

The Operational Efficiency of Commercial Food Refrigeration Systems: A Data Mining Approach

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ABSTRACT

The energy demands of food retail buildings account for approximately 3% of the UK's energy consumption and resultant carbon emissions. Previous studies (Spyrou et al. 2014, Tassou et al. 2011) demonstrate that the greatest component of the electricity demand of food retail buildings is the cooling demand of the food refrigeration systems (ranging from 30 to 50%). Therefore a better understanding of the electricity demand for refrigeration would enable the development of effective energy management tools, including the evaluation of service and maintenance interventions to reduce operational electricity demand. Various methodologies have been developed and employed in the past for the quick identification of faults during the operation of commercial refrigeration systems. The focus of these methodologies has traditionally been on the temperature of food on the shop floor. The aim of this work is to enhance the existing fault-finding methodologies employed by a global multichannel retail organization, by enabling the identification of events that cause an increase in electricity demand of the refrigeration systems. This paper presents a methodology that analyzes data from refrigeration systems and enables a more straightforward identification of faults. This includes data for electricity consumption, compressor run times, percentage of refrigerant in the receiver, temperature of air on and off the evaporator, discharge and suction pressures, etc. Control strategies and maintenance schedules as well as meteorological data for each site were also collected and analyzed. Data mining methods were employed to remove known operational patterns (e.g. defrost cycles) and seasonal variations. Events that have had an effect on the electricity consumption of the system were highlighted and faults that have been identified by the existing methodology were filtered out. The resulting data set was then analyzed further to understand the events that increase the electricity demand of the systems in order to create an automatic identification method.

INTRODUCTION

The energy demands of food retail buildings account for approximately 3% of the UK's energy consumption and resultant carbon emissions. Previous studies (Spyrou et al. 2014, Tassou et al. 2011) demonstrated that the greatest component of the electricity consumption of food retail buildings is the cooling demand of the food refrigeration systems (ranging from 30 to 50%). Therefore a better understanding of the electricity demand for refrigeration would enable reductions in the electricity consumption by identifying and implementing service and maintenance interventions. Currently

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there are a few modeling tools available that can be used to estimate the demand of commercial refrigeration systems, for example Ge and Tassou (2011), Green et al. (2014), Hovgaard et al. (2013), Larsen (2005), Lawrence Ricker (2010), Zhang (2006). However these do not readily take into account the operational behavior of the systems. Analysis of the operational behavior of the refrigeration systems can enable the development of more efficient management tools by incorporating intelligent operational monitoring and fault finding that leads to service and maintenance interventions.

There are many definitions of a fault available in the literature, for example see: Himmelblau (1978), Venkatasubramanian et al. (2003), and Worden and Dulieu-Barton (2004). In the retail environment, a fault in the refrigeration system is considered to be an incident that affects the temperature of the products in the display cases/cold rooms, or an incident that affects the shopping environment for the customers (e.g. water on the shop floor). The existing fault finding methodology of a retail organization focuses on these events. An alert is raised with the maintenance team when the products in the display cases/cold rooms have an estimated temperature higher than the threshold. The in-store technician of each store can also inform the maintenance team of any problems identified in situ (based on visual inspections e.g. water on the shop floor, dirt on the grilles; and/or aural inspections e.g. loud noise from the fans).

This study concentrates on the electricity demand of the refrigeration system. Therefore, for the purpose of this study, the authors consider the following definition of a fault:

- A **Fault** is an incident that has caused an increase in the electricity consumption of the refrigeration pack, which is unrelated to an increase in outside air temperature, and any periodic events (e.g. defrost cycles, stocking patterns).

As such, the aim of this work is to enhance the existing fault-finding methodologies employed by a global multichannel retail organization, by enabling the identification of incidents that cause an increase in electricity demand of the refrigeration systems.

The following sections present more information about the refrigeration systems used in this study, describe the available data, and propose a methodology for identifying faults. The proposed methodology is then applied to identify faults in a sample of ten stores, and two examples of uncovered faults are discussed.

THE COMMERCIAL REFRIGERATION SYSTEM

In order to understand the normal and faulty operation of refrigeration systems, the first step is to appreciate how the system operates. As shown in Figure 1 the commercial refrigeration system referred to in this paper can be divided into two main parts:

1. The **Pack**, which is made up of the compressors and the condensers, and it is located away from the sales floor area, usually found on the roof of the building.
2. The **Cases**, which is a selection of cold rooms and shop floor display cases, with the evaporator element built into each one. The cases are divided into two main categories, the *Low Temperature* (-18 to -22°C, -0.4 to -7.6°F) and the *High (or Medium) Temperature* (+3 to +5°C, +37.4 to +41°F).

The load on the refrigeration system is known to be driven by conditions of the local thermal environment around both packs and cases. At the cases, heat is gained from the local environment through radiative, convective and conductive heat transfer (Cortella 2002, Getu and Bansal 2007, Spyrou et al. 2014). The amount of heat gained is influenced by usage in terms of how often customers remove products, and the rate of restocking. During these actions there is ingress of warmer air circulating into the case thereby increasing the load on the refrigeration circuit. At the packs, the rate of heat taken out of the refrigerant circuit is a function of the temperature difference between the refrigerant entering the condenser (T_{suction}) and the local ambient air temperature (T_{ambient}), and the rate of airflow, driven by condenser fans, across the condenser heat exchanger. As the local ambient temperature increases the condensing temperature increases and in turn the condensing pressure increases. This causes a high-pressure difference across the compressors (P_{suction} and $P_{\text{discharge}}$), which increases the

load on the compressors and the condensers. This difference in pressure across the compressors has a large effect on the electricity consumption of the pack; it is therefore common practice to allow the suction pressure (P_{suction}) to float within limits, instead of setting it to an exact value, to use less energy. Overall the interdependence between each element of refrigeration systems means that a rise in external temperature affects the electrical load of the refrigeration system.

The electrical load of the packs incorporates the compressor rack and the condenser fan/heat exchanger. The remaining electrical load of the system would incorporate the load of the evaporator fans and defrost heaters (low temperature cases), as well as the load of lighting and circulation fans. In this study only the electrical load of the packs (E) will be analyzed, as the recorded electrical load for cases includes other shop floor services, which are not of interest of this study.

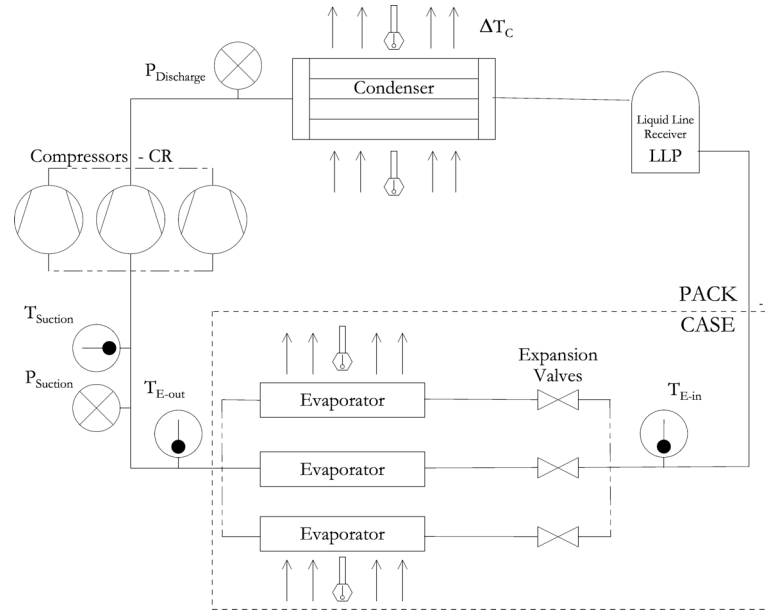


Figure 1 Refrigeration system diagram demonstrating the pack and case sides, with available instrumentation (data collection points).

DATA AND ANALYSIS METHODS

Data mining

This study approaches the subject of commercial refrigeration systems from the data point of view with the aim of gaining insights about the operational behavior of the systems. Table 1 gives a short description of the data available prior to this study, whereas the position of the instrumentation is indicated in Figure 1. The assortment of representative stores was chosen for the investigation using the selection criteria below:

- Electricity data had to be available for each pack between 1 November 2012 and 1 November 2013.
- System operation data (such as suction pressure and evaporator temperatures) had to be available for the same time period to match the electricity data.
- Stores had to have been fitted with an 'Einstein E2' front panel controller; this controller provided the most comprehensive operational data out of all the installed controllers in the estate of the organization.
- Selected stores all use the same refrigerant, R404A, to keep the system configuration as similar as possible.

Table 1 Available Data

Symbol [Units]	Description	Frequency Interval
E [kWh]	Electricity readings from the distribution board servicing each pack	Half Hourly
T_{ambient} [°C]	Ambient Temperature from the nearest available weather station to the store (UK Meteorological Office)	Hourly
MSI	Maintenance and Service Information data. Collected from the maintenance logbooks.	Time of addition
T_{Suction} [°C]	Temperature of gas refrigerant before it reaches the compressor	Minutes
P_{Suction} [bar]	Pressure of gas refrigerant before it reaches the compressor	Minutes
$P_{\text{S_setpoint}}$ [bar]	Target pressure for the refrigerant before it reaches the compressor	Minutes
$P_{\text{Discharge}}$ [bar]	Pressure of refrigerant before it reaches the condensers	Minutes
CR	Indication of the compressor running or not	Minutes
LLP [%]	Percentage of liquid in the receiver (only available if the receiver was fitted with an ultrasound reader)	Minutes
ΔT_{C} [°C]	Temperature difference of refrigerant before and after the condenser	Minutes
$T_{\text{E_in}}$ [°C]	Evaporator air in temperature, averaged across all cases	Minutes
$T_{\text{E_out}}$ [°C]	Evaporator air out temperature, averaged across all cases	Minutes

Methodology

Measurements of all variables shown in Table 1 were compiled for each store. Subsequent analysis was carried out in IDL (Exelis Visual Information Solutions). The dataset was checked for quality and completeness; where missing values were observed in the weather dataset (<10%), these were linearly interpolated. Standardized procedures were not used in this study to detect outliers; outliers were of interest and therefore needed to be retained. Electricity data was aggregated to hourly intervals to match the weather data frequency interval. It was expected that the electricity consumption of the refrigeration packs would be dependent on ambient temperature (Ge and Tassou 2011). For this reason a regression model (see Tabachnick et al. 2007 for more information) was built for each pack based on the ambient temperature profile for that region. This regression model simulates the electricity consumption of the pack based only on weather, in the form:

$$Y = \text{Const} + W \quad (1)$$

Where,

$$W = aT_{\text{ambient}} + bT_{\text{ambient}}^2 + cT_{\text{ambient}}^3 \quad (2)$$

Y is the predicted consumption for the pack in kWh, Const [kWh] is the constant term in the equation (assumed to be consumption not affected by weather), W [kWh] is taken to be the effect of weather on the pack. T_{ambient} [°C] is ambient temperature as described in Table 1, while a , b and c are the coefficients for T_{ambient} for each pack. In order to remove the effect of ambient temperature from the data set, W was subtracted from the actual consumption, E , of the store. Removing the effect of ambient temperature on the consumption of the system (W) makes the identification of faults easier as it removes the skewedness inflicted by an external factor. Based on what is known about the operation of the refrigeration packs, it was expected that the electricity demand would have some periodic patterns. For example, defrost cycles (scheduled to be carried out at specific time intervals depending on the type of case), time of day, and day of the week. For this reason the electricity data, after the effect of weather was removed, was transformed into the frequency domain using the Fast Fourier Transform (FFT) function in IDL (Exelis Visual Information Solutions, Oppenheim et al. 1999). The results showed that some frequencies have much higher amplitude than the rest, indicating that there are events that happen

periodically with that frequency. For example an event with a period of eight hours could be representing the defrost cycles that happen three times a day; an event with a period of 24 hours could be representing the normal daily operation of a store, i.e. opening at 6am, stocking at 8am, high footfall around lunch time, stocking at 3pm, high footfall around 5pm, restocking at 9pm and store closing at midnight. Similarly a seven-day event would represent the weekly operation of the store, and the variations in opening hours between weekdays and weekends. The FFT has also highlighted that there are other periodic events in some stores that need further investigation (for example in Figure 3(c) there is a 12-hourly peak that could not be explained).

Following standard digital signal processing principles, the data set was cleaned by removing the peaks representing the periodic events caused by known factors. These were: the four/six/eight-hourly peaks depending on the defrost settings of the pack, the 24-hour peak, and the seven-day peak. It is worth noting at this point that the ‘zero’ or DC peak was not removed. The reason for not doing so was that the removal of this peak results in the exclusion of all noise from the original signal; the faults of interest to this study would fall under the ‘noise’ category as they are expected to appear randomly in the dataset. After the removal of the peaks, an inverse FFT was used to transform the data back into the time domain. For more information see Oppenheim et al. (1999) and Stranneby and Walker (2004).

As the focus of this study was to identify incidents that cause an increase in energy, any outlier data points needed to be investigated. In order to do so, the mean and standard deviation of each electricity data set was calculated, and any data points that fell outside two standard deviations from the mean were selected for further investigation. The aforementioned methodology is summarized in Figure 2.

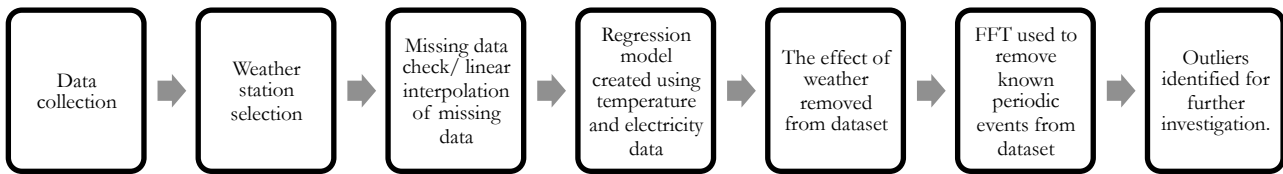


Figure 2 Methodology for the identification of incidents that cause an increase in electricity consumption

RESULTS AND DISCUSSION

The methodology described above was used to analyze two data sets and identify faults for further investigation.

Example A: Low temperature pack - Missed opportunity

Figure 3 presents the electricity consumption data of the pack and how it was transformed using the methodology presented in this paper. Figure 3(a) shows the original electricity consumption data. By looking at this figure one cannot be certain if there was a fault in the operation of this pack as there is only a small step change in the consumption towards the end of December. Figure 3(b) shows the regression model, equation (1), for the same store. Figure 3(c) shows the FFT transform of the data, indicating the peaks that were removed, and the 12-hourly peak that cannot be explained with the available information. The final dataset and the outlier data selected for investigation are indicated in Figure 3(d).

The data for the outlier periods of time was closely investigated, and it was found that the compressor run times, CR, of the pack were much higher during those periods of time (Figure 3(e)). This was expected, as the more time the compressors are run, the more electricity they consume. However there were no obvious reasons for the extra compressor need. By looking at the suction pressure floating set point ($P_{S_setpoint}$), Figure 3(f), this becomes clearer. $P_{S_setpoint}$ was not floating as expected; it was set to the minimum value (0.81bar, 81kPa) for both of the high electricity consumption periods.

This has caused the need for more compressors to be running at any given time to achieve the required suction pressure, leading to higher electricity consumption. Allowing the set-point to float in this example would have saved 20% of the pack's electricity consumption for that period of time (calculated from Figure 3(d)).

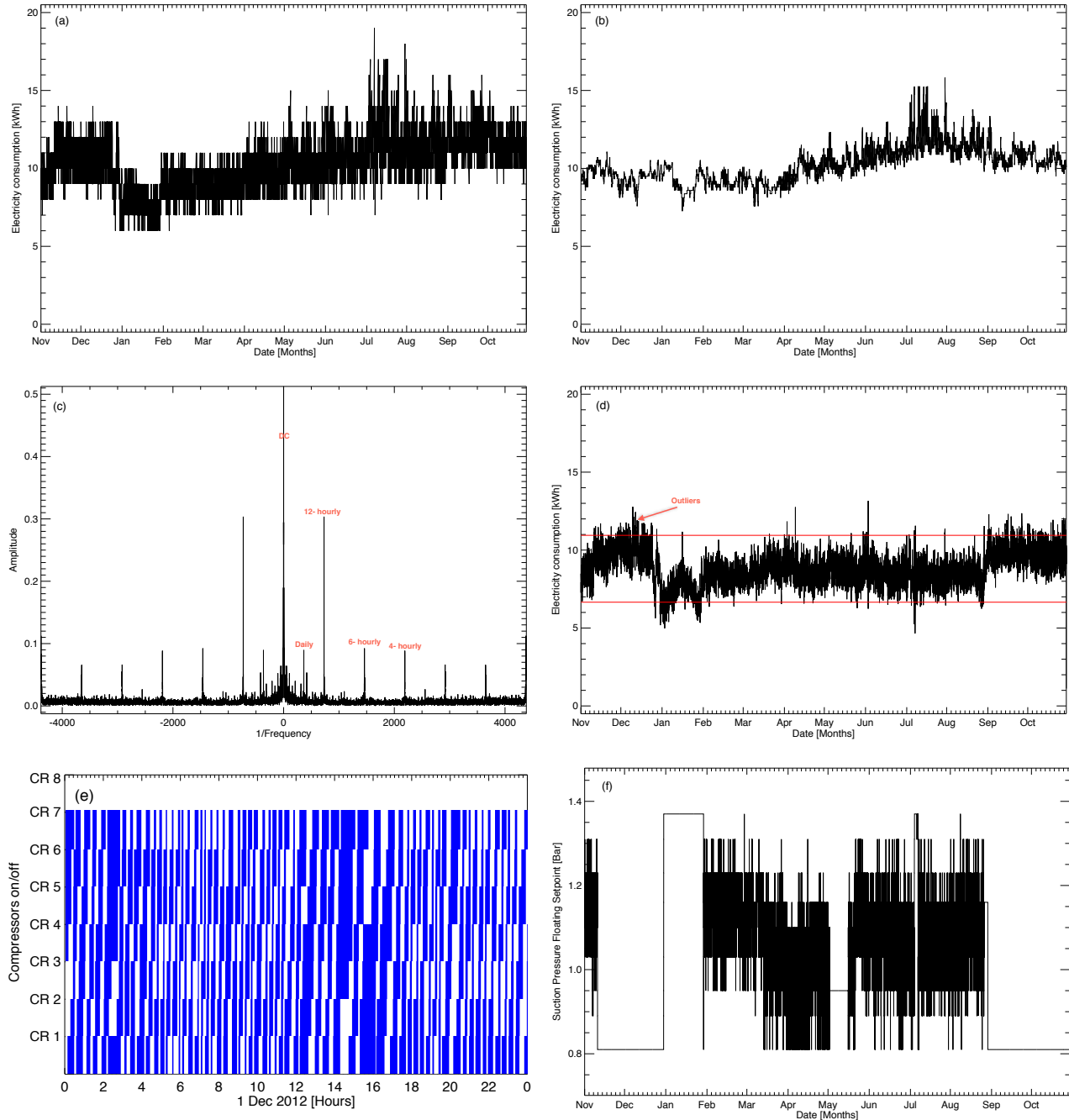


Figure 3 (a) Electricity consumption of example A. (b) The modeled (Y) electricity consumption of example A. (c) FFT of the electricity consumption of example A. (d) The resulting data set, indicating outliers. (e) The compressor run times of the pack on Dec 1, 2012. (f) The suction pressure floating set point over the whole year.

Example B: Low temperature pack - Oversized system

Data for this store is presented in Figure 4. After applying the methodology to the original electricity data (Figure 4(a)), it became clear that there was a 15% reduction in the consumption occurring on February 5, 2013, Figure 4(b). This was caused by the installation of passive display doors that do not have anti-fog heaters installed. As seen in Figure 1, the direct electricity consumption saving from this is not included in the data used in this work, as it would be affecting the case consumption. However there was an indirect effect of this installation, as the new passive display doors do not produce any heat, which reduced the overall cooling demand of the system.

The rest of the store data was fully investigated, and it was identified that after the installation of the new doors the suction pressure of the pack was floating around the minimum value of 0.81bar (81kPa), Figure 4(d). This could be considered normal, if the cases were at a higher temperature than the set-point, but there were no temperature alarms from the cases. Additionally the compressors in the pack were found to drop off too quickly, after ~ 5 minutes of operation (Figure 4(c)). Both of these issues were unusual, and after discussions with the refrigeration engineers, it was concluded that both concerns could be caused by the following factors: (i) the installation of the passive doors caused the pack to be oversized for the number of cases connected to it, or (ii) a shortage of refrigerant in the system. As there were no records of temperature alarms from the cases, it can be assumed that there was enough refrigerant in the system; therefore this must be an oversizing problem. Fitting more cases to this pack, or switching one of the compressors to a variable speed would allow this pack to work more efficiently and use less energy.

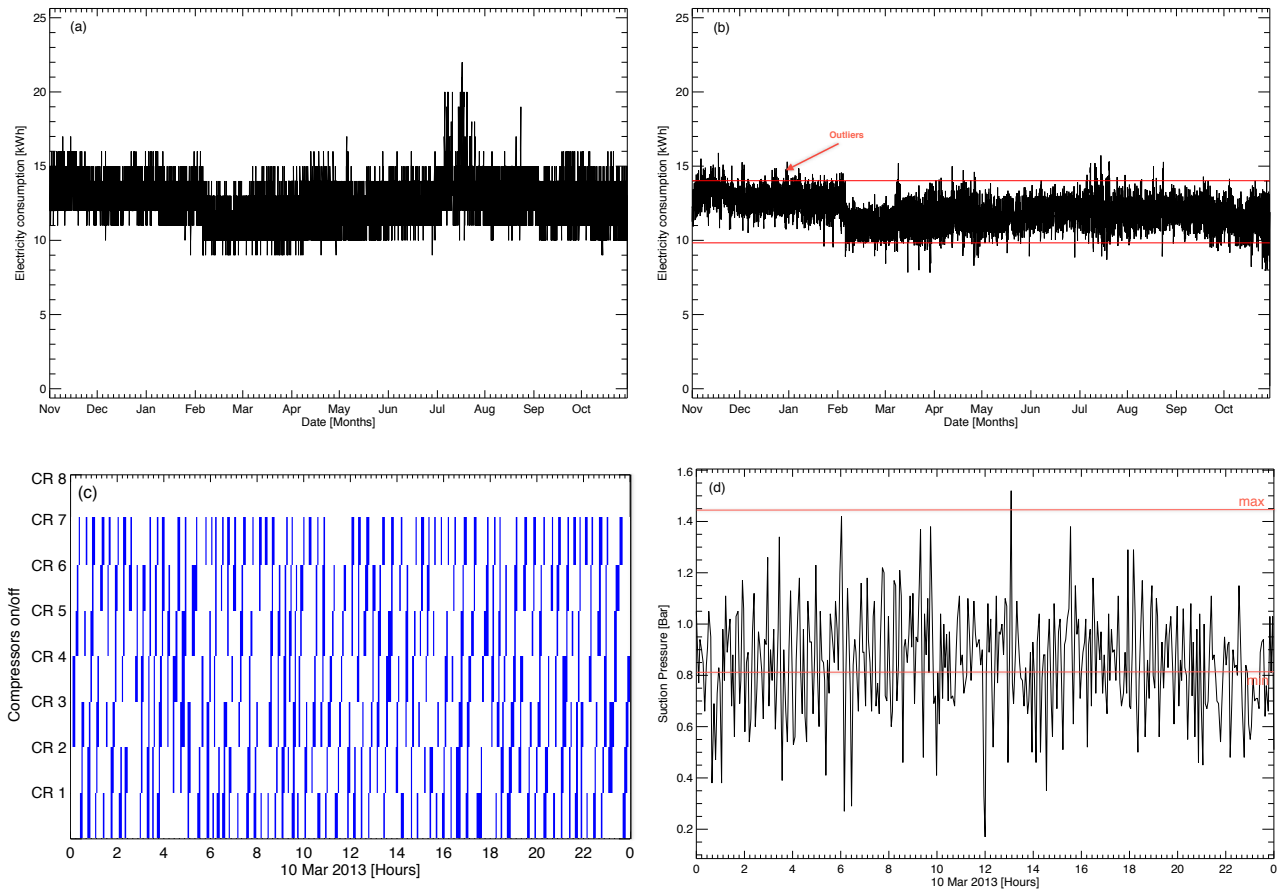


Figure 4(a) Electricity consumption of example B. (b) The resulting data set for example B, indicating outliers. (c) The compressor run times of the pack on March 10, 2013. (d) The suction pressure of the pack on March 10, 2013.

CONCLUSION

This paper has presented a methodology that analyzes the electricity consumption data from refrigeration systems and enables a more straightforward identification of faults. The examples included have demonstrated that this methodology can form part of a more advanced automatic fault-finding solution; potential faults were difficult to identify in the original electricity data set. However treating the data with the methodology described in this paper has made it simpler to identify potential faults, and look for probable causes. It was also shown that by monitoring the suction pressure of the packs, alongside the compressor run-times, one could identify further opportunities for electricity consumption reduction.

Future work will include the data analysis of more packs by implementing this methodology in an algorithmic form. The outcome of this work will inform the development of an automatic, real-time, fault-finding algorithm, able to quickly identify faults not already highlighted by the pre-existing methodology.

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