Imperial College London

Machine Learning-Based Analysis of Supermarket Refrigeration Systems

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BACKGROUND

Supermarkets account for 3% of the total UK energy consumption[1] and are responsible for 1% of the country's greenhouse gas emissions[2]. Specifically, refrigeration can represent up to 50% of supermarket electricity consumption[1] and hence constitutes one of the largest operational costs for retailers. The need to minimise financial losses and meet sustainability targets provides a strong incentive for supermarkets to better manage their refrigeration systems.

A cost-effective solution is to exploit the vast predictive power of machine learning techniques to assess the performance of supermarkets refrigeration systems by making use of the immense amount of historical sensor data.

The objective of this project is to apply machine learning techniques to retail refrigeration system data from Sainsbury's supermarkets and investigate the possible insights to be gained.

STORE SELECTION

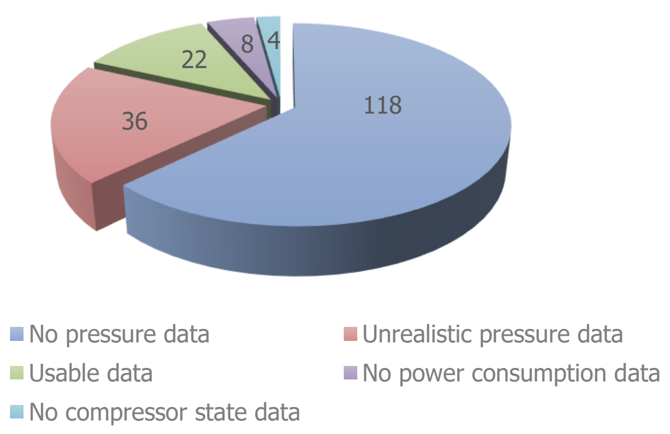

Figure 1 Breakdown of data availability for the 188 stores considered

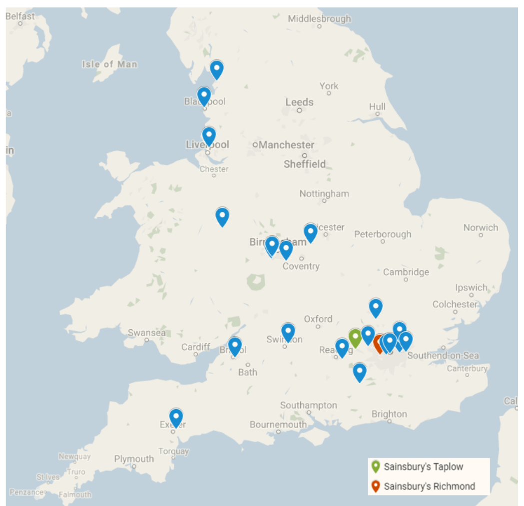

Figure 2 Locations of the 22 stores with usable data

Sensor data was collected and analysed for a list of 188 Sainsbury's supermarkets equipped with CO_2 booster systems and the sample was narrowed down to 22 stores with both available and plausible refrigeration data. A correlation analysis between compressor power consumption and linked variables was applied to assess the quality of the data. The Richmond and Taplow stores were selected for case studies due to their similar size and the good correlation coefficients obtained.

COOLING LOAD CALCULATION

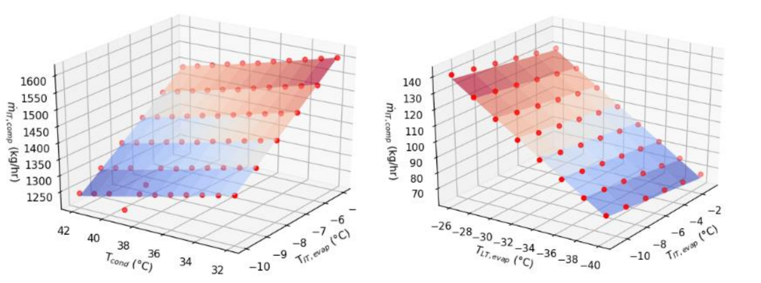

Figure 3 Mass flow rate fits for high-pressure (left) and low-pressure (right) compressors

As the cooling load depends on the mass flow rates of refrigerant through the system, simulations were run for a range of operating conditions using Bitzer's *Web Tool* and regression was used to fit equations to the data, allowing the mass flow rates to be calculated at any point.

Based on a theoretical CO_2 booster model, the supermarket cooling load - i.e. the rate at which heat is removed from the refrigerated case cabinets - was calculated for Richmond and Taplow at 15-minute intervals over a period of 10 months.

The cooling load was found to be closely related to outside temperature, although the computed values were erroneous at high temperatures, when the refrigeration system operates transcritically.

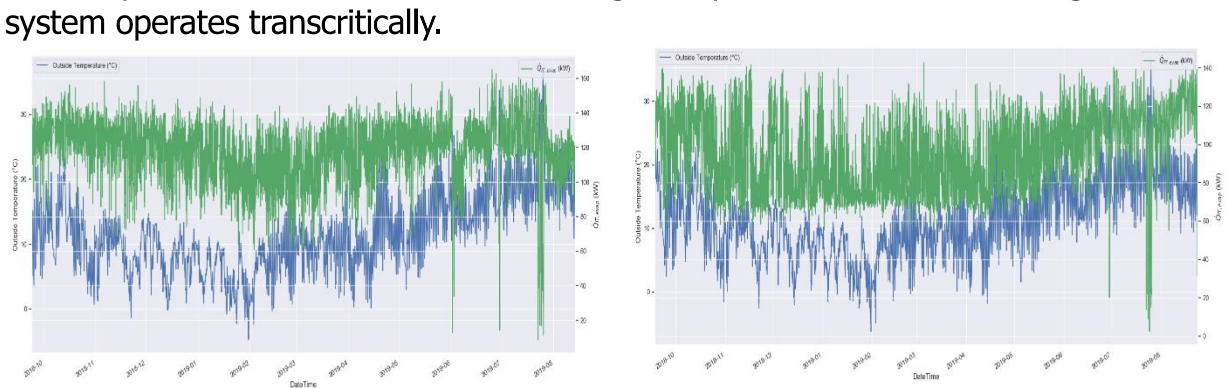

Figure 5 Cooling load vs outside temperature Richmond (left) and Taplow (right)

MACHINE LEARNING MODELS

Two machine learning algorithms - an Artificial Neural Network (ANN) and a Random Forest (RF) - were built and trained using the cooling load data and tested on unseen data for both winter and summer months.

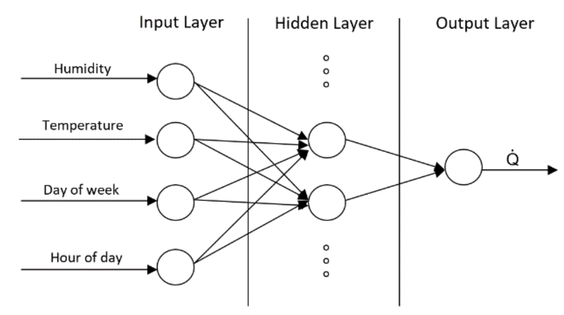

Figure 6 Schematic of ANN model

Machine learning models work by learning the relationship between specified inputs and outputs. An ANN is formed of layers and nodes and learns by adjusting a set of connection weights, while a RF aggregates the results of a large number of decision trees. The models include many hyperparameters that can be tuned through trial and error to provide the most accurate predictions.

RESULTS

Table 1 Testing error and accuracy of ANN and RF models for both stores

	Mean absolute error (kW)		Accuracy (%)	
	Richmond	Taplow	Richmond	Taplow
ANN	15.3	13.0	87.6	84.6
RF	16.5	13.4	86.3	84.5

Generally, a higher number of nodes/trees lead to increased accuracy. The RF algorithm predicted the peaks in the cooling load better than the neural network, but greater overall accuracy was obtained with the ANN.

With both algorithms, better testing accuracies were obtained for Richmond than Taplow. However, the difference was not considered to be large enough to allow for definite conclusions to be drawn about the relative performance of these stores

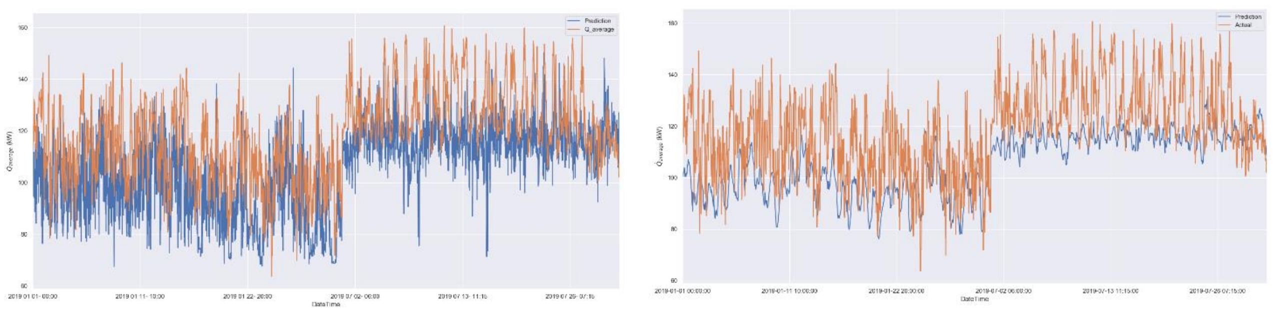

Figure 7a Richmond - Predictions for January/July data with RF (left) and ANN (right)

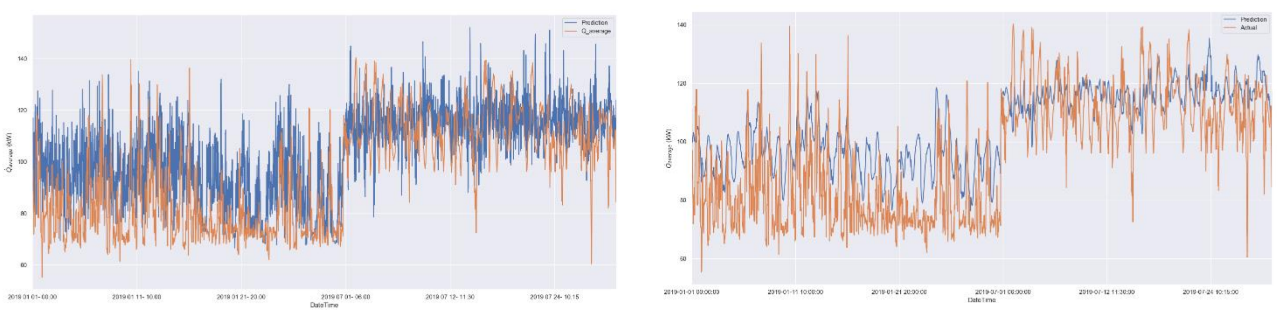

Figure 7b Taplow - Predictions for January/July data with RF (left) and ANN (right)

CONCLUSION

The fact that relative errors of less than 15% could be obtained without even optimising the machine learning algorithms is promising, and it is likely that the predictions could be improved with hyperparameter tuning and using larger training datasets. The models should also be applied to a greater number of supermarkets to better compare and contrast the results.

Crucially, however, the effectiveness of the machine learning models is limited by the quality of the training data, which suffers from large amounts of noise on intra-daily scales. To accurately estimate cooling load and extract the maximum benefit from the machine learning approach, it is likely that mass flow sensors would have to be retrofitted to current refrigeration systems.

The fact that less than 12% of all the considered stores had usable data highlights the need for better metering in general.

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[1] Tassou, S.A. & Ge, Y.T. (2008) Reduction of refrigeration energy consumption and environmental impacts in food retailing. In: J.-K. Kim (Eds.) J. Klemeš, R. Smith (ed.). Handbook of Water and Energy Management in Food Processing. Cambridge, Woodhead Publishing, Cambridge, UK. pp. 585–61

[2] Tassou, S. a., Ge, Y., Hadawey, a. & Marriott, D. (2011) Energy consumption and conservation in food retailing. Applied Thermal Engineering. [Online] 31 (2-3), 147–156