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Identification of refrigeration load parameters for display cabinets from monitoring data

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ABSTRACT

Supermarket refrigeration systems typically consist of a number of display cabinets. These display cabinet interact thermally with the store room in which they are located. This thermal interaction is generally described as a refrigerant load acting on the display cabinets.

A mathematical description of the refrigeration load can be used for multiple purposes. It is an integral part of dynamic models of display cabinets, but can also be used for fault detection, benchmarking or systems optimization. If laboratory measurements are not available to identify the necessary parameter, the parameters of the refrigeration load model must be identified from monitoring data.

This paper demonstrates how to identify refrigeration load parameters from monitoring data, using data from a Danish supermarket. The paper also highlights some of the main challenges with the dataset. The prediction accuracy achieved is satisfactory, although some inherent challenges remain.

Keywords: Refrigeration, CO2, Supermarket, Display Cabinet, Refrigeration Load

1 INTRODUCTION

A typical supermarket refrigeration system consists of a number of display cabinets and cold rooms (hereafter simply referred to as display cabinets), a compressor rack and a gas cooler. The display cabinets interact thermally with the store room in which they are located, resulting in a refrigeration load acting on the cabinet. The refrigeration load here is the sum of the external heat flow acting upon the display cabinet. The refrigeration load is primarily affected by heat and moisture infiltration from the environment into the display cabinet, as well as dissipation of electrical energy within the refrigerated space. Figure 1 provides an overview of the relevant heat flows.

Mathematical descriptions of the refrigeration load acting upon an individual display cabinet are a crucial component of display cabinet models. Many authors use physical relationships, as for example in Chaomuang et al., 2019 or Ben-abdallah et al, 2018. Determining the mass flow of air infiltration is a significant part of parametrising these models, as for example in Fidorra, 2021; Månsson et al., 2021; Al-Sahhaf, 2011. Others authors also use empirical correlations, as for example Ge et al., 2008 or machine learning approaches like Pei et al., 2021 for the refrigeration load.

The simulation models of individual display cabinets, in combination with a simulation model of the compressor rack, can be used to investigate the dynamic interactions between display cabinets and the compressor rack (Schulte et al., 2023; Schulte et al. 2024).

Due to the interactions within the system, the evaporation pressure in a supermarket refrigeration system fluctuates constantly. It is believed that these fluctuations are mainly caused by various frequent and uncoordinated control actions of the various controllers in the system (Schulte et al., 2024), mainly the case controllers and the compressor capacity controllers. This can lead to chaotic behaviour as described in Larsen et al., 2007 and lead to increased energy demand for the refrigeration system (Schulte et al., 2023; Schulte et al. 2024).

Beyond the dynamic simulation of display cabinets, the refrigeration load can also be used in a multitude of other usages. Examples include fault detection on individual display cabinets, benchmarking of existing supermarket refrigeration systems or setpoint optimization of supermarket refrigeration and conditioning systems.

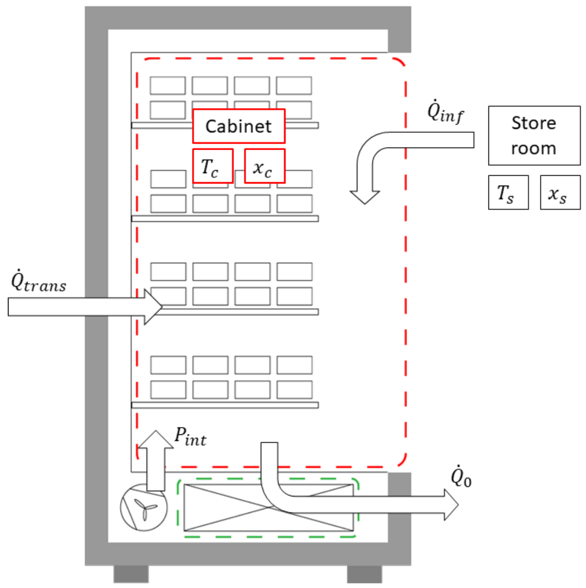

Figure 1 Principal overview of the heat flows in a display cabinet

In the absence of laboratory data, a model of the refrigeration load must be derived from monitoring data. A laboratory provides a very controlled environment to collect data, in contrast to monitoring data, which typically includes chaotic influences of real-world supermarkets, such as customers. Both present distinct advantages and challenges.

Fast transient disturbances, such as a customer opening a cabinet door, act on the cabinets. However, when analysing the data, it can be seen that these disturbances only lead to a slow dynamic response in the display cabinet temperature. This is due to the high thermal mass of the goods and the metal in the cabinet absorbing the fast dynamics, acting as a low pass filter. It is therefore assumed that for many applications the refrigeration load of a cabinet can be described as quasi-stationary. Under these assumptions the mean refrigerant side refrigeration load has to be equal to the sum of the air side heat flow rates.

The data used in this investigation was collected within the ESO-2 project (Fredslund, K., 2013). It was gathered in a supermarket in Otterup, Denmark, over a period of four years from the beginning of 2012 to the end of 2015. During this time, the sampling frequency was one minute for all relevant sensors and actuators. Those include pressure, temperatures and valve opening degrees at all evaporators, as well as store temperature, humidity and ambient temperature. For further analysis, if not stated otherwise, the data is aggregated into hourly mean values.

The supermarket in Otterup consists of eleven evaporators, four on the low temperature (LT) side and seven on the medium temperature (MT) side. Table 1 gives a summary of the evaporators in the supermarket.

Table 1 Evaporators installed in the supermarket

Cabinet	Type	Size	Cabinet	Type	Size
MT1	Room with doors (Evaporator 1)	20m²	MT2	Room with doors (Evaporator 2)	20m²
MT3	Open vertical	2.5m	MT4	Open vertical	3.75m
MT5	Open vertical	3.75m	MT6	Open vertical	3.75m
MT7	Closed horizontal	3.75m			
LT1	Room	11m²	LT2	Closed horizontal	2.5m
LT3	Closed horizontal	3.75m	LT4	Closed horizontal	3.75m

Most of the evaporators on the MT side are open vertical display cabinets, while the LT side consists of three closed horizontal cabinets and a storage room. MT1 and MT2 are located in the same room, which is considered a special case. They may be viewed as one evaporator due to their proximity, or as independent due to spatial influences. While both options have their merits, this paper considers them as independent.

Table 2 shows the relevant data contained in the monitoring data set. In the left column are the measurements that exist for each individual display cabinet. On the right are the measurements that only exist once for the system.

Table 2 Measurements in the monitoring data set

Per display cabinet	General
valve opening degree	receiver pressure
evaporation pressure	store room temperature
refrigerant outlet temperature	store room relative humidity
air temperature cabinet	ambient temperature
air temperature evaporator outlet	total mass flow MT
	total mass flow LT

2 DATA QUALITY

Evaluating the completeness of the dataset it was revealed that only sporadically larger outages occurred. A possible reason for these larger gaps may be shutdowns of the refrigeration system by technicians for work. On the other hand, frequent but short sections of missing data were observed. These gaps are generally not longer than three minutes. In order to address this issue, the smaller gaps were linearly interpolated This was considered acceptable as it closes many of the observed gaps without introducing a significant error. The store room temperature and humidity, as well as the ambient temperature, were allowed to be interpolated for gaps of up to ten minutes.

In addition to completeness, data in supermarket monitoring systems must be checked for validity, as measurements may be erroneous. There are limited ways to do this. The best way is to compare the data with redundant measurements. If this is not possible, manual inspection of the data is often the only viable option. Two variables will be further investigated to illustrate both methods, the refrigerant mass flow rates of the display cabinets and the store room temperature.

The refrigerant mass flow rate for each cabinet is calculated based on valve size and monitoring data. In particular the valve sizes are known from Fredslund, K. 2013. To validate the calculated mass flow rates two mass flow meters were available, to give the cumulative mass flow rate of both the MT and LT cabinets. Hourly averages were used for comparison. If no data on the valve size is available it can also be estimated from monitoring data (Leerbeck et al., 2023). Figure 2 shows the comparison of the mass flow rate measurements. The dashed black lines indicate the ten percent deviation lines. In general, the mass flow rates calculated by the valves agree well with those measured by the mass flow meters. At higher mass flow rates, the values estimated by the valves slightly overestimate the actual mass flow rate, while at low mass flow rates the valves appear to underestimate the mass flow rate. Only a small number of outliers exist, the number of outliers is small compared to the total number of data points.

It should be noted, that the valve areas for the LT expansion valves had to be adjusted by approximately ten percent. The need for this correction was already mentioned in Fredslund, K., 2013. Despite further investigation, no conclusive answer could be found to explain the need for this correction. Overall, it can be concluded that the expansion valves can be used to estimate the mass flow for each cabinet.

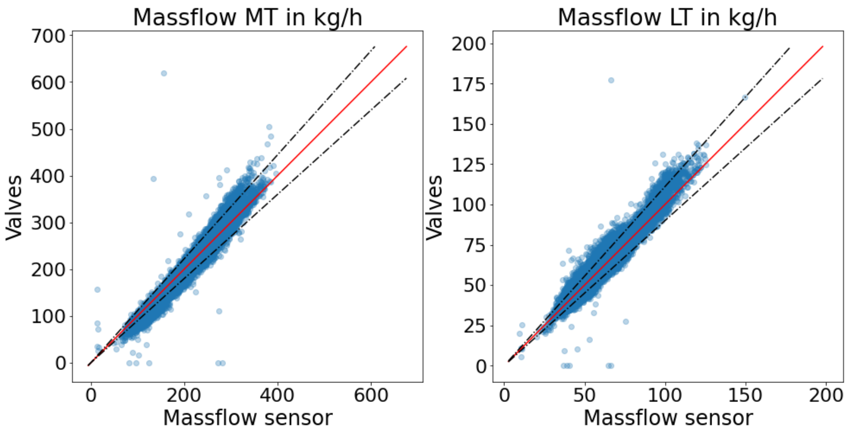

Figure 2 Comparison of mass flow rates from the mass flow meters and the estimate over the expansion valves. The dashed line indicates the ten percent deviation line.

The second variable to be validated is the store room temperature. As there is no redundant data available for the store room temperature only a basic sanity check can be performed. Figure 3 shows the store room temperature in relation to the ambient temperature. The validity of the data is questionable because even in the winter, with ambient temperatures around the freezing point, the sensor readings show a temperature of up to 26 °C. It was expected that the indoor temperature for a supermarket is in the range of 19 °C to 21 °C, therefore this is a significant deviation. No obvious reason for the deviation could be found. The most plausible reason is poor sensor placement, but this could not definitively be confirmed. An analysis of the effect of correcting the temperature is given in section 5.2.

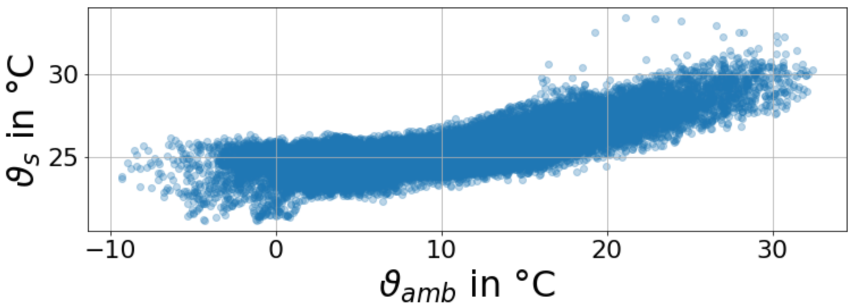

Figure 3 Store room temperature in relation to the ambient temperature. Noticeable are the high sensor readings especially at low ambient temperatures.

3 DATA SELECTION AND CORRECTION FOR STORED ENERGY

Before using the data for parameter estimation outlying data points have to be removed. For that two methods are used. First, defrost times and adjacent pull-down times are removed from the data set based on the time of day. Times of defrost have to be removed, as the represent transient states and are not steady-state. The defrost times are either known or can be identified form the data itself, as is shown in Figure 4. Here the known defrost times are marked in red. If not known directly the defrost times can be identified by a characteristic decrease in heat flow, followed by a sudden increase in heat flow rate. Transient states such as opening or closing the store can be identified and removed in a similar manner.

In addition, Figure 4 shows the effect of customer interactions and night blinds on the refrigeration load, as cabinet MT6 is an open vertical cabinet. During the opening hours of the store, the refrigeration load is significantly higher than during the closing hours. During opening hours, the customers increase the infiltration into the display cabinets, while during closing hours the night blinds reduce the infiltration.

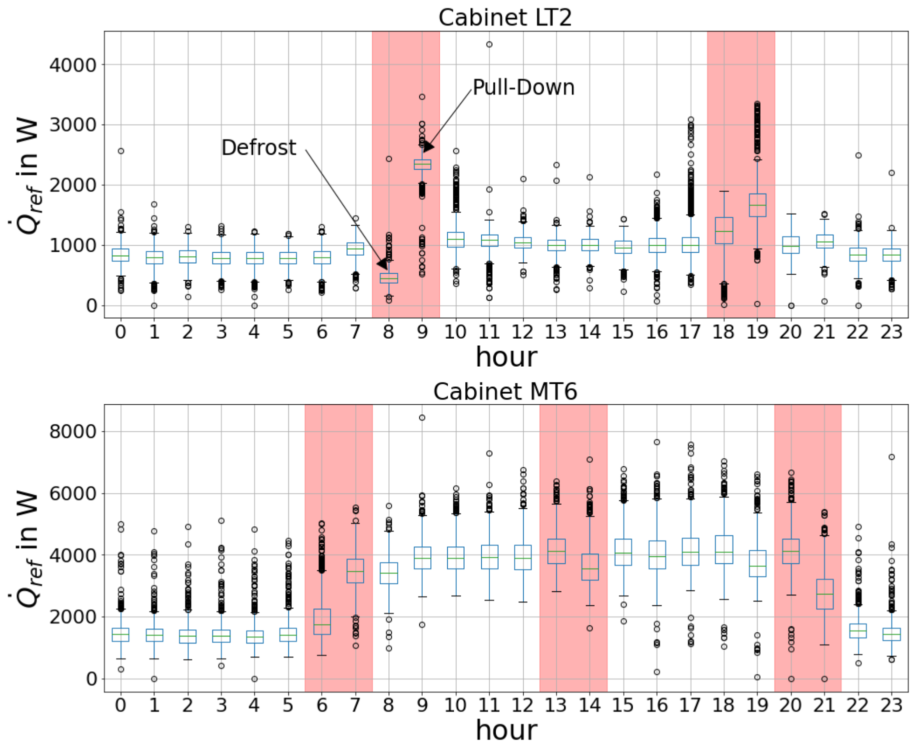

Figure 4 Box plot of the hourly average refrigeration load. Red marks are the known times of defrost.

Another approach is to use the cabinet air temperature to identify defrost or transient conditions. Figure 5 displays the refrigeration heat flow rate in relation to the average cabinet air temperature for the corresponding hour and the refrigeration heat flow rate in relation to the cabinet air temperature for the previous hour. Unusually high refrigeration heat flow can be observed when the cabinet air temperature was increased either in the corresponding hour or in the previous hour. A cut-off at -12.5°C for LT cabinets and 6°C for MT cabinets is used to split the data set. In Figure 5 the cut-off value is shown by a red vertical line. The cut off value was visually determined based on the temperature at both the current and previous hour. When using this method, it is crucial to select the cut-off point carefully to avoid excessive exclusion of data.

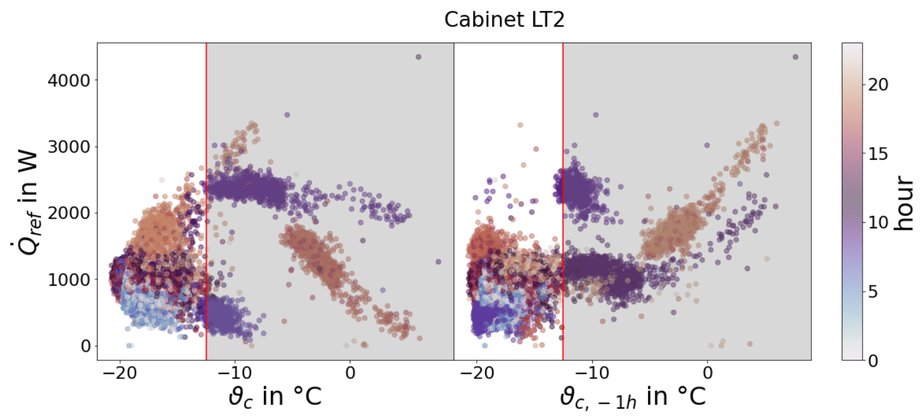

Figure 5 Hourly average refrigeration load in relation to the cabinet air temperature of the corresponding and previous hour. The red vertical line indicates the cut-off value.

While the time-based determination is effective in eliminating transient conditions resulting from periodic events like defrost, the temperature-based determination is suitable for infrequent events. Both methods were applied to the data in this paper.

The majority of display cabinets in the supermarket use a hysteresis control to regulate the air temperature, by allowing the expansion valve to open or not. This method causes the cabinets alternate between periods of cooling and periods of temperature rise. The data used in this study was aggregated to hourly averages based on wall time, without considering the periodic behaviour of the control. Consequently, energy can be stored within the aggregation interval due to the difference in air temperature at the beginning (minute 00) and end of an hour (minute 59). The refrigeration load therefore is biased by the temperature difference from the beginning to the end of the sample hour. To correct for this, a linear correction factor $k_{\Delta T}$ was used.

$$k_{\Delta T} = a \cdot (T_{c,00} - T_{c,59}) + 1 \qquad \text{Eq.(2)}$$

The slope a of the correction factor $k_{\Delta T}$ in Eq.(2) is identified from the data, by linear regression. To limit the correction's influence at the extremes, the correction factor is clipped at 0.5 and 2. This limit prevents overcorrections of strong outliers.

4 MODEL EQUATIONS

Under quasi-steady-state conditions the refrigeration load $\dot{Q}_0$ of a display cabinet is equal to the sum of several heat flows into the display cabinet. Depending on the level of specificity, these may include the heat flows resulting from air infiltration $\dot{Q}_{inf}$, heat transmission through the outer surface $\dot{Q}_{trans}$, internal loads P_{int}.

$$\dot{Q}_0 = \dot{Q}_{inf} + \dot{Q}_{trans} + P_{int} \qquad \text{Eq.(3)}$$

Heat flows as a result of defrost or restocking are neglected for the further investigations because they describe transient effects and quasi-steady-state conditions are assumed for the parameter estimation. This decision is consistent with the data preparation described in section 3 where these transient states are explicitly removed.

$\dot{Q}_{inf}$ refers to the heat flow as a result of air infiltration into the chilled space. In general, the air infiltrating the chilled space is both warmer and has a higher absolute humidity than the air in the cabinet. Because of this, the resulting heat flow consists of both the sensitive cooling of the air and the latent dehumidification of the air. It is assumed, that the condensate fully freezes. The solid ice further needs to cool to its final temperature. For open type cabinets this the major heat flow into the display cabinet.

$$\dot{Q}_{inf} = \dot{m}_{inf} \cdot \left[(T_s - T_{final}) \cdot (c_{p,air} + x_s * c_{p,vap}) + (x_s - x_{sat,final}) \cdot (\Delta h_v + \Delta h_m + q_{ice}) \right] \qquad \text{Eq. (4)}$$

Equation (4) describes the state change of moist air infiltrating the chilled space. It changes from store room conditions to a final state in the chilled space. Two options arise for the final state. The first option is to choose the state of the air after the evaporator. This option follows the path of the air from entering the air curtain and then traveling towards the evaporator, where it cools down. The other choice is the temperature of the air in the cabinet, as this is the final temperature the air reaches in the cabinet. For the humidity ration the saturated humidity ratio at the chosen temperature is selected.

The specific heat flow for the cooling of the ice q_{ice} is the result of cooling the ice below the freezing point. The general equation is described in Eq. (5). The temperature of the ice T_{ice} is chosen to be equal to the evaporation temperature of the refrigerant.

$$q_{ice} = \begin{cases} 0 & \forall\, T_{ice} > 273.15K \\ c_{p,ice} \cdot (273.15K - T_{ice}) & \forall\, T_{ice} \leq 273.15K \end{cases} \qquad \text{Eq. (5)}$$

For further investigations two simplifications of Eq.(4) will be considered. First, the contribution of the water vapour to the heat capacity of the air is neglected. This assumes, that the contribution to the heat capacity is relatively small. Second, the cooling of the ice is neglected. The reasoning is the same as for the water vapor.

The infiltration mass flow can vary significantly due to external factors such as customer interactions, night blinds or door openings. Therefore, it is important to consider that the mass flow may fluctuate over time or with the number of door openings. To address this issue, the infiltration mass flow was split into three individual mass flows: one for the opening hours, one for the closing hours and, where applicable, one for the door openings. It was assumed that the infiltration mass flow through the door opening would be proportional to the amount of time the door was open during the hour.

$$\dot{m}_{inf} = R(7{,}21) \cdot \dot{m}_{inf,open} + R(21{,}7) \cdot \dot{m}_{inf,closed} + d_{door} \cdot \dot{m}_{inf,door} \qquad \text{Eq.(6)}$$

In Eq.(6) the rectangular function R represents a value of one in between the specified hours and zero otherwise. The infiltration mass flow for the door opening is weighted by the door opening fraction d_{door} which is a dimensionless value between zero and one. Alternatively, the infiltration mass flow could also be modelled by a Fourier series or similar approaches.

Heat flow as a result of transmission is described according to Eq.(7). The transmissive heat flow not only includes the actual transmissive heat flow, but also includes the radiative heat flow. Given the typically expected temperature variations for both the store and the display cabinet the radiative heat flow can be linearized around the typical temperature difference. This allows for the formulation of an effective transmissive heat flow. This in turn reduces the number of parameters that need be estimated.

$$\dot{Q}_{trans} = UA \cdot (T_s - T_c) = \overline{UA} \cdot (T_s - T_c) + \sigma \cdot \epsilon \cdot A_{transp} \cdot (T_s^4 - T_c^4) \qquad \text{Eq.(7)}$$

The internal load P_{int} is the result of electrical energy dissipated inside the chilled space, such as fans, lighting or anti-sweat heaters. It is assumed that the internal load remains constant over time. As an alternative, it was considered to neglect the internal load from Eq.(3). This acknowledges the possibility that the internal load may not be reliably estimated from the monitoring data.

Various combinations of the aforementioned simplifications were examined. Table 3 provides an overview.

Table 3 Variants of simplifications applied to the correlation

	Var1	Var2	Var3	Var4	Var5	Var6	Var7
Include $c_{p,vap}$	x						
Include q_{ice}	x	x					
Use evaporator air outlet temperature	x	x	x		x		
Use internal load	x	x	x	x			
Use door openings	x	x	x	x	x	x	

5 RESULTS

Based on the modelling in section 4 a multiple linear regression problem arises. Eq.(8) presents the regression problem in its most general form. It shows the model outcome Y as a function of the parameters $\dot{m}_{inf,open}$, $\dot{m}_{inf,closed}$, $\dot{m}_{inf,door}$, UA and P_{int}, as well as the features x_1 to x_4, that result from section 4. Dependent on the chosen variant from Table 3 the calculation of the features and the number of parameters change. As information on door openings is only available for the two rooms (LT1, MT1 & MT2) the parameter $\dot{m}_{inf,door}$ is only used for these evaporators.

$$Y = \dot{m}_{inf,open} \cdot x_1 + \dot{m}_{inf,closed} \cdot x_2 + \dot{m}_{inf,door} \cdot x_3 + UA \cdot x_4 + P_{int} \qquad \text{Eq.(8)}$$

As the parameters have a physical meaning it is important to avoid estimating parameters with negative values, as they are not plausible. Therefore, in this case, a non-negative linear regression code from the Python package *scikit-learn* was used. The regression code uses the method described in Bro and Jong, 1997.

Before performing the identification, the correlation of the features is investigated. After that the results are analysed with regard to the influences of the model variant and the temperature correction in the store.

5.1 Correlation analysis

Figure 6 shows the resulting correlation matrices for the individual cabinets. The rows and columns are named by the parameter that corresponds to the respective feature. Depending on the cabinet, the number of observations varies between approximately 14.000 and 18.000 individual observations. Because the features for the infiltration mass flow are separated by non-overlapping time intervals the corresponding features are ideally separated. The UA value is highly correlated with both open and closed infiltration mass flow as the equations for these features are very similar. As a result, the precision of the estimated parameters may be weakened.

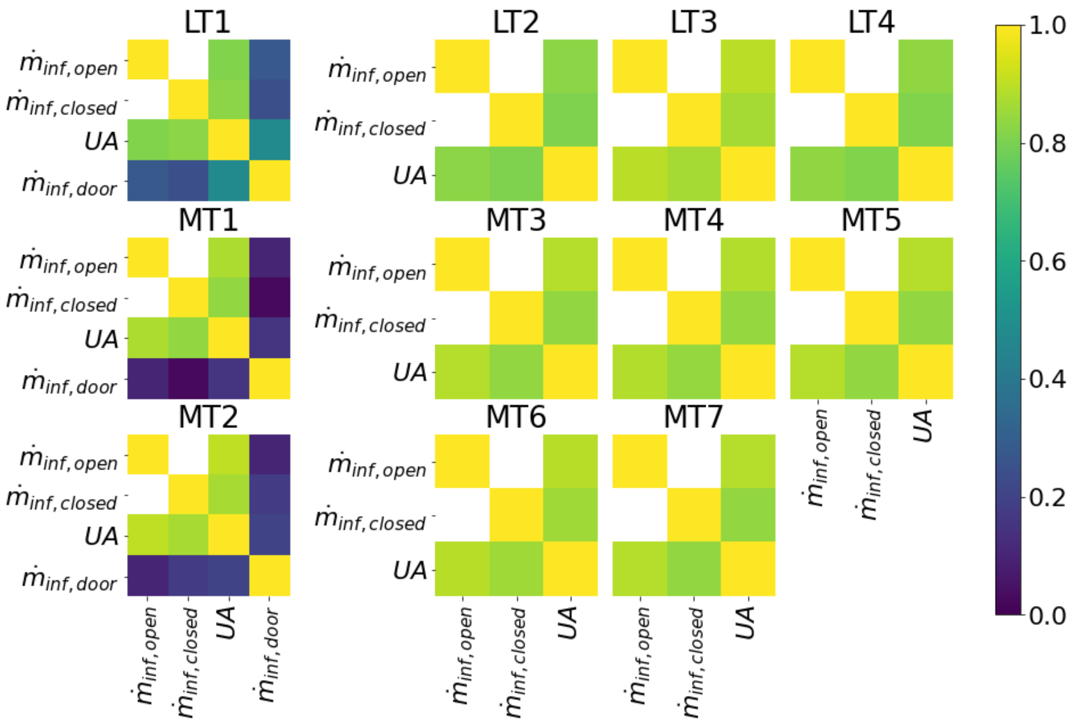

Figure 6 Correlation matrix of the features, named by the corresponding parameter.

5.2 Regression results

First, the model variants are compared in terms of their ability to represent the monitoring data. This was done by using the variants of the refrigeration load from Table 3, in addition to a dummy regressor. The dummy regressor represents the mean value and serves as a baseline for the model's performance. Figure 7 shows the MAE normalized by the respective mean value of the refrigeration load for all investigated model variants and display cabinets. The dummy regressor performs significantly worse for open type cabinet, but reasonably well on closed cabinets. This is because open type cabinets are significantly influenced by infiltration and show a strong correlation of the refrigeration load with the store room conditions, while closed cabinets exhibit a more constant refrigeration load. This means, that for closed type cabinets it might be acceptable to use the mean refrigeration load, instead of a mathematical model.

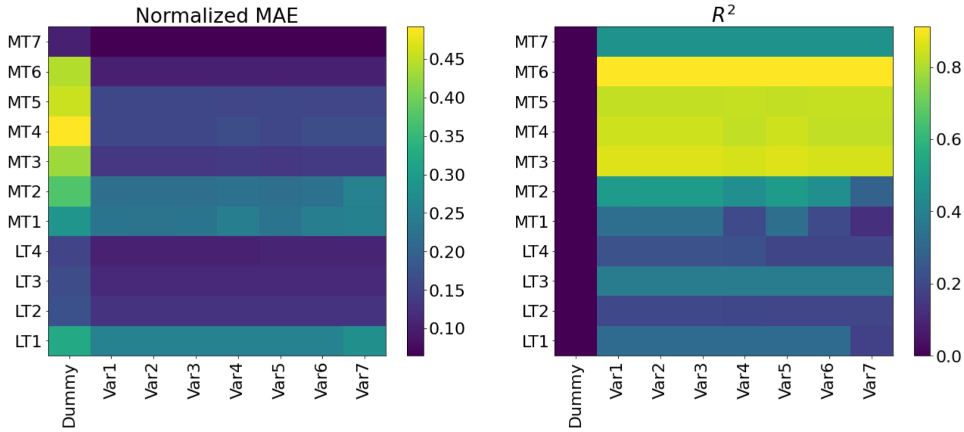

Figure 7 Normalized mean average error and coefficient of determination for the different model variants.

Similar prediction performance is observed for all variants. Neglecting the heat capacities of water vapour and ice does not significantly influence the model performance. A slight decrease in model performance is observed when the cabinet air temperature is used in the infiltration term. This decrease is relatively minor and only affects some of the cabinets. Neglecting door opening information has a slightly more significant influence on the model performance. It should be noted that the influence is only visible for cabinets where information on door openings is available.

As mentioned in section 2, the temperature in the store room appears to be implausible. Therefore, the store room temperature was adjusted from an offset of zero Kelvin to minus seven Kelvin. It was observed that this adjustment did not significantly affect the prediction performance, but it did influence the absolute value of the estimated parameters. Figure 8 shows the estimated coefficients for the model "Var4" in relation to the correction of the store room temperature. For most coefficients, their absolute value increases with the temperature correction. The increase is approximately ten percent per Kelvin correction. In a few instances a decrease or the existence of a maximum in the coefficients can be observed.

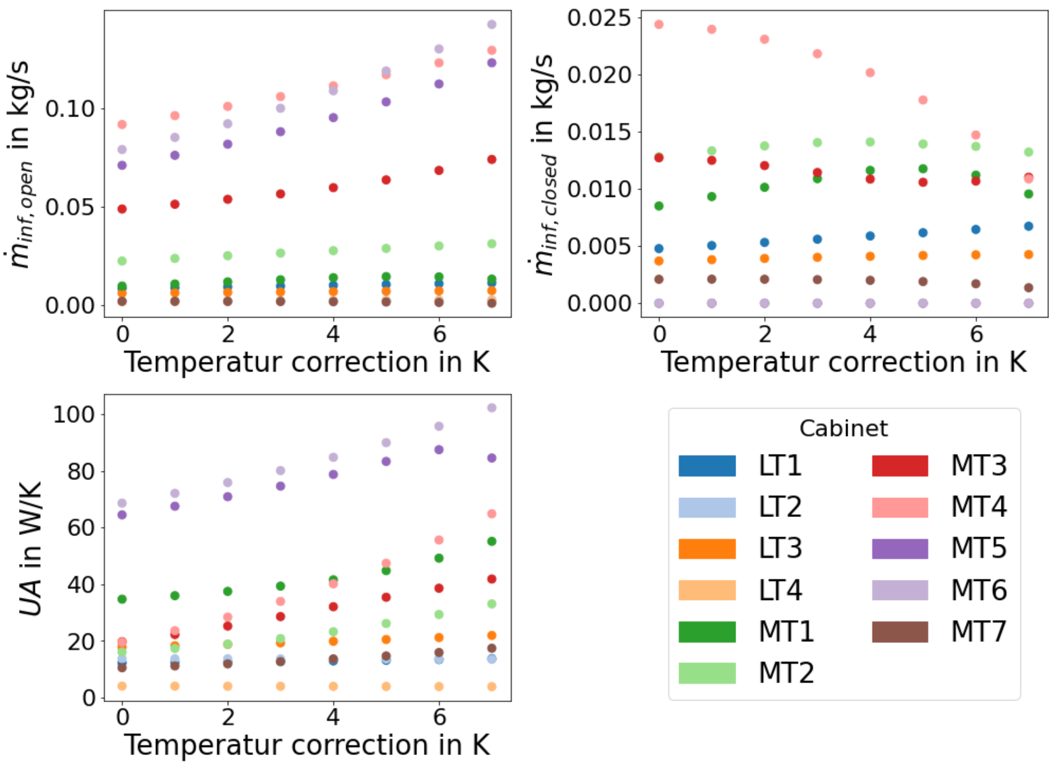

Figure 8 Estimated parameters in relation to the correction of the store room temperature.

Assuming an offset of approximately minus six Kelvin plus/minus one Kelvin will bring the temperature into a reasonable range, an uncertainty of the parameter of around ten percent can be expected due to the temperature correction. It is unclear how much error would exist if no temperature correction was necessary, especially around open display cabinets where the temperature is not completely homogeneous.

In addition to the temperature correction, the choice of model variant may also affect the estimated parameter. Figure 9 displays the parameters for different model variants at a temperature correction of minus six Kelvin. It is noticeable that two groups of similar parameters emerge across the model variants. These groups are distinguished by whether they use the evaporator air outlet temperature or the temperature in the display cabinet as the final state for the infiltration. In all other cases the influence of the model variant appears to be negligible.

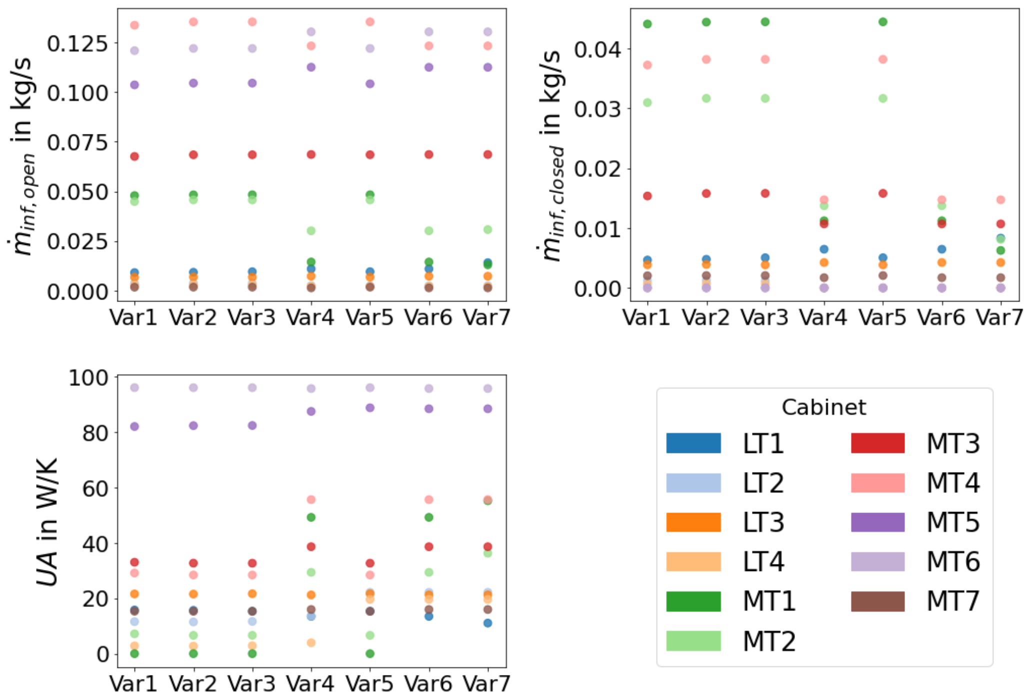

Figure 9 Estimated parameter of the model, based on the chosen variant of the model.

The influence of the model variant on the infiltration mass flow rate during closing hours and on the UA value is most notable. This effect is apparent on the evaporators MT1, MT2, MT4, and to a lesser extent on MT3. Using the temperature in the display cabinet results in a lower infiltration mass flow during closing hours and a higher estimated UA value. Since MT1 and MT2 are cold rooms, it can be assumed that the infiltration mass flow is very low during closing hours. It seems as if using the display cabinet temperature is the better choice as the UA values are very low when using the evaporator outlet temperature. However, it is important to note that this assertion is of low confidence due to the limited data available.

6 CONCLUSIONS

Four years of monitoring data from a Danish supermarket was used to identify refrigeration load parameter. Although sporadic missing data was quite common in the monitoring data, it was rectified by interpolating over small gaps. The mass flow rate estimated by the expansion valves was validated against mass flow meter data.

Several variants of the model equations were evaluated and it was found that neglecting lesser terms in the model equation has no significant impact on the estimated parameter or the prediction performance, as the high noise of real-world data makes distinguishing these effects nearly impossible. When available information on door openings should be included. The final state chosen for the infiltrating air has a significantly impacts the estimated parameter.

The temperature readings in the store room appear implausible. This limitation has significant implications for the estimated parameters, leading to large uncertainty in the parameter. Each Kelvin shift in store room temperature result in approximately ten percent change in the estimated parameter. The prediction performance of the models remains unaffected.

Overall satisfactory regression performance was achieved. Given that real world refrigeration load data is often affected by a number of uncontrolled influences, such as customers, the systematic influences could be identified to a satisfactory level.

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NOMENCLATURE

MT	Medium Temperature	ϑ	Celsius Temperature (°C)
LT	Low Temperature	T	Temperature (K)
$\dot{Q}$	Heat Flow Rate (W)	P	Electrical Power (W)
$\dot{m}$	Mass Flow Rate (kg/s)	c_p	Specific Heat Capacity (J/kg*K)
x	Humidity Ratio (kg/kg)	q	Specific Energy (kJ/kg)
Δh_v	Specific Heat of Vaporisation (J/kg)	Δh_m	Specific Heat of Melting (J/kg)
R	Rectangular Function	d	Door opening fraction
UA	Overall Heat Transfer Coefficient (W/K)	A	Area (m²)
σ	Stefan-Boltzmann Constant	ϵ	Emissivity
MAE	Mean Absolute Error	R^2	Coefficient of Determination
Y	Model Prediction	x	Feature for Regression
k	Correction factor		

Subscripts

s	Store	*amb*	Ambient
ref	Refrigeration	*c*	Cabinet
0	Refrigeration	*c,-1h*	Cabinet, shifted by one hour
inf	Infiltration	*trans*	Transmission
rad	Radiative	*int*	Internal
final	Final state of the infiltrating air	*sat*	Saturated
ice	Ice	*transp*	Transparent
open	Opening Hours	*closed*	Closing Hours
door	Through the open door	ΔT	Temperature difference
00	Beginning of the hour	*59*	End of the hour
exv,in	Expansion valve inlet	*evap,out*	Evaporator outlet

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