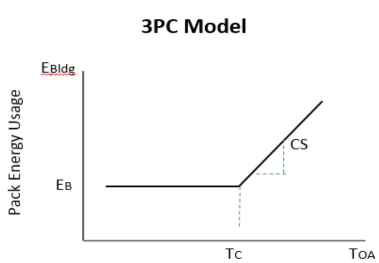


Figure 2(a) : Original 3PC Building Model

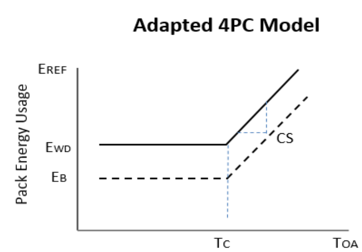


Figure 2(b) : Proposed 4PC Refrigeration Pack Model

Adopting Equation 1 to make it more applicable to a refrigeration pack environment yields the updated 4PC model presented in Figure 2(b) above, and defined in Eq (2) as follows:

$$E_{Ref} = E_B + E_{WD} + CS \cdot (T_{OA} - T_C) \tag{2}$$

where E_{Ref}, the refrigeration pack usage, has the additional term, EWD introduced in the 4PC model, being defined as the within day variation usage, discussed in further detail below in Section 3.3 below. The presented analytic approach proposes the decomposition of the main terms of this 4PC model into three separate subcategories to allow separate analysis of the subcategories defined.

These subcategories are defined as follows;

1. **Part A (EB) :** the pack energy baseload usage and an estimate of packs hourly base usage 365x24x7
2. **Part B (EWD)** : the within day pack energy usage over and above the baseload observed within the hourly usage profiles
3. **Part C (CS .(T_{OA} – T_C))** : the additional energy usage observed within the energy profiles over and above the baseload and within day variation, and due exclusively to the increase in ambient temperatures

3. ENERGY USAGE CHARACTERISATION BY SUBCATEGORY

Following on from the analytic approach outlined in the previous section, this section attempts to detail some technical background behind the subcategorisation, and calculations involved, and some useful observed commentary highlighting the value and effectiveness of the approach in extracting useful insight as to pack performance from using the approach.

3.1 Part A Pack Baseload Usage

Pack baseload is primarily a function of the design and size of the actual pack components, i.e. the number and type of compressors, the condenser size, and what the pack services, and as such it's energy usage is effectively "baked in", running 24 x 7 x 365, and therefore not considered to be a good source of opportunity for energy saving. However while accepting that pack energy usage is heavily influenced by initial pack design (size and quantity of compressor), it is in the maintaining of proper system setup that is probably the most significant factor in achieving consistent and lower baseloads. Having the ability to detect peer-to-peer energy usage baseload differences for equally designed packs is one way therefore such a screening analytic approach could be used to first pass detect packs with poor setup conditions.

3.2 Part A Baseload Usage Calculation and Observations

For paper definition purposes Part A Baseload Usage will be defined as the 4am morning hourly aggregate energy usage for the winter months of November through to March. It is contended that this definition allows for the legitimate exclusion of ambient temperature impacts on high summer condensing temperature and daily variation effects. Summation of the annualized Part A baseload impact on the packs energy budget then subsequently becomes a straightforward exercise.

Figure 3(a) and 3(b) below are some comparative aggregated hourly time series plots of some sample HT and LT packs respectively, taken from 2013 raw ½ hourly energy usage meter data.

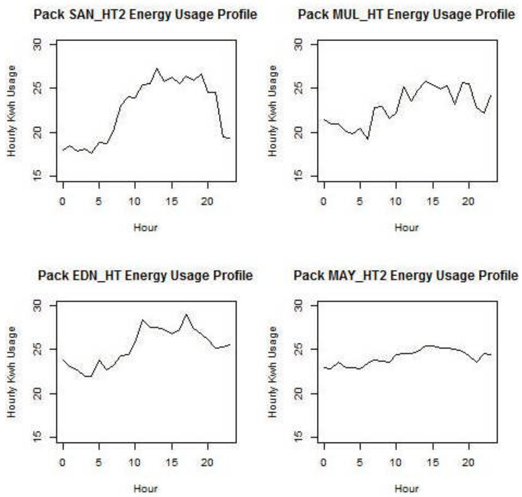


Figure 3(a) : Sample HT Aggregated 24 Hourly Usage

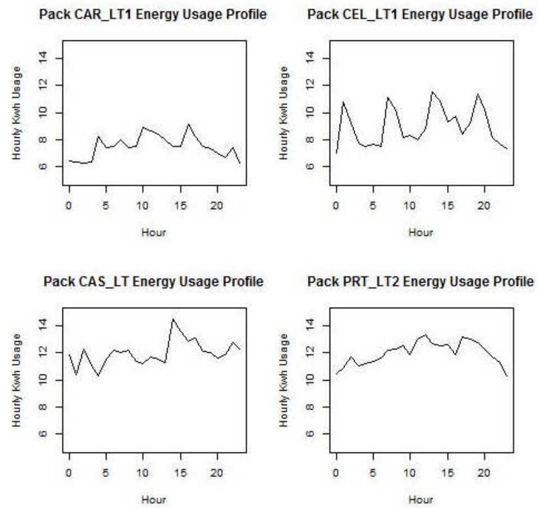


Figure 3(b) : Sample LT Aggregated 24 Hourly Usage

With reference to the four comparable estate sample aggregate HT baseloads presented in Figure 3 above, and focusing on the 4am minima values as per definition, it can be seen that large differences can exist in baseloads. In the HT example in Figure 3(a) one can see that pack MAY_HT2 varies by almost 30% from its peers (with similar pack design and loads) and thus would be flagged for further investigation as it may represent an energy saving opportunity. Similarly for LT packs plots in Figure 3(b), CAR_LT1, would be flagged as anomalous, due to a much lower baseload than its comparable pack peers, although in this case this is possibly due to a meter problem given its such low value.

3.3 PART B Within Day Variation Usage

Part B is primarily a function of daily pack demand variation and how it may vary throughout the day, and is an attempt to understand the underlying significant factors contributing to these levels of variability observed within the day. From Figure 3(b) it can be clearly seen that the daily demand usage variation profiles for LT and HT types are quite different, but both showing evidence of periodicity to a larger or lesser extent, with the LT packs displaying generally lower levels of variability, which would again be in support of the observed lower overall variation previously seen in the LT pack type as referenced in Figure 1 earlier.

3.4 Part B Within Day Usage Calculation and Observations

For paper definition purposes Part B within day variation is defined as the daily summation of additional hourly usage beyond the previously calculated baseload hourly usage, again taken for the winter month period only, from November through to March. Taking this approach allows for the isolation of the within day energy usage variation and protect the reporting from the known impacts of ambient air temperatures on hourly usage which will further discussed in the followon section.
It is accepted that this may be a simplification of the calculation of the within day usage variation, and as the following use case appears to show an interaction between HT refrigeration cases, and the stores HVAC operations, but for the purposes of analytic approach demonstration is considered acceptable from a first pass screening analytics perspective. And again by adopting this approach, allows for the summation calculation of the annualized Part B within day usage variation impact to become a straightforward exercise.

With reference to the aggregated hourly time series plots presented in Figure 3(a) above, one can see clear periodicity observable in the within day energy usage profiles on HT packs, with clear 4am minima, and 5pm maxima features in evidence. Secondly LT packs presented in Figure 3(b) in general display much flatter within day variation ranges, although several packs demonstrate specific patterns, most notably CEL_LT1 which has a clear six hourly periodicity signal, and which the author contends is linked to the Freezer Room defrost cycle, but not explored further in this paper. Finally the daily hourly usage pattern observed within HT packs varies significantly across packs, with % within day variation ranging from 10% in MAY_HT1 to nearly 30% in SAN_HT2 Possible reasons for this within day variation is discussed in more detail in Section 3.5 below.

3.5 Part B Within Day Variation Investigation Use Case

Again as a valuable demonstration as to how such an analytics approach can be used to garner greater insight into the refrigeration energy usage variation, and specifically for Part B usage variation which demonstrates the 4am minima, 5pm maxima characteristic behaviour as outlined previously, further deeper analysis is possible by exploiting a seasonal feature present in all retail stores, that of the 25th of December, the only universal non trading day of the year. As a consequence the 25th of December energy profile is different to the rest of the year, where there is a known noticeable drop in pack energy usage when compared to other days. And so by conducting an hourly usage aggregation exercise for the 25th of December day, and by comparing it to another arbitrary day close to the 25th, it is possible to compare the resultant 24 hour within day usage plots, to see if there any significant differences present, and particularly if the hourly periodicity seen previously in HT packs, is still present. Two such sample HT comparative pack energy profiles are presented in Figure 4, where it can be clearly seen that the within day variation profiles in the Decemeber 25th plots are almost flat.

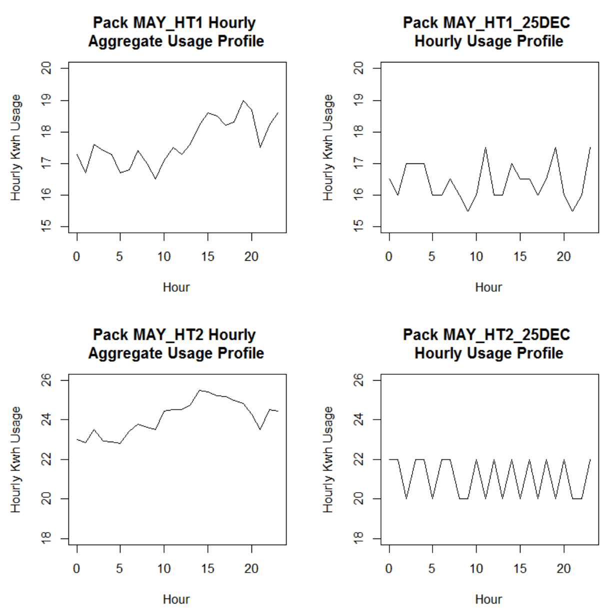


Figure 4 : Sample Hourly Time series of HT Pack Energy Usage Profiles including 25th December

There is a well known retail refrigeration industry phenomenon where the supermarket's open HT chill cases interact to a greater or lesser extent with a store's air conditioning systems **[Evans et al., 2015], [Woradechjumroen et al., 2014**]. From this it can reasonably concluded, from the data analysis conducted on the 25th of December feature therefore, that the lack of within day variation observed, is as a result of the non-interaction of the stores' HVAC and the open case HT refrigeration systems during the time when the store is closed for the 24 hour period. Furthermore it can therefore be concluded that detecting packs exhibiting high within day usage variation, may be a useful indicator in identifying packs with negative HVAC and HT interactions, with consequential high energy wastage conditions in operation.

3.6 Part C Summer Season Pack Variation Usage

From the preliminary analysis presented earlier, in Figure 2 above, it is clear that there is annual seasonality in evidence in the both LT and HT pack energy usage. It has been well documented the impact of ambient air temperature on refrigeration pack energy usage, and more specifically on a refrigeration pack's ability to cope with the pack's continued ongoing heat rejection requirements during the warmer summer months with higher ambient conditions **[Motta et al., 2015]**. In effect Part C variation usage analysis is an overall assessment of the pack's condenser performance, and its ability to reject heat efficiently.

3.7 Part C Summer Season Pack Variation Usage Calculation and Observation

An hourly energy usage plot versus ambient OAT temperature profile of a typical HT packs is presented in Figure 5 below.

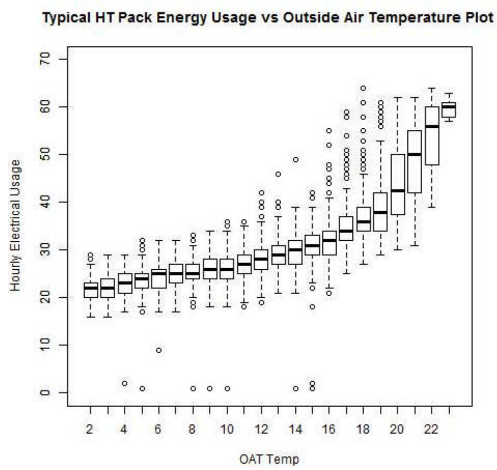


Figure 5 : Typical Pack Energy Usage versus OAT Ambient Temperature plot

With reference to the 4PC model presented earlier in Section 2, the usage profile presented in Figure 5 is clearly non-linear, with multiple Tc change points (Tc), and varying slopes (CS) , as defined in Eq(2), in evidence. Therefore in order to properly assess condenser performance behaviour, it is understood that deeper analytical techniques would be required to calculate the multiple differentiated rates of change needed to detect these change points over the condenser operating ambient temperature range. And so for now, to avoid this deeper analytic requirement, and in keeping with the paper's overall objective of creating pragmatic screening type analytic approaches to detecting energy usage anomalies, and equally without the need for ingestion of additional data sources like local weather station data, the proposed analysis defines and fixes this Part C summer period energy usage variation as the contribution, over and above the everyday Part A and Part B usage, for the summer months from May to September. Additionally in this simplified approach there is an assumption presented, that given the country small size (in this case Ireland) there is no significant variation in across country temperatures and that all packs within the country operate within generally homogeneous external environmental operating conditions.

While this is considered a simplified approach, and not entirely accurate, it is contended, and as the following overall summary will show, that such an approach is still a useful first pass exercise in comparing pack/condenser behaviours across large estates, and as such can be considered an effective screening method for detecting possible packs with condenser capacity or operational deficiencies.

4. APPLIED ANALYTIC APPROACH RESULT SUMMARY

And so when the outline screening analytic methodology is applied, using one year's worth of ½ hourly energy raw data for all available 350 packs within the estate, numbering 200 HT and 150 LT packs, and using the estimate definitions for the various subcategories detailed earlier, it is possible to assess the overall estate performance through the generation of pack type summary box plots which details the percentage contribution of annualized pack energy usage by subcategory, for both HT and LT packs, and which are presented in Figure 6(a) and Figure 7(a) respectively , with Figures 6(b) and 7(b) giving higher resolution, and therefore a clearer view of the detected Part B and Part C anomalies.

Figure 6 (a) : 2013 HT Pack Energy Usage Breakdown

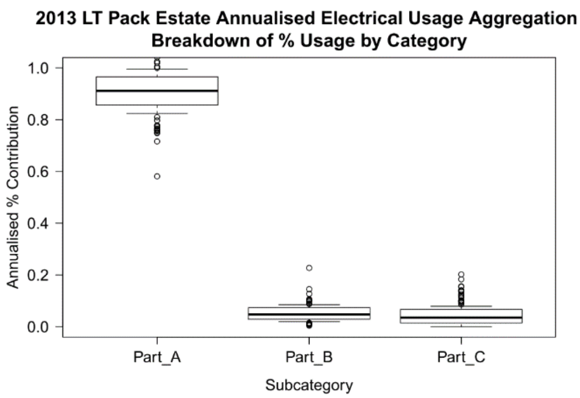


Figure 6(b) : 2013 HT Pack Energy Usage with Outliers

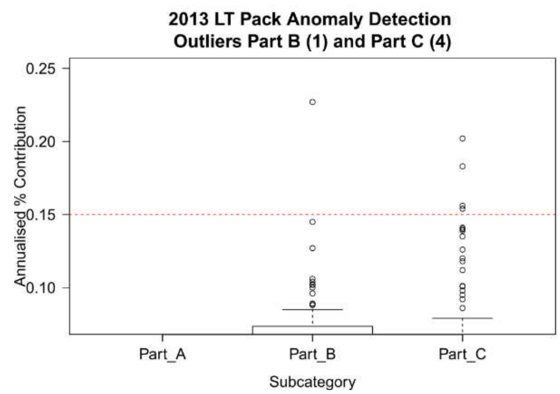


Figure 7 (a) : 2013 LT Pack Energy Usage Breakdown

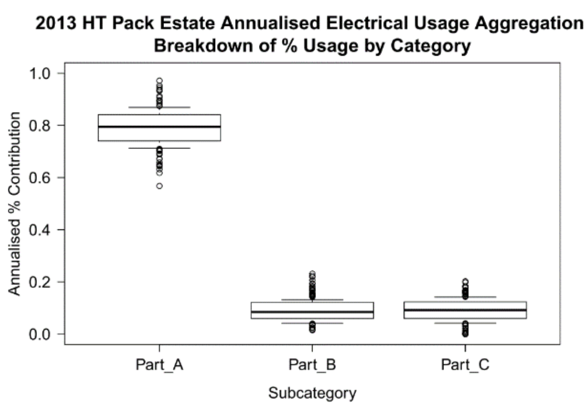
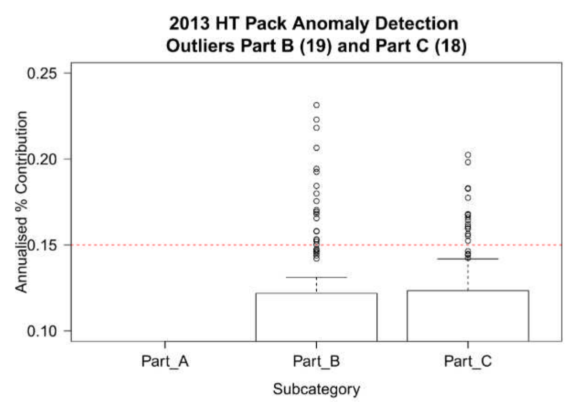


Figure 7(b) : 2013 LT Pack Energy Usage with Outliers



5. CONCLUSIONS

With reference to Figures 6 and 7 above, the following are some of the summary conclusions from the application of the presented analytic approach

1. The median for annualized Part A baseload contribution for the LT packs in the estate was calculated at 91%, and an equally high HT pack median of 80% within the estate, thus confirming the earlier contention that within either pack types, LT or HT, the energy usage is almost exclusively dependent on baseload, and influencers here being the initial pack design, store case load and proper system setup, with the latter offering the best opportunity for

energy savings through low cost interventions. Also it should be noted the baseload pack outliers (low percentages approaching 60%) that exist in both HT and LT packs, possibly indicating a metering read problem.

2. The outlined screening analytic has managed to detect a much higher level of HT Part B within day usage variation packs than LT packs (estimated to be 19 HT systems above the 91% percentile versus 1 LT system above the 99% percentile respectively when using an arbitrary cutoff limit of 15%), and thus supporting the contention that there is significant correlation between within day variation and store HVAC and HT Case systems interaction, with HT packs, with open front cases more likely to have high within day energy usage than their LT pack counterparts with closed front case types.
3. The Part C effects of ambient air temperature on pack usage for HT packs appears for the most part to be more sensitive than LT packs when comparing the anomalous pack detections observed (estimated to be 18 HT systems above the 91% percentile versus 4 LT systems above the 97% percentile respectively when using an arbitrary cutoff limit of 15%). While individual root cause analysis would need to be carried out on the anomalous packs for obvious condenser design issues, like under sizing, or equipment maintenance issues like fan failures, it is contended that this mismatch may be as a result of the higher levels of heat rejection required more generally in HT packs than their LT counterparts.

6. NOMENCLATURE

HT : High temperature chill refrigeration pack and case systems
LT : Low temperature freezer refrigeration pack and case systems
HVAC : Heating, Ventilation and Air Conditioning
EB : Pack baseload usage (Kwh)
CS : Cooling slope
T_C : Temperature change point at which there is a usage response with an increase in ambient
T_{OA} : OAT ambient temperature (deg C)
EWD :Within day variation usage (Kwh)

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