THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Supermarket refrigeration systems for demand response in smart grids

-An in-depth study to evaluate and enable utilisation of the thermal inertia of supermarket refrigeration systems for grid balancing purposes

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Cover:
[Conceptual illustration showing the control system for a refrigeration system in a supermarket.]

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Tack så mycket!

Abstract

With an increasing share of intermittent renewable energy sources in the electrical grid, the need for adapting the demand to the available supply of electricity becomes increasingly important. Within this thesis, the demand response capacity by supermarket refrigeration systems are investigated and methods for enabling it is developed.

Article 1 explores the temperature control system in depth, concluding that the majority (80.5%) of return air temperature sensors in RDCs were located in an area where a thermal gradient interfere with the perceived temperature, i.e. the temperature readings falsely indicated a higher return air temperature than the actual mean temperature of the passing air. The issue is analysed in detail and mitigated through a strategic re-positioning of the affected temperature sensors.

Article 2 presents a computationally efficient yet accurate dynamic hygro-thermal model of an RDC with the capability to include effects of door openings. Thus, the model contributes to enabling demand response by supermarkets as it could provide the forecasts of the necessary temperature constraints, limiting the duration for which the supermarket could attend to a demand response request.

Article 3 presents a field study where wireless gyroscopes were attached to the RDC doors in an operational supermarket to record the speed, duration, angle and frequency that the doors are operated at. Novel insights in significant differences in behaviour between medium and low temperature RDCs could be concluded.

Article 4 presents a method for the thermal characterisation of RDCs based on and adaption of the Co-Heating methodology. The method evaluates infiltration rates within the 10% limit compared with the condensate collection method. In addition, data on thermal performance, such as the heat transfer coefficient for the envelope and its thermal inertia, can be measured in a systematic way.

The thesis together with the four appended articles presents a suite for the evaluation of temperature development in refrigerated display cabinets in operational supermarkets, which represents the main constrain for the demand response capacity.

Contents

Acknowledgements **i**

Abstract **iii**

Nomeclature **ix**

1 Introduction **1**
1.1 Background 1
1.2 Problem statement/Thesis objective 3
1.2.1 Limitations 3
1.3 PhD-Contributions 4
1.3.1 List of included publications 4
1.3.2 Patents 5
1.4 Thesis organisation 5

2 Bases for demand response by supermarkets **7**
2.1 Thermal response and limits of RDCs 8
2.2 Control and levels/scales 9
2.3 Temperatures in operational RDCs 9
2.4 Thermal impact and performance of RDCs in a supermarket 11

3 Theoretical framework **13**
3.1 Primary and secondary thermal loads on RDCs – literature overview 13
3.2 Models for the evaluation of supermarket energy demand 16
3.2.1 Black-box models 16
3.2.2 Grey-box model 17
3.2.3 Physics-based models 19
3.2.4 Modelling refrigerated display cabinets in supermarket conditions 21
3.3 Conclusion 23

4 Overall research methodology and results **25**
4.1 Article 1 - Exploratory investigation of return air temperature sensor measurement errors in refrigerated display cabinets 27

4.2 Article 2 - Hygro-Thermal model for real-time estimation of demand response flexibility of closed refrigerated display cabinets in smart grids . . . 30
4.3 Article 3 - Analysis of door openings of refrigerated display cabinets in an operational supermarket . . . 32
4.4 Article 4 - Co-Heating method for thermal performance evaluation of closed refrigerated display cabinets . . . 34

5 Discussion **39**

6 Conclusions **43**
Future work . . . 44

Bibliography **45**

Appendix **51**
Article 1 . . . 52
Article 2 . . . 75
Article 3 . . . 102
Article 4 . . . 111

List of Figures

2.1 Temperature development during two separate demand response scenarios. Blue illustrates the temperature decrease due to forced heat extraction to absorb electrical energy. Red illustrates a load shedding scenario where the refrigerated display cabinet (RDC) postpone its heat extraction demand until the upper temperature limit is reached. The lower bars illustrate the opening of the expansion valve, i.e. active cooling, for the respective scenario. 8

2.2 Conceptual drawing depicting the control systems and the temperature sensors within the RDC. The local control adjusts the temperature of the RDC, forcing the supervisory control for the compressors to adjust the heat extraction rate and thereby the electrical energy demand. 10

2.3 Conceptual system adapted from [Månsson, 2016], illustrating how a centralised and de-centralised RDC connects to the indoors of the supermarket. 12

3.1 Overview of the scope and limitations of a selection of the reviewed works on energy demand in supermarkets for demand response evaluation. Dotted fields represent the covered areas of the respective study. Red fields indicate areas that were inadequately depicted. . . 14

4.1 Overview illustrating scale of interest and methods used in the PhD-Project. Green rectangles, A1-A4, represent the included articles. Yellow shapes represent the excluded earlier studies presented in [Månsson and Ostermeyer, 2013, Månsson, 2016, Månsson, 2019]. . 26

4.2 The return and discharge air temperature of two neighbouring RDCs, namely RDC2 and 3, where an unexpected difference (ΔT) in temperature levels can be seen. Even outside of the stores' opening hours when there are no customer interactions, the temperatures differ between the RDCs. 28

4.3 The discharge air passing the glass door is heated by heat gains through the door. The thermal gradient created thereby continues along the entire path of the discharge airflow, through the return air grille towards the front of the heat exchanger further back. This results in a warmer air layer close to the floor of the RDC in the area of the RA temperature sensor. 29
4.4 Temperature data for one month before and after the relocation of the return air temperature sensor in a supermarket outside of Hamburg. The relocation occurred on day 33. *Notice:* RDC_4 *is used for meat and therefore has a lower temperature.* 29
4.5 Illustrating the domains and main temperatures evaluated withing the model. (0,1,4) Discharge air (2)Return air (3) Return air after fan *Left*: The RDC is depicted with arrows, indicating the flow direction and order. *Right*: Conceptual line graph showing the temperature development for the circulating air within the RDC. . 31
4.6 Plot showing the temperature development for T_{DARA} for the RDC exposed to Scenario 1-4. Here it can be seen that it takes $159-217$ seconds for the RDC to heat up to $8°C$, or $59-74$ seconds to cool down to $4°C$. The dash-dotted line shows the temperature development including the temporal effects of door openings. 32
4.7 Photo from the supermarket showing doors 3-6, from right to left. The SensorTags (*Texas Instruments, Dallas, USA*) can be seen in the upper corner opposite to the hinges of each door. Also, the Bluetooth gateway (*BeagleBone, Michigan,USA*) can be seen in the top centre of the photo 33
4.8 Histogram showing the total opening duration for MT and LT RDCs presented separately. The black vertical lines mark the median values as reference. Both histograms show similar distribution and values. 34
4.9 The mean door opening angles of MT and LT RDCs showing a significant difference between the opening angle distribution and the mean between the MT and LT RDCs. 34
4.10 Box-plot showing the distribution of door openings per hour for MT and LT RDCs during both weekdays and Saturday. Significant differences in magnitude between MT and LT RDCs can be noticed as well as the shifted shape of the profiles between weekdays and Saturday. Additionally, it can be seen that there is a large spread in the number of openings per hour between the different RDC within the same category (MT or LT). 35
4.11 Illustration of the sensors and heater placement in the RDC for the Co-Heating experiments. Sensors 5 and 6 are located in the ambient air in front of and besides the RDC, respectively. Sensors 4 and 1 failed and were, therefore, excluded. *Left:* Section drawing. *Right:* Front view. 36

Nomeclature

Acronyms

Amb	Ambient
ANN	Artificial neural network
CFD	Computational fluid dynamics
CHP	Combined heat and power
DA	Discharge air
DAG	Discharge air grille
DR	Demand response
Env	Envelope
EU	European union
HVAC	Heating, ventilation, and air conditioning
In	Indoors
Inf	Infiltration
LT	Low temperature
MPC	Model predictive control
MT	Medium temperature
RA	Return air
RAG	Return air grille
RDC	Refrigerated display cabinet

Notations

ΔT	Temperature difference $[°C]$
C	Heat capacity $[J/K]$
i	Count $[-]$
K	Heat transfer coefficient $[W/K]$
m	Mass $[kg]$
$\dot{m}$	Mass flow rate $[kg/s]$
$\dot{Q}$	Power / Rate of heat flow $[W]$
S_i	Scenario i
T	Temperature $[°C]$

Chapter 1

Introduction

1.1 Background

All the European Union (EU) countries are required to support renewable energy generation, such as solar, wind and biomass as part of the green energy targets. Following the Revised Energy Directives the EU should have reached an overall share of 32% of renewable energy by 2030. As this aim refers to the overall EU average, some member states will be performing significantly better and other worse. The national target ranges from 10% in Malta to 49% in Sweden [Schöpe, 2008]. Consequently, such an increased share of intermittent, uncontrollable and/or slower responding renewable energy sources does create issues for the utility grid to balance the supply and demand side.

In a traditional electrical grid, the supply is almost exclusively adapted to the demand by adjusting the electrical energy generation. The variations are often balanced by the use of smaller gas turbines, hydroelectric, etc. that are able to adjust their power outtake rapidly. Gas turbines most commonly are using fossil fuel, and the hydroelectric capacity is geographically limited to regions with a satisfying topology, which consequently limits the applicability of such solutions.

Therefore, in a national, continental or global scenario where the share of renewable energy sources is increased and the use of fossil fuels is to be minimised, the problem of balancing the energy demand and supply will become significantly more severe. Hence, it is necessary to implement energy storage along with demand-side management to adapt the demand to the available supply [Farhangi, 2010]. For different markets, the needed capacity and requirements for providers of balancing services may vary.

In general, for daily peak avoidance, approximately 2 hours of load shifting are needed, and for shifting of larger day/night variations, a load shifting capacity of 12 hours is needed [Hovgaard et al., 2012]. For the initial phase of Firm Frequency Response, a fast responding load shifting capacity for a duration of 30 seconds is required, while for the second phase, up to 30 minutes of load shifting is required [Saleh et al., 2018].

Flexible energy users that could be utilised for demand response typically incorporate processes with large inertia. Specific industries such as metal smelters are one example of individual businesses that could provide significant local demand response capacity for the electrical grid. The inclusion of smaller home appliances such as dishwashers, refrigerators etc. is attractive as the accumulated capacity on national level becomes significant. The large variation in technical interface and function for the vast number of variations of appliances does, however, make the inclusion challenging. Additionally, the incentive for the end-user may be insignificant as the provided capacity is marginal for each individual. Thus making it further challenging to develop an attractive business-case.

In the search for alternative and commonly available larger actors, supermarkets, and more specifically their refrigeration systems, were identified as a potential and accessible actor for demand response. Their potential as storage facilities lay within the thermal inertia found in the refrigerated display cabinets (RDCs) and their content.

To illustrate the potential capacity on a national level, in Germany alone, there were about 38 000 supermarkets with an accumulated energy demand of 10 TWh [Funder, 2015], translating to an average power demand of 1.14 GW nationally or 30 kW per supermarket. Whereof approximately, 30-50% of this electrical energy originates from the refrigeration system, i.e. the potential capacity, on a national level can be estimated to represent approximately 1-1.5% [Månsson, 2019] of the overall electrical energy demand in countries such as Sweden, Denmark and Germany.

By engaging in a demand response scheme, new financial incentives such as decreased cost of energy or potentially selling the response capacity to the grid appear. The corresponding cost reductions would be influential for the profitability of supermarkets as their operating margins are generally low [Spyrou et al., 2014]. Hence, although the cost of energy only represents a very limited share of the turnover, there is the potential to increase profitability by 15% if the energy demand is reduced by 50% [Arias, 2005]. Or as stated in [Dixon-O'Mara and Ryan, 2017], a 20% cut in energy costs represent the same bottom-line benefit as 5% sales increase.

Based on the above, there is a significant demand response capacity available in supermarkets that could potentially benefit the grid for demand-side management, if adequate incentives are introduced. However, there are also technical barriers for the implementation of such schemes, as introduced and partly mitigated in this thesis.

1.2 Problem statement/Thesis objective

In an electrical grid with a large share of intermittent or uncontrollable energy sources, there is a need for intermediate energy storage, or demand-side management to balance the energy supply and demand. For this purpose, the refrigeration systems of supermarkets have been identified as a potential resource for demand response in such a setting.

The demand response capacity is yet to be evaluated in further detail, and strategies for utilising the full capacity must be developed. Independent of the distribution or concept of refrigeration within the supermarket, the temperature of the RDCs dictates the actual capacity, which must be included as a constraint in the larger optimisation problem to balance the supply and demand by the utility grid. To allow this inclusion, a detailed understanding of the thermal loads and adequate computationally effective models for RDC must be present. However, in the reviewed body of literature, there exist no such models, nor methodologies for defining the thermal performance necessary for demand response evaluation.

Therefore, the aim of this thesis is to further investigate and enable the demand response capacity of supermarket refrigeration systems by presenting a comprehensive methodology defining the thermal loads, thermal performance and temperature development in RDCs.

1.2.1 Limitations

This thesis, and the appended articles, are limited to evaluate the demand response capacity based on sensible and latent heat transfer, and temperatures in the RDCs. Food safety considerations are limited to the upper and lower temperature levels, but no further consideration is given to other factors potentially influencing shelf-life and bacterial growth.

The thesis focus on the temperature constraints, limiting the buffering capacity of supermarket refrigeration system. Thus, the topic of demand response in a smart grid setting is only briefly introduced to provide context.

Within this thesis, the refrigeration system, refers to a vapour-compression refrigeration system with a circulating refrigerant that absorbs and removes heat from the RDCs and subsequently ejects that heat elsewhere.

1.3 PhD-Contributions

1.3.1 List of included publications

Article 1 - Exploratory investigation of return air temperature sensor measurement errors in refrigerated display cabinets
Tommie Månsson, Angela Sasic Kalagasidis, York Ostermeyer
Journal: Energy Efficiency

Article 2 - Hygro-Thermal model for real-time estimation of demand response flexibility of closed refrigerated display cabinets in smart grids
Tommie Månsson, Angela Sasic Kalagasidis, York Ostermeyer
Journal: Applied Energy (Submitted, Under review)

Article 3 - Analysis of door openings of refrigerated display cabinets in an operational supermarket
Tommie Månsson, Adones Rukundo, Magnus Almgren, Philippas Tsigas, Christian Marx, York Ostermeyer
Journal: Journal of Building Engineering

Article 4 - Co-Heating method for thermal performance evaluation of closed refrigerated display cabinets
Tommie Månsson, Angela Sasic Kalagasidis, York Ostermeyer
Journal: International Journal of Refrigeration

Not included

Energy in Supermarkets -An overview on the energy flows and refrigeration controls
Tommie Månsson
Thesis: For Degree of Licentiate of Engineering 2016, Sweden

The Potential of thermal energy storage in food cooling processes in retail markets for grid balancing
Tommie Månsson, York Ostermeyer
Conference: NSB2014, Sweden

Potential of supermarket refrigeration systems for grid balancing by demand response
Tommie Månsson, York Ostermeyer
Conference: Smart Greens 2019, Greece

1.3.2 Patents

Sensor-Holder *DE 10 2018 002 949 Al 2019.10.17*
Inventor: Tommie Månsson, York Ostermeyer
Patent for Sensor-Holder developed to mitigate the issues discovered while performing the spatial temperature analysis of RDCs as presented in Article 1 - *Exploratory investigation of return air temperature sensor measurement errors in refrigerated display cabinets.*

1.4 Thesis organisation

Chapter 1 - *Introduction*, presents the background of the investigated problem of demand response by supermarkets with a summary of the PhD-project contributions.

Chapter 2 - *Bases for demand response by supermarkets* is intended to give a more detailed background and common understanding of the processes involved in a supermarket that contributes to demand response.

Chapter 3 - *Theoretical Framework*, gives an overview of the current body of knowledge, specifically the limitations in the modelling of supermarket energy systems and integration of RDCs.

Chapter 4 - *Overall research methodology and results* briefly give an overview of the methodologies and research approach within this thesis, with a brief summary for each included and appended study.

Chapter 5 - *Discussion*, discusses the overall contributions and limitations of the this thesis together with some more holistic aspects of the utilisation of supermarkets as a resource for demand response purposes.

Chapter 6 - *Conclusion*, concludes this thesis by summing the main findings and its combined contribution.

Chapter 2

Bases for demand response by supermarkets

A generic demand response operation of a supermarket refrigeration system can be composed of the following operational steps:

0. **Demand Response - *Request***
1. **Demand Response - *Action***
2. **Post Demand Response**

Additionally, proactive (*optional*) actions such as:

Pre-cooling/Pre-heating

can be included to optimise the capacity if the supermarket was noticed prior to the demand response request. The refrigeration system could then adapt the refrigeration strategy by either pre-cooling the RDCs to increase the time it takes to re-heat to the upper temperature limit or "pre- heat" the RDCs by keeping the temperatures closer to the upper limit, which would extend the duration for which the refrigeration system can absorb energy by extracting heat.

At *Step 0 - Demand Response Request*. There are two ways that the grid can communicate to request a demand response from the supermarket: either through a so-called direct request to decrease or increase the load for a defined duration, or through an indirect signal, which might be a change in the tariff or other measures to incentives the wished behaviour.

The supermarket response action (*Step 1*) to this signal can then vary from an increase in electrical demand to a level corresponding to the rated power of the compressors or a complete reduction of electrical power demand to almost *nil*. For the latter, [Postnikov et al., 2019], suggests a proportional reduction of compressor power rather than a complete shut-down to avoid the risk of the refrigerant condensing within the system, causing damage to compressors due to hammering. After the demand response action period (*Step 2 - Post Demand*

Response) the refrigeration system must transition into normal operations where the temperature levels of the RDCs are harmonised, and compressors initialised adequately to avoid self-induced peak loads, as described in [Saleh et al., 2018, Albayati et al., 2020, Postnikov et al., 2019].

2.1 Thermal response and limits of RDCs

In a scenario where a supermarket would absorb energy by increasing its electrical power demand by the compressors, the heat extraction rate by the RDCs must increase too, resulting in a decreasing temperature of the stored goods. In contrary, if the supermarket is requested to decrease its electrical power demand, the heat extraction decreases and, consequently, the temperature of the RDCs increase, as illustrated in Figure 2.1, where the two scenarios are indicated by red (Compressor OFF) and blue (Compressor ON).

In case the supermarket was given a notice prior to the demand response request, it could adapt the refrigeration strategy by either *pre-cool* the RDCs, or "*pre-heating*" them by keeping them at a temperature closer to the upper limit to allow a longer duration of cooling for the demand response.

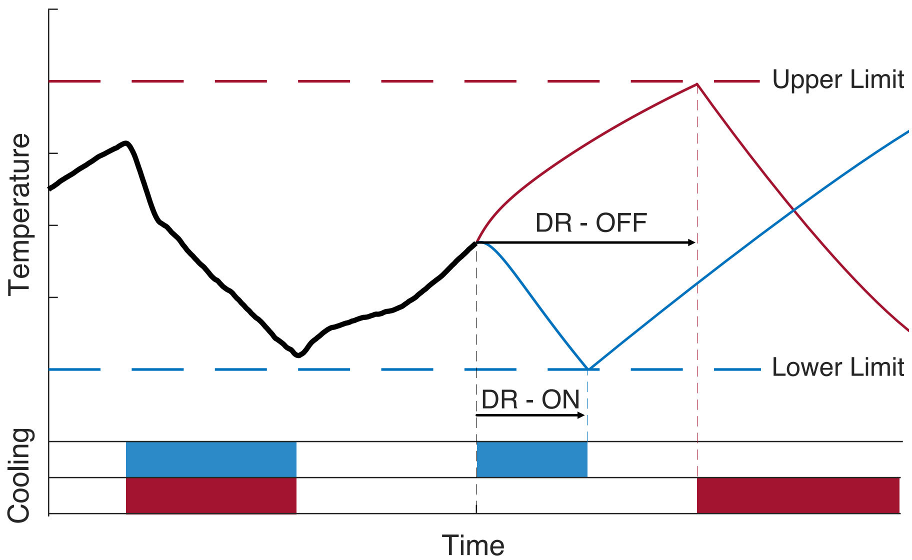

Figure 2.1: Temperature development during two separate demand response scenarios. Blue illustrates the temperature decrease due to forced heat extraction to absorb electrical energy. Red illustrates a load shedding scenario where the refrigerated display cabinet (RDC) postpone its heat extraction demand until the upper temperature limit is reached. The lower bars illustrate the opening of the expansion valve, i.e. active cooling, for the respective scenario.

The duration for which the supermarket can follow the demand request ultimately depends on the temperature development of the RDCs [Saleh et al., 2018], which is a complex issue. The thermal loads acting on the RDCs vary between individual RDCs due to both their thermal performance, and variations in ambient conditions and customer interactions [Månsson, 2016].

Second, the complexity of the issue arises from the diverse factors influencing the thermal loads and the available thermal mass in the refrigeration system, which together defines the temperature change rate of the RDC. As an example, customers extracting food or staff restocking would cause a change in the available mass, and increase the thermal loads due to infiltration, i.e. such a scenario would significantly differ from the closed hours of the store where no interactions occur.

2.2 Control and levels/scales

Within the supermarket, the refrigeration system can be visualised as depicted in Figure 2.2. Here it can be seen that the two temperature reading from the discharge air and return air are gathered by the local control system to monitor and adjust the temperature of the RDC. Based on these readings, local control requests cooling from the supervisory control system by opening the valve to circulate the refrigerant through the evaporator of the RDC. To balance the heat extraction rate of the RDCs connected to the refrigeration system, the supervisory control then adjusts the compressor work and thereby the needed electrical power.

From the system hierarchy, it can be seen that the discharge and return air sensors dictate the electrical power demand. Thus, the temperature readings from these, along with the accepted temperature range determine, the heat extraction demand of the supermarket, and thereby the electrical energy demand for refrigeration. Hence, the accuracy and reliability of the temperature readings are essential.

2.3 Temperatures in operational RDCs

RDCs are divided into medium temperature (MT) and low temperature (LT). Generally, closed LT RDCs are better insulated, and the doors typically seal the cabinet better in comparison to MT RDCs, which commonly has a less insulated envelope and a door design with gaps between the door blades and frame, allowing ambient indoor air to infiltrate. The higher infiltration rate and lower insulating capacity result in higher thermal loads, both sensible and latent. Hence, the MT RDCs would respond faster to a change in ambient temperature.

When utilising supermarkets for demand response purposes, this transient temperature development along with the temperature limits will define the duration an RDC can participate, and thereby ultimately dictates the capacity of the supermarket.

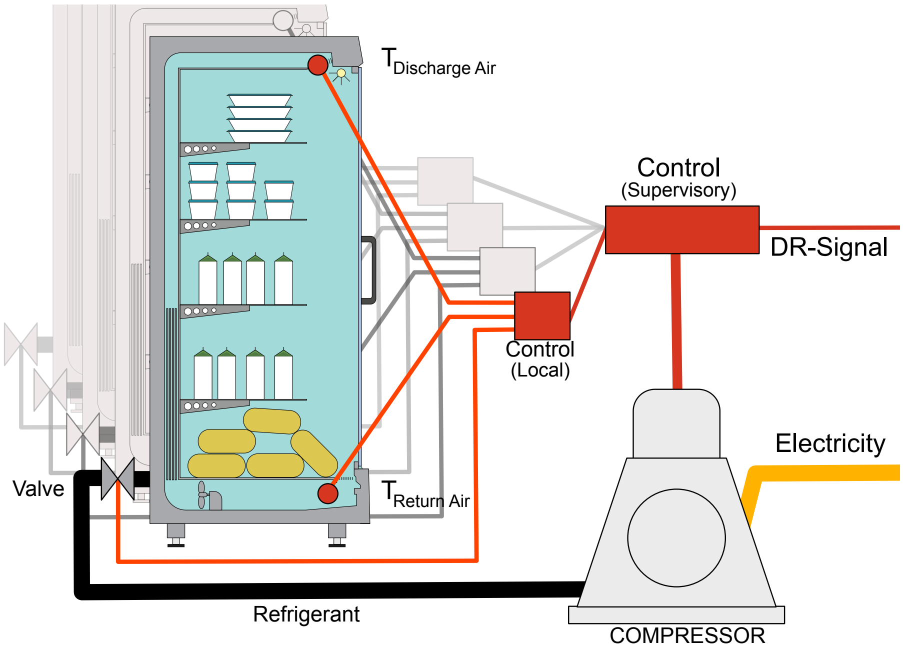

Figure 2.2: Conceptual drawing depicting the control systems and the temperature sensors within the RDC. The local control adjusts the temperature of the RDC, forcing the supervisory control for the compressors to adjust the heat extraction rate and thereby the electrical energy demand.

For MT RDCs the upper temperature limit ranges from $2-8°C$, and the sub-cooling is limited by the freezing point of water ($0°C$), which, if passed, will cause undesirable frost damage to occur on the refrigerated goods. For animal-based products, the lower part of the range ($2-4°C$) typically represents the upper limit, whereas products such as produce, beverages, etc. have less strict manufacturer recommendations of temperatures to ensure shelf-life and product quality, which are often in the upper part of the range of, $6-8°C$, giving them a bit more flexibility.

For LT RDCs, the lower limit for pre-cooling is significantly more flexible as the products are already solidified. However, the upper limit is restricted commonly to $-18°C$ for food preservation and food safety purposes, with the exception for ice cream.

Based on the above, it can be concluded that MT RDCs pose a more considerable challenge to include in demand response than LT RDCs. The MT RDCs do, however, represent the majority ($> 70\%$) of the electrical energy demand for refrigeration [Hirsch et al., 2015]. Thus, the inclusion of these has a significant impact on the aggregated capacity for demand response.

2.4 Thermal impact and performance of RDCs in a supermarket

Concept and distribution of the refrigeration system to which RDCs are connected to are decisive for the thermal impact of the RDCs on the indoors of a supermarket. At large, this can be categorised as centralised and de-centralised RDCs, as depicted in Figure 2.3. For centralised systems, the warm side of the refrigeration system, i.e. the compressors and condensers are located outside the supermarket sales area. Hence, since the RDCs operate at lower temperatures than the ambient temperature in the supermarket, they act as heat sinks for the indoors. However, for de-centralised RDCs the complete refrigeration unit is integrated in RDCs. Thus, the de-centralised refrigerated RDCs act as heat sources as it rejects the heat from the condenser and compressor to the indoors. There exist several technologies for refrigeration, as presented in a review by [Tassou et al., 2010].

Independently of how the refrigeration is generated or distributed to RDCs, thermal loads for the RDCs consist of internal and external sources. For doored RDCs, the internal thermal loads originate from lights, anti-sweat heaters, electrical defrost systems and fan motors. Together, internal thermal loads represent 7-35% of the overall thermal loads for the RDCs. Infiltration of indoor air and heat conduction through the envelope constitute external loads, each contributing about 23-50.6% and 13-70% respectively [Faramarzi et al., 2002, Orlandi et al., 2013]. External heat loads by radiation was found to be only 1.3% [Faramarzi et al., 2002], making it the least influential contribution.

The large variations in the presented numbers are mainly due to differences in operational conditions within the studies. For example, in [Orlandi et al., 2013], during night-time, the doors are closed, and the lights are turned off, resulting in a significant reduction of internal loads and infiltration. Thus, the thermal loads by conduction through the envelope then represent a larger share (70%) of the overall thermal load.

These day- and night-time variations direct the attention to the dynamics of the thermal loads. The thermal load caused by conduction through the envelope can be readily described because they are sensible loads with small temporal variations as the temperature differences between the RDCs and the ambient are stable. In contrary, the infiltration is a highly non-linear and stochastic thermal load, which depends on customer behaviour and includes both sensible and latent heat.

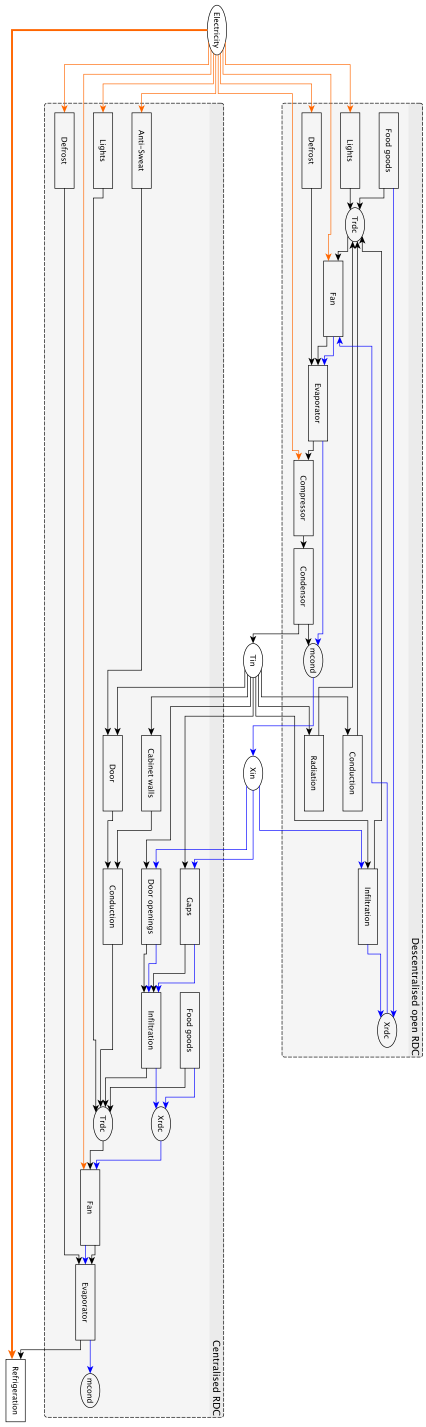

Figure 2.3: Conceptual system adapted from [Månsson, 2016], illustrating how a centralised and de-centralised RDC connects to the indoors of the supermarket.

Chapter 3

Theoretical framework

The modelling of demand response of supermarkets is an emerging research field, driven by research on smart grids. At present, possibilities and challenges with different modelling approaches are described in a limited number of publications that can be roughly grouped into top-down and bottom-up models. Differences between these two approaches refer to the differences in spatial and time scales used to describe the processes. The focus of energy producers and distributors is typically on grid levels, where end-users are considered as simplified energy sinks to ensure a sufficiently low computational cost of the models. This approach is considered in the thesis as top-down, to indicate descending spatial scales of interest. For supermarket companies, the focus is rather on the food safety and energy demand of individual processes, which is commonly approached bottom-up, by ascending spatial scales of interest.

This chapter gives a review of available models of supermarkets and their refrigeration systems, from both the top-down and bottom-up approaches, which have been found relevant to the current work.

3.1 Primary and secondary thermal loads on RDCs – literature overview

From a top-down perspective, starting from the electrical grid, there is a need to predict the electrical power demand and available buffering capacity of the actors participating in a demand response scheme [Atzeni et al., 2013]. Thus, for a supermarket the electrical power demand and the individual temperatures of the RDCs must be known and predicted.

In a smart-grid setting, the optimisation problem to lower the environmental impact of energy generation at the lowest cost can be approached through so-called model predictive control (MPC), where the demand of flexible users is forecasted and optimised to the available electrical power supply.

Typically, as in the case of supermarkets participating in a demand response scheme, the models implemented in MPC must be capable of predicting the electrical power demand within a finite time horizon. The precision and computational effort of the prediction models depends on the resolution of details needed for the supermarket and the modelling approach, as discussed further below.

When approaching the body of literature on models for demand response in supermarkets, it was found that the majority of the presented models are data-driven and partially structured based on the physical systems with a top-down approach. The scale of interest in the reviewed studies stretches from the electrical grid down to the temperature of the stored foodstuff in the RDCs.

In Figure 3.1, the selection of the reviewed models is arranged to illustrate the scale of interest and approach. Areas that were found inadequately depicted in the models are shaded red to illustrate the spatial location and scale of the identified knowledge gap. As can be seen, the main area of concern is the connection between indoors of the supermarket and the RDCs.

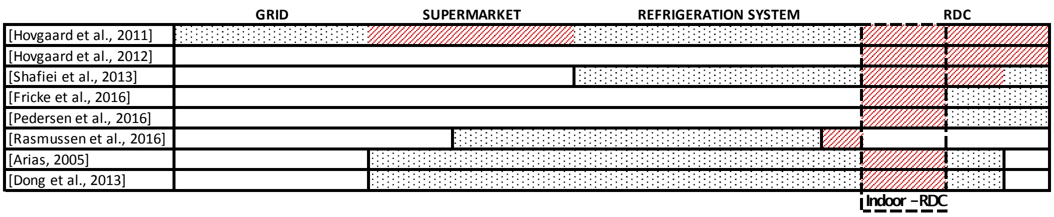

Figure 3.1: Overview of the scope and limitations of a selection of the reviewed works on energy demand in supermarkets for demand response evaluation. Dotted fields represent the covered areas of the respective study. Red fields indicate areas that were inadequately depicted.

As an example of a top-down approach and large scale study to generate a 42-hour prediction of electrical power demand by refrigeration in a supermarket,[Rasmussen et al., 2016] adopted data-driven grey-box methodology where the electrical power demand was estimated based on, the time of the day and outdoor temperature. The model was connected to a weather forecasting algorithm, which along with the model generated a 42 hours forecast of the electrical energy demand by refrigeration. Although the model successfully predicted the electrical power demand, the model is not suitable for MPC for demand response, as the constrains of temperatures within the RDCs are excluded. Thus, the demand response capacity cannot be evaluated.

The work of [Hovgaard et al., 2011] was among the first to consider the effects of thermal performance of a supermarket building and its refrigeration system on the demand response. Following [Madsen and Holst, 1995], the sales area was assumed to be a uniformly tempered zone where the temperature was calculated based on the heat gains from the outdoors and from other interior zones. In this approach, the major thermal loads occurring in the shop area were assumed to be proportional to the temperature difference between the indoors and outdoors. Consequently, the cooling demand, demand response strategy and related conclusions were based on this assumption, although the assumption itself was not sufficiently supported with the provided results. As will be demonstrated in Section 3.2, the strong correlation between outdoor weather conditions and cooling demands in supermarkets is one of the misconceptions of the data-driven top-down approaches.

In a subsequent study by [Shafiei et al., 2013], the effects of indoor climate on the thermal loads of RDCs were modelled with an increased level of details. Here, the thermal inertia of the cold air and the stored foodstuff inside an RDC were modelled as two thermally connected isothermal lumps, for considering temperature constraints in the operational RDCs. Besides the heat exchange with the foodstuff, thermal loads from the surrounding and heat extraction by evaporator were also included in the heat balance for the RDCs, all as sensible loads only. It is worth noting that, by improving the spatial resolution of the heat balance within the supermarket and RDC, the impact of outdoor weather conditions on the power demand for refrigeration appeared as less influencing. The successful validation of the modelled power demand by the compressors supports this observation. However, unresolved yet significant discrepancies between the modelled and measured temperature of the RDCs indicate that the proposed thermal model of the RDC might be insufficiently accurate for demand response control integration and prediction.

Several studies [Hovgaard et al., 2011, Fricke et al., 2016, Pedersen et al., 2017] emphasise the importance of predicting the foodstuff temperature accurately for food safety, and to maximise demand response capabilities. These low-level constraints drive the modelling approach towards detailed models of whole supermarkets, where the overall refrigeration system and its connection with RDCs, indoor and outdoor environments, and customer interactions are described by deterministic and physically sound models, as presented in [Arias, 2005, Dong et al., 2013]. However, the improved precision and extent of the results is achieved on behalf of the increased computational demand. Therefore, the modelling approach for simulating the demand response of supermarkets must be carefully chosen to balance these counteracting features. In the following section, the benefits, drawbacks and limitations of the most common modelling approaches are discussed.

3.2 Models for the evaluation of supermarket energy demand

Computer models for the evaluation and prediction of energy demand by supermarkets are generally divided into three main categories;

- **Physics-based -***Deterministic equations, detailed sub-models and structure based on physical systems.*
- **Grey -** *Main structure based on physical system which is the tuned based on data.*
- **Black -** *No model structure assumed, only input and expected output used for tuning*

Both grey and black-box models are data-driven and therefore needs input and expected output data to be tuned or trained. Consequently, this type of model can only be used for the evaluation of existing systems. In contrary, physics-based models are based on established physical relations and can be used for evaluation of decisions in the design and development process of new supermarkets.

For control system integration, the available computational resources are often limited. Thus, Grey and Black box models have commonly been preferred as they only need limited computational power after the training is completed. However, for demand response purposes, the extents and constraints within these models might not be sufficient. Making physics-based models appear as an attractive alternative if a sound balance between details and computational effort can be established.

In the following sub-sections, the focus is directed to the causation proposed within the models and the level of details, both spatial and temporal.

3.2.1 Black-box models

Artificial neural network (ANN) is an example of a black-box model where the user provides input data and the expected output to tune the weights within the network.

As an example from [Datta and Tassou, 1998], ANNs were used to predict the electric energy demand of a supermarket in UK to optimise the demand for buying energy at a low price on a half-hourly basis. Here, the training data-set input consisted of, day of the week, time of day, outdoor temperature, outdoor humidity, indoor temperature and indoor humidity for *two* months with a granularity of 15 minutes, with the 30-minute electrical power demand as output. The validation showed good conformity for both methods with mean errors of less than 8%.

In another example from [Mavromatidis et al., 2013], ANNs were used to predict the energy demand for fault detection in the refrigeration system, based on the assumption that irregularities in energy demand indicate potential technical defects. Here, the training data-set consisted of, the day of the week, hour of the day, ambient temperature, and temperature of the cold aisle and the 30-minute average electrical power demand for refrigeration as output. The ANN was then trained with a five months data set and showed good conformity (8%) with the validation data-set.

As shown by the two studies presented above, trained ANN can be used for power demand predictions. However, only if a training data-set can be generated, i.e. the supermarket must be operational under normal conditions prior to implementation. Additionally, it is essential to ensure that no operational errors are included in the data set used for training. Or alternatively, one additional output is added where the network is taught to observe and identify operational failures.

Returning to the concern presented earlier on the misconceptions of the data-driven top-down approaches where the strong correlation between outdoor weather conditions and cooling demands in supermarkets was mentioned. An important feature of ANNs is that they are able to approximate any function [Cybenko, 1989], i.e. if assuming inadequate causation, the ANN will be able to correlate input and output data if sufficient training-data is provided. This would, however, only generate valid results for data limited to the bounds of the training data-set. Thus, the implementation of models where inadequate or false causation is proposed might lead to inappropriate predictions.

Another limiting factor is that technical advances cannot be included in the model, unless updated training data is provided.

3.2.2 Grey-box model

The grey-box modelling is also a data-driven approach where the structure of the model can be described as partly based on a theoretical structure depicting the problem. Here the unknown parameters are defined through, for example, regression analysis. The model can, therefore, be applied to problems where parts of the involved system are stochastic, too complex to be depicted or unknown, making it a popular choice for modelling of supermarkets from a top-down perspective for demand response purposes. Some examples of grey-box models for evaluation of energy demand in supermarkets are presented below before concluding the limitations and opportunities.

As a first example from [Schrock and Claridge, 1989], the authors used change-point multiple regression models with two regimes that used weather, operational variations and the number of customers in the store for estimating the daily and hourly energy demand of a supermarket. The model was, in analogy with [Mavromatidis et al., 2013], intended for the early identification of operational problems by comparing the actual electricity use with the prediction of the model. The model was found to predict the daily energy use well ($< 2\%$

residuals), whereas the stochastic behaviour of the hourly energy demand was not possible to validate. Thus, the limited model does not depict the non-linear and stochastic system of the supermarket adequately.

Twenty-seven years later, intending to investigate how global warming affects the 60-year ahead energy demand for a supermarket, [Braun et al., 2014] used a similar approach as [Schrock and Claridge, 1989], to evaluate the weekly electrical energy demand based on the outdoor temperature and humidity ratio from 2012. Interestingly, the authors identified some limitations of the model, such as that exclusion of wind and solar radiation might affect the results.

In addition, as in the case of ANN, the model is not able to take into account technological advances or improvements to the supermarket, which are likely to occur during the investigated period of 60-years. Thus, the model could not be validated using the intended validation data-set from 2013 as the studied supermarket had changed certain components in the heating system. Therefore, the presented forecast was highly uncertain.

In the previously introduced forecasting model by [Rasmussen et al., 2016], the authors created three variations of an adaptive linear time series model tuned based on the measurement of hourly energy demand by refrigeration and ambient temperature. The model was then connected to a numerical weather prediction to forecast the energy demand for the coming 42 hours.

The data used as input for tuning the model was limited to three months (May-July) of operation where one potential issue could arise as the data show a clear upward trend related to the measured outdoor temperature, and the absolute temperatures are limited to the extremes within the season of late spring/early summer. Despite the promising results from the validation within the observed horizon, it would be desirable to evaluate how the model would perform for prediction past spring and summer as the outdoor climate changes significantly during winter.

In contrast to the studies described above,[Spyrou et al., 2014] developed a linear regression model for both electricity and gas demand and performed a factor analysis to find the most influencing variables.

The presented model used factor analysis to select a smaller number of input variables that influence electricity demand. The authors started by taking a large number of variables into account and then reduced the number by excluding not statistically significant ones. The original parameters were: Sales floor area, Total floor area, Year of construction, Ceiling Height, No. of Trading Floors, Food:Non-Food Ratio, CHP, Electrical rating (of CHP plant), 24h Operational Opening hours, Volume of Sales, Sales/SFA, CoolingDegreeDays, HeatingDegreeDays, Easting and Northing.

Interestingly, the final set of parameters for the model presented in this study differs significantly from those previously presented in [Schrock and Claridge, 1989, Braun et al., 2014, Rasmussen et al., 2016]. In [Spyrou et al., 2014], the authors found that:

Salesfloor area $[m^2]$

Sales volume[£]

Food/Non-Food ratio$[-]$

Year of construction [Pre-Post 2002]

are the most influential and the only needed parameters to estimate the annual electrical energy demand of a supermarket. The area influence is 44.6% of the electrical energy demand, the turnover is related to 26.3%, and Food:Non-Food ratio and year of construction represents the remaining 29.1%.

Consequently, as turnover is found to correlate significantly with the energy demand, this would imply that energy demand increases with monetary inflation, which is dubious. It is reasonable to believe that the turnover of sales is related to the number of customers in the store and interactions with RDCs, which both ultimately affecting the electrical energy demand.

Hence, correlation and causation are very important to distinguish between these grey-box models. In [Schrock and Claridge, 1989, Braun et al., 2014, Rasmussen et al., 2016], the models imply causation as they relate electrical demand with outdoor conditions. The causation does not seem implausible, but not obvious. When assessing the supermarket's energy vectors, a connection between outdoor conditions and energy demand is found through the influence of the HVAC-system due to both sensible and latent thermal loads of infiltration into the building, conduction through walls, customer clothing and behaviour [Månsson, 2016]. Also, the refrigeration system would be influenced as the temperature for cooling the refrigerant in the condenser would change. Secondary effects such as that the heat extraction rate of the refrigeration system is connected to the indoor air enthalpy [Lindberg et al., 2008], which is dictated by the response of the HVAC-systems to the building control system.

3.2.3 Physics-based models

In contrast to the above presented grey- and black-box models, which attempt to predict future energy demand based on historical data, physics-based models use psychical relations to depict the processes within the supermarkets to generate the pursued output. The temporal and spatial resolution of those simulations can be arbitrarily chosen, and the systems can be extensively used to investigate the effects of various of actions.

Based on the reviews of supermarket simulation tools presented in [Fidorra, 2016, Sluis, 2004], the only[1] available software dedicated to whole building simulations of supermarkets is Cybermart [Arias, 2005]. There are, however, other whole building energy simulation software such as Energy Plus, EQUA IDA ICE etc. which have the capability to be applied to supermarkets and have some built-in functionalities for this purpose.

Cybermart was created to evaluate the impact of different refrigeration system designs on energy demand, environmental impact and life cycle cost. By considering interactions between the building envelope, user interactions, HVAC and the refrigeration system, the software predicts the energy demand, heating demand, indoor environment and individual parameters within the refrigeration systems. Validation cases included seven different supermarkets, and good conformity between the calculated and measured values was achieved for each case.

In Cybermart, the RDCs are modelled on the basis of their nominal performances related to the indoor conditions of the supermarket, as described in [Fahlén, 1999], combined with the adjustment factors for day and night-time variations as provided by [Howell, 1993].

Similarly, in Energy Plus the RDCs are modelled based on nominal performance parameters at rated conditions [Sarhadian et al., 2002], which are combined with fixed relations to estimate their off-rated performance. Also, the variations between the day- and night-time scenarios are described by the factors from [Howell, 1993]. The methods applied in both software adequately depict the average heat extraction demand of the supermarkets RDCs over larger temporal scales. However, individual performance differences of RDCs are not included, limiting the insight into the spatial and temporal resolution of the results.

An example of a somewhat simplified model of a whole supermarket can be found in [Dong et al., 2013]. While this model considers heat and mass transfer through a retail store building, including heating, ventilation air conditioning and refrigeration systems as in [Arias, 2005], RDCs are modelled as quasi-steady-state heat sinks. Regardless of this simplification and the decreased level of details modelled within the refrigeration system, the overall calculated energy demand is within a 3% margin of the measured values. The methodology of [Dong et al., 2013] was applied to a German supermarket in [Marciniak, 2015], and similar validation results were obtained. Both [Dong et al., 2013] and [Marciniak, 2015] pointed out two major limitations of physics-based models: a mismatch between the modelled and actual configuration of a supermarket due to outdated technical documentation and necessary simplifications of physical relations, or spatial and temporal scales of processes that the user must be aware of. These areas hint at the issue of the balance between computational effort and accuracy, which must be carefully considered for models used in MPC for demand response purposes.

[1]In [Fidorra, 2016], the SuperSmart-Tool was presented as a future available dedicated software for energy simulations of supermarkets. This software was, however, not found at the present date.

Energy performance of open RDCs represents a particularly challenging modelling task due to complex airflow paths within and around the RDCs. In a two-part study presented in [Wu et al., 2015a] and [Wu et al., 2015b], computational fluid dynamics (CFD) is used to describe steady-state interactions between HVAC and open RDCs. The multi-scale approach is used to improve the computational performance, and the supermarket is separated into three main spatial scales of interest; Sales area ($> 10\ m$), RDC ($1\ m$) and Shelves ($1\ cm$). Within each domain/scale, the Navier-Stokes equations with a $k - \epsilon$-turbulence model including the heat and moisture transport by convection, conduction and radiation are solved numerically. For the sales area, the mesh contains 4 199 910 nodes, for which the eight unknown variables are solved, then mapped and applied to the decreasing scales. The cited works show that the use of non-isothermal CFD gives a highly detailed representation of reality. However, even after splitting the computational domain into different spatial scales, substantial computational efforts are required to solve the problem at each scale, i.e. 60, 36 and $16h$ for sales area, RDC and shelves respectively. Consequently, for a supermarket with several unique RDCs and shelves, the simulation time would be much longer. Thus, with the currently available computational power, such an approach is infeasible for prediction models.

To achieve a balance between computational time and accuracy, it may be beneficial to weight the efforts in accordance with the influence that each component has on the overall outcome. For whole building energy demand and comfort simulations, the refrigeration system represents approximately 50% of the overall electrical energy demand, and it is directly linked to the indoors through the RDCs. Thus, specific attention should be directed to this area. Also, following the aim of this thesis, the RDCs are an area of particular interest.

To extend from the RDC towards the actual electrical energy demand by the refrigeration system, models for these levels are also needed. For dynamic models for refrigeration equipment, usually, a modular model structure of the refrigeration system is used with separate modules for compressor, condenser, evaporator and pipework. A comprehensive review of dynamic modelling of vapour-compression systems is provided in [Rasmussen, 2012] in which both physics-based and data-based (grey/black-box) models for each component are presented.

3.2.4 Modelling refrigerated display cabinets in supermarket conditions

For a detailed analysis of airflow and heat transfer between air and products, CFD is a commonly applied method among researchers and in the industry. It has the capability to generate detailed insights on temperature, humidity and airflow within the RDC to evaluate the impact of various thermal loads, especially infiltration. The high level of details and included physics allows for the evaluation of the influence of operating conditions and various RDC design contributions.

Based on the reviews of [Smale et al., 2006, Norton and Sun, 2006], the majority of CFD studies are focused on open RDCs, whereas only a few studies are focused on closed RDCs, i.e. [D'Agaro et al., 2006b, Orlandi et al., 2013, Chaomuang et al., 2019a, Chaomuang et al., 2020].

For full-scale RDC simulation, transient 3D CFD is advisable to capture the large scale turbulence and longitudinal variations[D'Agaro et al., 2006a]. Thus, computational effort increases significantly compared with 2D.

Although CFD does provide highly accurate results, depicting important phenomena, there are critical limitations due to the computational effort needed [Laguerre et al., 2012, Ben-abdallah et al., 2018]. Hence, simplified heat transfer models may be a suitable compromise between computational effort and accuracy for use in prediction models.

One such example was presented in [Hasse et al., 1996], where the dynamic thermal behaviour of a cold-storage was modelled based on connected modules representing the different dynamic features.

In more recent studies, [Laguerre et al., 2012] developed a steady-state model of an open RDC to evaluate the influence of operating conditions on air and product temperatures. The results were then incorporated in [Laguerre et al., 2014] to investigate the cold-chain for food from the factory to the consumer. The steady-state model from [Laguerre et al., 2012] was then further developed in [Chaomuang et al., 2019b] to include transient temperature variations in a closed RDC. A similar modelling approach was also used in [Ben-abdallah et al., 2018] to depict the dynamics of an open RDC.

Worth noting in the cited works by [Laguerre et al., 2014, Laguerre et al., 2012, Ben-abdallah et al., 2018, Chaomuang et al., 2019b] is that the models calculate the temperature of the air and goods based on the discharge air temperature (DA) and mass-flow, i.e. the heat extraction by the evaporator is not included in the model. Additionally, neither of the presented models includes the dynamic variations introduced by door operations.

3.3 Conclusion

For the inclusion of supermarkets in a demand response scheme, it is necessary to forecast the power demand and available buffering capacity of their RDCs. Based on the studied literature, it is concluded that the temperature and thermal performance of the RDCs dictates the duration for which the supermarket can respond to a demand response request. Computationally efficient yet accurate models are needed at a local scale to find the temperature and energy demand of the RDC. Progressing upwards to the grid scale, various models are needed to preserve the necessary data on available buffering capacity and power demand of each supermarket and pass them to an aggregator, where various optimisation processes can be performed.

Although there exist intricate models depicting the energy demand of supermarkets, neither of the reviewed studies has included RDCs at a spatial and temporal level of detail necessary to include the constraints in a demand response model used for MPC. Following this, the direction of this thesis has been to develop such a model and the necessary input data to depict the dynamics.

Chapter 4

Overall research methodology and results

This chapter introduces and briefly summarises the results from the appended articles, together with an overview of the overall PhD-project research methodology. Each article contributes with one or several key findings that together commit to the overall aim of the thesis, which is to evaluate and enable supermarkets as a resource for demand response in a smart grid setting.

The work presented in this thesis builds on the findings from the previous licentiate thesis [Månsson, 2016], where the topic of demand response by supermarket refrigeration systems was approached from a building level. By considering interconnections and dependence of the sub-systems existing within the supermarket, the previous thesis has mapped the thermal vectors at various spatial scales and level of details, from sensors in RDCs to the thermal envelope of the building. A literature review was conducted in the pursuit of thermal models capable of performing building scale simulations of demand response scenarios for supermarkets. At that time, there existed no such models in the available literature. While adequate models for building scale simulations of supermarkets such as the ones presented in [Arias, 2005, Dong et al., 2013], or general building energy simulation software Energy Plus and EQUA IDA ICE do exist, none of them provides a sufficiently detailed description and integration of the RDCs thermal performance.

The research within this thesis was, therefore, approached bottom-up, starting from an in-depth analysis on how the temperature of the RDCs is controlled by the refrigeration system (Article 1), proceeding to quantifying and predicting the heat extraction demand and temperatures of RDCs through the development of a dynamic hygro-thermal model (Article 2), generating the necessary data on customer interactions (Article 3), and, finally, on the actual thermal performance of RDCs (Article 4). Together, these four articles provide novel insights into the demand response capacity by supermarkets and the necessary steps in the methodology on how to assess it. The work is based on experimental investigations in the laboratory and field, and on numerical modelling, as illustrated in Figure 4.1. While all experimental studies and modelling in Article 2,3 and 4 were designed from scratch, the numerical CFD modelling presented in Article 1 was created using modules included in the commercially available modelling platform Comsol Multiphysics.

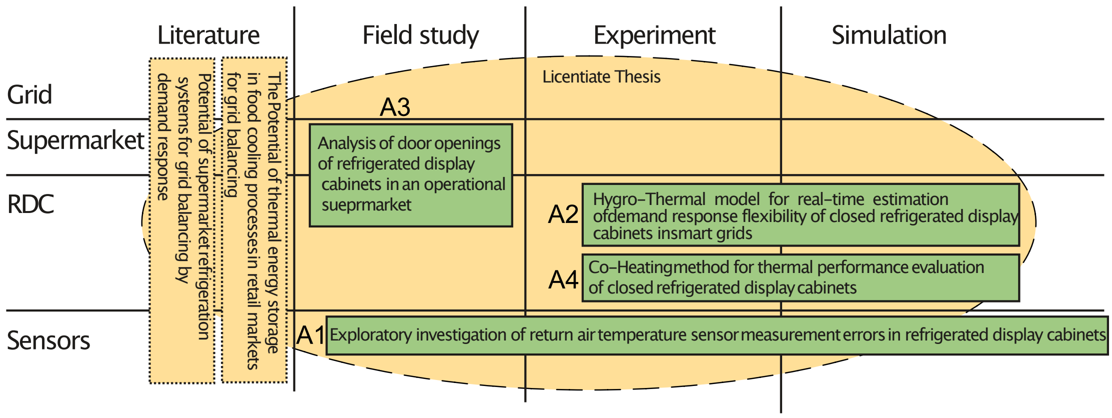

Figure 4.1: Overview illustrating scale of interest and methods used in the PhD-Project. Green rectangles, A1-A4, represent the included articles. Yellow shapes represent the excluded earlier studies presented in [Månsson and Ostermeyer, 2013, Månsson, 2016, Månsson, 2019].

The following sections introduce key aspects and results of each study. Further details can be found in the respective appended article.

4.1 Article 1 - Exploratory investigation of return air temperature sensor measurement errors in refrigerated display cabinets

In Article 1, the RDCs were approached bottom-up through in-depth analysis on how the refrigeration system controls the temperature of the RDCs. The temperature readings provided by the return and discharge air sensors governs the heat extraction rate by the RDC. Thus, inaccurate temperature readings consequently result in inadequate temperature adjustments. This study addresses the relevance and impact of the spatial position of the return air temperature sensors in RDCs.

The data-set, which formed the basis for this study, contained temperature sensor readings from temperature sensors in an operational supermarket, and was first approached with the intention to investigate the daily variations. However, in an early stage of the study, discrepancies between measured and expected temperature readings were discovered. For many of the reviewed RDCs, the temperature difference (ΔT) between return air (RA) and discharge air (DA) temperature varied significantly, which would indicate differences in sensible heat extraction. In Figure 4.2, an example of the temperatures for two neighbouring almost identical RDCs with similar content is shown. For weekdays and for different types of RDCs, this was expected, but for almost identical RDCs during non-opening hours (nights and Sundays) when there are no people in the shop, the RDCs were expected to have similar operational patterns.

A hypothesis of a thermal gradient interfering with the return air temperature sensor measurements was established and tested. The thermal gradient is a consequence of a thermal boundary layer that is inevitably formed along the return airflow path along the warmer door, as depicted in Figure 4.3. Consequently, measurements by the return air temperature sensor positioned in this area would be significantly influenced by the temperature gradient, i.e. the sensor would indicate higher temperatures than the actual average return air temperature. Thus, the control system would respond with an inadequate cooling strategy, attempting to ensure that the RDC content is kept within the prescribed limitations.

The hypothesis was validated through CFD simulations and physical experiments, through which it was confirmed. Thereafter, a field study was conducted where the position of 221 return air temperature sensors in operational RDCs was investigated. Among these, 80.5% had sensors located within the area where the thermal gradient could occur, i.e. closer than 50 mm to the floor. Return air temperatures were then recorded during one month with the original position of the sensors, and for one more month after the sensors were re-positioned by means of a mock-up sensor holder. As an example of the effects, the temperature readings from 12 RDCs one month before and after the re-positioning is shown in Figure 4.4.

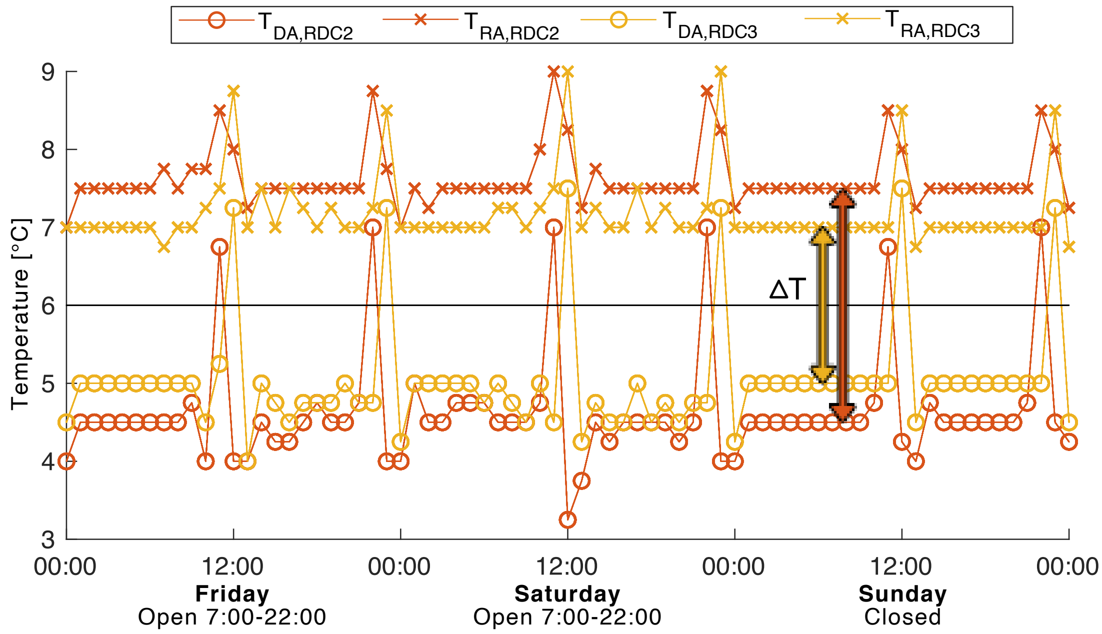

Figure 4.2: The return and discharge air temperature of two neighbouring RDCs, namely RDC2 and 3, where an unexpected difference (ΔT) in temperature levels can be seen. Even outside of the stores' opening hours when there are no customer interactions, the temperatures differ between the RDCs.

As it can be seen, the measurements show that the return air temperature sensors were moved from a warmer to a cooler location, confirming the existence of the temperature gradient layer that was revealed by the simulations and experiments. The relocation of the sensors has resulted in both a decreased energy demand for refrigeration and a less fluctuating operation pattern. Supermarket owners, have also communicated a decrease in needed service appointments.

Today, the developed and patented Sensor-Holder has been installed with positive results in 4 000 RDCs by a spin-off company[1] in Northern Germany.

[1]ChillServices GmbH, Hannover, Germany

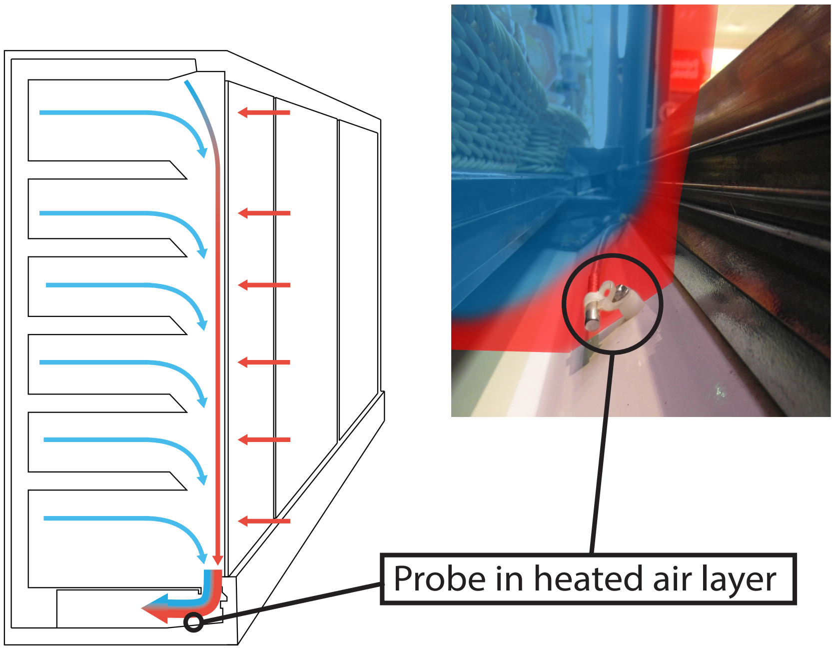

Figure 4.3: The discharge air passing the glass door is heated by heat gains through the door. The thermal gradient created thereby continues along the entire path of the discharge airflow, through the return air grille towards the front of the heat exchanger further back. This results in a warmer air layer close to the floor of the RDC in the area of the RA temperature sensor.

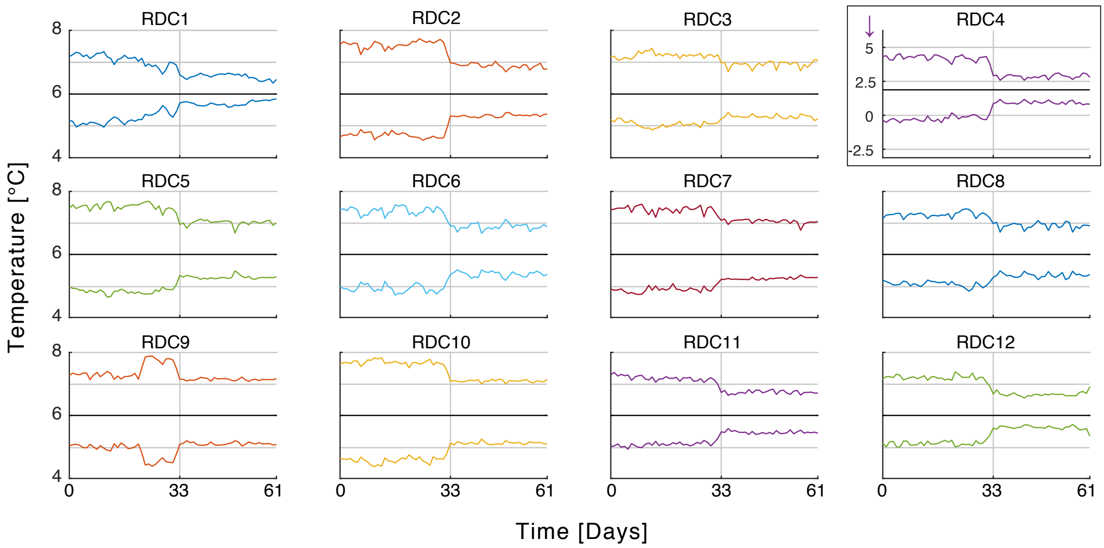

Figure 4.4: Temperature data for one month before and after the relocation of the return air temperature sensor in a supermarket outside of Hamburg. The relocation occurred on day 33. *Notice: RDC_4 is used for meat and therefore has a lower temperature.*

4.2 Article 2 - Hygro-Thermal model for real-time estimation of demand response flexibility of closed refrigerated display cabinets in smart grids

As discussed in Chapter 2, for a supermarket control system with the ability to receive and respond to a demand response signal, it is essential to predict how these actions will affect the temperature development, to ensure food safety, and to communicate the demand response capacity. Additionally, the RDCs' heat extraction rate must be harmonised to ensure that the refrigeration system is operated at optimal levels for energy conservation.

In the pursuit of a computationally effective method for predicting the temperature and heat extraction from RDCs, a modular approach has been chosen where an RDC is divided into three hygro-thermally coupled isothermal domains, representing the net air volume, interior cladding and heat exchanger. This approach assures that the essential control signals for demand control are provided, i.e. the discharge air temperature (DA) and the temperature at the return air grill (RAG).

The spatial resolution of the model is depicted in Figure 4.5. The light brown-yellow domain represents the net volume of the RDC where the majority of thermal loads are introduced, increasing the temperature form (1) T_{DA} to (2) T_{RAG}. To estimate the temperature of the net volume domain, the model uses the same approximation as by the control system, i.e. $T_{DARAG} = 0.5T_{DA} + 0.5T_{RAG}$. Hence, the resulting T_{DARAG} temperature is a reflection of the variable used for the control of the RDC interior temperature to ensure food safety. Further details on the validation and accuracy of the proposed model can be found in Article 2.

The intended application of the model was to be used for near future predictions of temperature development in RDCs at operational conditions, provided that the latter is known or can be predicted. Four possible near future operation conditions are assumed and labelled S1 to S4:

S1 No Refrigeration – 0 Openings/h,door

S2 No Refrigeration – 6 Openings/h,door

S3 Active Refrigeration – 0 Openings/h,door

S4 Active Refrigeration – 6 Openings/h,door

In Figure 4.6, the predicted temperature development for an RDC exposed to these four scenarios is shown. From the results, it is possible to evaluate for how long the RDC can be left without active refrigeration before the upper temperature limit is reached, or for how long the RDC can be cooled before the low limit is reached. Thus, for a single RDC, this would directly translate to the demand response capacity of the RDC. Alternatively, through aggregation, this

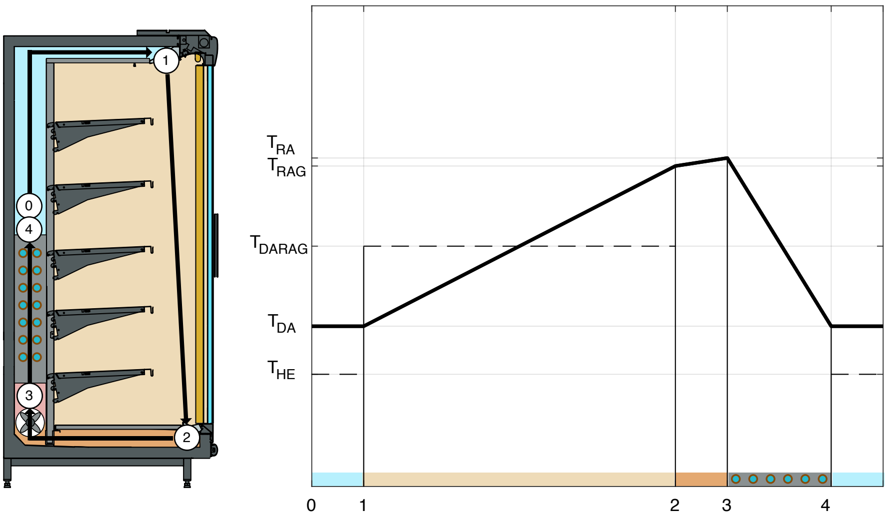

Figure 4.5: Illustrating the domains and main temperatures evaluated withing the model. (0,1,4) Discharge air (2)Return air (3) Return air after fan *Left*: The RDC is depicted with arrows, indicating the flow direction and order. *Right*: Conceptual line graph showing the temperature development for the circulating air within the RDC.

model could potentially estimate the capacity of a supermarket participating in a demand response scheme.

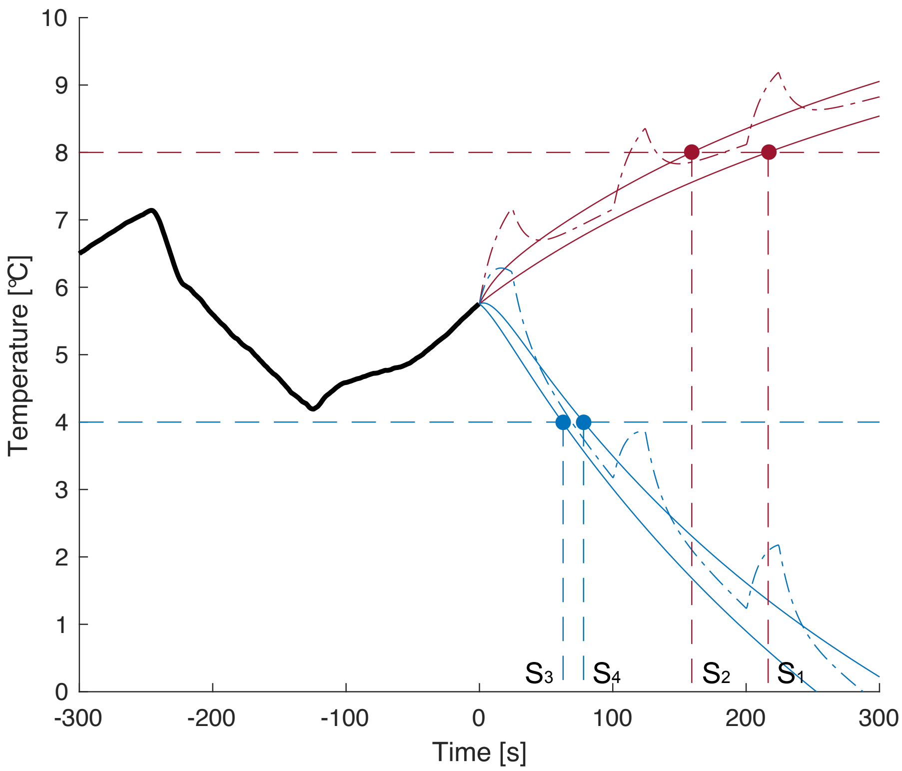

Figure 4.6: Plot showing the temperature development for T_{DARA} for the RDC exposed to Scenario 1-4. Here it can be seen that it takes $159 - 217$ seconds for the RDC to heat up to $8°C$, or $59 - 74$ seconds to cool down to $4°C$. The dash-dotted line shows the temperature development including the temporal effects of door openings.

4.3 Article 3 - Analysis of door openings of refrigerated display cabinets in an operational supermarket

Customer interactions with an RDC such as door openings cause a significant increase in infiltrating air and thermal loads of the RDC. Thus, understanding the stochastic patterns and temperature development within the RDCs due to the door openings is crucial to assess its demand response capacity.

The primary motivation for the study presented in Article 3 is to generate a comprehensive data-set to quantify and analyse these operational variations for RDCs. To achieve this, an in-house data-logging platform was developed to record the movement of 85 RDC doors for one month. The door operations were monitored by attaching a wireless gyroscope to each door, which communicated to gateways that transferred the data from the store in Germany to a server in Sweden. A photo showing the setup in the store is presented in Figure 4.7.

The data from the gyroscope, i.e. the rotational speed of the door $\dot{\omega}(t)$ [$°/s$]

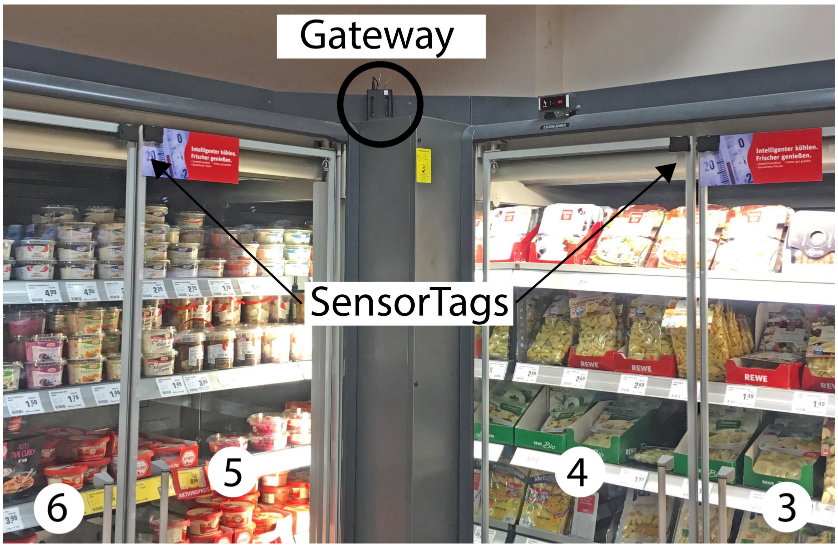

Figure 4.7: Photo from the supermarket showing doors 3-6, from right to left. The SensorTags (*Texas Instruments, Dallas, USA*) can be seen in the upper corner opposite to the hinges of each door. Also, the Bluetooth gateway (*BeagleBone, Michigan, USA*) can be seen in the top centre of the photo

was post-processed to calculate the position of the door blade in time. The data was categorised by type of RDC, i.e. a distinction was made between the LT and MT RDCs.

It was found that the duration for which the doors were opened were in a similar range of magnitude for the LT and MT RDCs (12.7 s $vs.$ 14.0 s), as shown in the histograms in Figure 4.8.

Interestingly, significant differences in the opening angle between the LT and MT RDCs were found, as shown in Figure 4.9. The wider opening angle of MT RDCs (68.4°) would potentially yield a larger infiltration to occur compared with LT RDCs (49.0°). Further differences refer to the frequency of door openings, which are significant both between the two types of the RDCs and within each group. The latter indicates differences in customers' shopping habits during weekdays and weekends (see Figure 4.10).

The generated data-set is unique and an important source of information in understanding the stochastic nature of customers' interactions with RDCs. By quantifying actual opening speeds, angles, duration and frequencies, it provides essential inputs for development and implementation of demand response models for supermarkets.

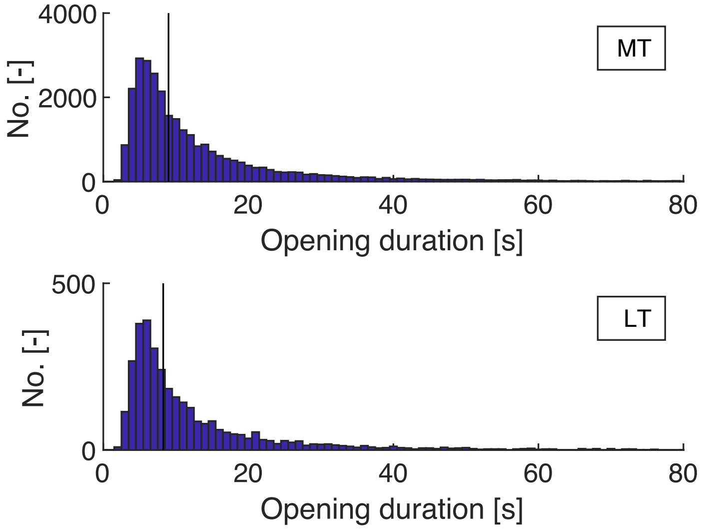

Figure 4.8: Histogram showing the total opening duration for MT and LT RDCs presented separately. The black vertical lines mark the median values as reference. Both histograms show similar distribution and values.

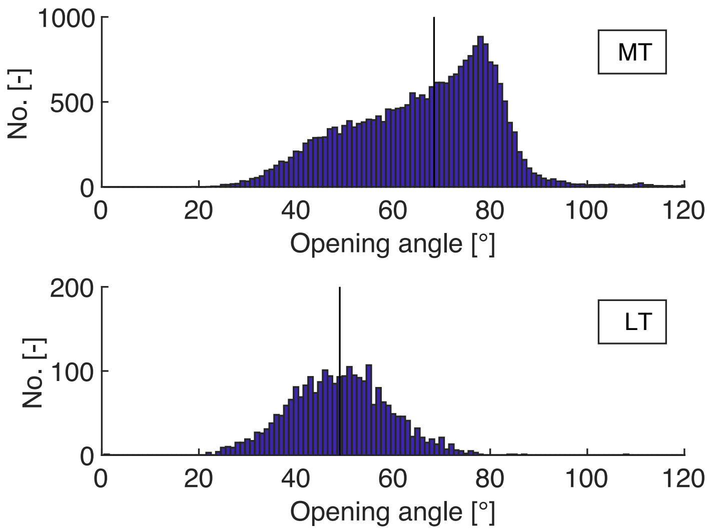

Figure 4.9: The mean door opening angles of MT and LT RDCs showing a significant difference between the opening angle distribution and the mean between the MT and LT RDCs.

4.4 Article 4 - Co-Heating method for thermal performance evaluation of closed refrigerated display cabinets

The main objective of the study presented in Article 4 was to generate thermal performance data for an RDC to be used together with the thermal model

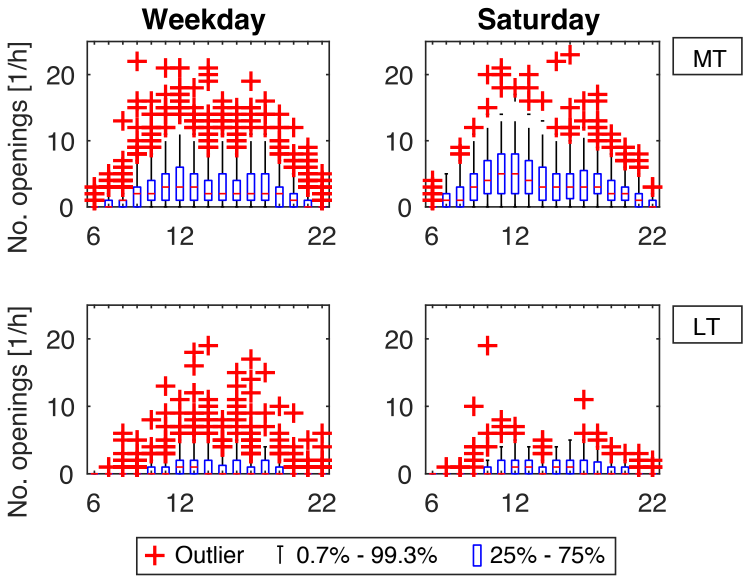

Figure 4.10: Box-plot showing the distribution of door openings per hour for MT and LT RDCs during both weekdays and Saturday. Significant differences in magnitude between MT and LT RDCs can be noticed as well as the shifted shape of the profiles between weekdays and Saturday. Additionally, it can be seen that there is a large spread in the number of openings per hour between the different RDC within the same category (MT or LT).

presented in Article 2. Thus, to configure the thermal model, the heat transfer coefficient for the envelope (K_{Env}), the heat capacity of interior (C_{RDC}), the infiltration rate trough gaps ($\dot{m}_{Inf,Idle}$) and the infiltration caused by a door opening ($m_{Opening,Door}$) must be defined.

Based on a comprehensive literature review and interviews with RDC manufacturers and supermarket companies, it was concluded that a method with which all these inputs could be evaluated consistently was not available. The currently available methods are focused only on the quantification of infiltration only [Faramarzi, 1999, Navaz et al., 2005, Amin et al., 2009], without generating any further thermal performance data needed to configure the thermal model of the RDC. Hence, in the search for an alternative, and more comprehensive experimental methods to evaluate these parameters, the Co-Heating method was discovered.

This method was originally used for the evaluation of the overall heat transfer coefficient of a building "as built" [Sonderegger and Modera, 1979]. The methodology implies that a building is heated to an elevated indoor temperature ($T_{In} = T_{Amb} + \Delta T$) while the supplied heating power is monitored ($\dot{Q}_{Supply}$). The overall heat transfer coefficient ($K_{Building}$) is then found as:

$$K_{Building} = \dot{Q}_{Supply}/\Delta T \tag{4.1}$$

The reason for elevating the indoor temperature is to minimise the significance of solar and occupants-related heat gains in comparison to the building's inherent thermal performance. For an RDC located indoors, in a stable environment, these conditions are readily met, contributing to the accuracy of the method. The much smaller thermal inertia of an RDC in comparison to a building allows the experiment to be shortened and performed with reasonable resources.

The Co-heating test was performed on an RDC from KMW model $FR4D-VSST-G$ equipped with four glass doors, which is a common model used in supermarkets in Germany. The temperature conditions were measured with six temperature sensors placed inside the RDC and two additional sensors in the ambient air, as shown in Figure 4.11. The measured temperatures were then averaged to reduce the influence of errors due to spatial temperature variations and instrument uncertainties.

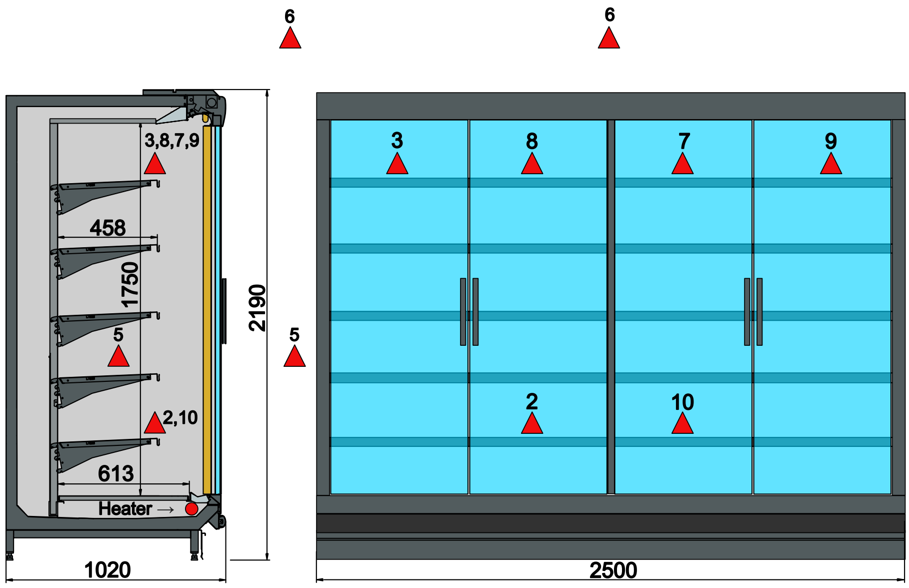

Figure 4.11: Illustration of the sensors and heater placement in the RDC for the Co-Heating experiments. Sensors 5 and 6 are located in the ambient air in front of and besides the RDC, respectively. Sensors 4 and 1 failed and were, therefore, excluded. *Left:* Section drawing. *Right:* Front view.

The Co-heating methodology has been adapted for an RDC by performing measurements in the following three steps. First, the temperature of the sealed RDC is elevated by an electrical heating rod with a known constant power. The temperature development is recorded. Once a steady-state temperature is reached, the heat transfer coefficient for the envelope of the RDC can be evaluated, and the transient regime of the heating process can be used for making an estimation of the heat capacity of the RDC.

In the next step of the experiment, the seal is removed from the RDC while the heated rod is kept at constant power. Due to the larger heat losses caused by air exchanges, a new lower steady-state temperature is reached, from which the mass flow rate due to infiltration can be evaluated. It is worth noting that the differences in densities between the warmer indoor air and the cooler ambient air may have a significant impact on the infiltration mass flow rate, and a correction procedure has been proposed in the article.

Finally, in a third step, the doors are operated with periodic controlled openings, yielding a yet lower quasi-steady-state temperature from which the infiltration by a door opening can be derived. Thus, K_{Env}, C_{RDC}, $\dot{m}_{Inf,Idle}$ and $m_{Opening,Door}$ can be evaluated following the adapted variation of the Co-heating methodology.

Results of the experiments in steps 2 and 3 were validated against parallel experiments, following the condensate collection method, which is an established method for the quantification of air infiltration of RDCs. The measured infiltration at both idle state and during door openings differed by less than 10% between these two methods and the validation was considered successful. Additionally, the time, equipment and associated costs for running the tests were compared, and it was concluded that the adapted Co-Heating methodology could substitute the condensate collection method for the evaluation of infiltration while providing additional results on the thermal performance.

Chapter 5

Discussion

In Article 1, the influence of the spatial position of return air temperature sensors was concluded to affect the control strategies for the refrigeration system significantly. It is worth noting that the presented study and the patented sensor holder were not a part of the original problem statement for the PhD-project but rather coincidental results of an observation of the issue. These findings lead to an interesting realisation on how the low-level details such as the location of temperature sensors can affect the refrigeration systems operational strategies, and thereby alter the demand response capabilities of supermarkets.

Although the re-positioning of return air temperature sensors improves the control, it might be beneficial to re-think the overall current control strategies by including more and faster responding humidity and temperature sensor pairs positioned by each door in the longitudinal direction of the RDC. Thereby, the latent thermal loads could also be included in the control strategies, and by increasing the spatial and temporal resolution, indications of individual door openings or failures could potentially be seen.

In Article 2, a dynamic hygro-thermal model of an RDC was introduced with the intention to be integrated into predictive control. Within the model, the spatial resolution is limited to estimating the discharge and return air temperatures of the RDC to ensure a low computational demand while providing an adequate level of details for the demand response management. Increasing the spatial resolution of the model by inclusion of domains for foodstuff and a more detailed evaporator would further strengthen the model, giving more detailed insights into the involved processes and possible optimisations for demand response purposes. However, the limited computational power available within the control system must be considered carefully.

Additionally, the uncertainties caused by the stochastic behaviour of customers affecting the thermal loads on RDCs should be taken into account when deciding on the level of details for the thermal model. Unless the thermal loads are depicted with high accuracy, the resulting prediction of interior temperature development will remain uncertain. At present, there exists no prediction models for the mentioned customer interactions, and the corresponding measured data are rather limited. The presented data and methodology in Article 3 provide novel insights and can act as a stepping-stone towards the development of predictive algorithms. The developed system might, however, be overly complex and accurate for the purpose of gathering input data for controls and predictive models.

Interestingly, if the door operations were to be included as an input parameter for the control system, as suggested earlier, the generated data would both contribute to enabling more optimised in-situ controls and potentially serve as input for prediction algorithms to forecast user interactions. This will, in turn, provide the necessary input for predicting the demand response capacity with an increased accuracy due to decreased uncertainties.

For the configuration of the hygrothermal model presented in Article 2, thermal performance parameters defining the boundary conditions are needed. In Article 4, the Co-Heating method was adapted to generate the needed thermal performance parameters of an RDC. One of these parameters is the infiltrating air quantity per door opening, which is rather challenging to define and to measure. As concluded in the study on door opening characteristics, Article 3, there exists a great variation in the opening duration, speed and door blade angle. Thus, these factors potentially affect the amount of infiltrating air. Hence, performing Co-Heating experiments with other RDCs, door types, and customer interactions would generate data that further decrease the uncertainties of the thermal prediction models.

As presented in the thesis, the constraints limiting and defining the demand response capacity of a supermarket are low-level details affecting the temperatures of the RDCs, i.e. temperature monitoring, controls, thermal loads and customer interactions. Thus, a bottom-up approach must be considered to ensure the inclusion of these parameters as constraints.

On the other hand, when viewing the topic of demand response by supermarkets from a more holistic perspective, as briefly introduced in the background, financial incentives such as reduced cost of energy are strong arguments for the implementation of new technologies in supermarkets. However, there appears an interesting and potentially conflicting issue when it comes to the balance between reducing costs by energy efficiency measures versus the reduced bottom-line cost of energy by incentives for demand response.

After enabling the supermarkets to utilise the electrical power demand flexibility that the refrigeration system holds, there are two options. Either an individualistic approach where the supermarket focus on local cost-reductions only, or to optimise the use of the flexibility in a manner that generates the largest overall savings for the utility grid, which must be incentivised for the supermarkets to commit. If they utilise the enabled flexibility benefit from weather variations, savings of approximately 2% could be achieved [Hovgaard et al., 2011], i.e. the offered benefits from the utility companies must provide more attractive incentives for the supermarkets to engage in demand response.

Individualistic approaches, as such, may reduce the energy demand locally, making the supermarket companies appear as positive contributors in the strive to reduce environmental impact. However, depending on energy sources and how the demand affects the supply side, it may be argued that it is better to use a larger quantity of electricity at ”the right time” than a small quantity at ”the wrong time” when electricity is generated from renewable sources instead of fossil.

Thus, to ensure that the supermarkets engage in what is best from a holistic perspective, the incentives must be adequately designed, which is challenging. For example, if the incentives for demand response are based on rated power demand by the refrigeration system, the supermarket companies might adopt more energy-intense refrigeration strategies than necessary to maximise the earnings. Alternatively, if the financial incentives are unattractive, the potential resource of demand response by supermarkets might remain unused, or kept to benefit the supermarkets locally.

Another aspect, causing a slight concern when including supermarkets as an essential resource for increased inclusion of renewable energy sources is the continuously changing trends of consumers and technology. Thus, the use of supermarket refrigeration system depends on the consumer habit to require refrigerated food goods to a sufficient extent, and that the technology utilised for refrigeration is powered by electricity, both seeming very plausible for the foreseeable future.

Chapter 6

Conclusions

This thesis aimed to further investigate and enable the demand response capacity of supermarket refrigeration systems to be utilised at the grid level. Based on the findings from Chapter 2 and 3, it was concluded that for the inclusion of supermarkets in a demand response scheme, it is necessary to forecast the power demand and available buffering capacity of their RDCs, in terms of temperature development in and heat extraction demand by the included RDCs. Since the adequate models and methodologies could not be identified in the available literature, the direction of this thesis has been to develop such model and generate the necessary input data to depict the dynamic thermal behaviour of an operational RDC. Additionally, as the temperature of the RDCs and, thereby, the monitoring for controls are essential, special attention was directed to this area.

Based on the findings in Article 1, the majority (80.5%) of return air temperature sensors in RDCs were found to be located in an area where a thermal gradient interfere with the perceived temperature, i.e. the temperature readings falsely indicated a higher return air temperature than the actual mean temperature of the passing air. Thus, the control system was unable to adjust the temperature efficiently and accurately. Hence, to mitigate the issue, a re-positioning to a more representative position was suggested, which was supported by the follow-up measurements on both the temperature readings and heat extraction rates in operational RDCs.

A computationally efficient yet accurate dynamic hygro-thermal model of an RDC with the capability to include effects of door openings has been developed and presented in Article 2. The model was validated showing good conformity between measured and calculated temperatures, heat extraction demand and run-off condensate water vapour.

By using assuming different operational scenarios of an RDC, ranging from a nigh-time idle state to normal operations during opening hours, the model's ability to predict the near future temperature development and heat extraction demand of an RDC was demonstrated. Thus, the model contributes to enabling demand response by supermarkets as it could provide the forecasts of the necessary temperature constraints, limiting the duration for which the supermarket could attend to a demand response request.

Article 3 presented a novel methodology for generating data on customer interactions with RDCs, i.e. the speed, duration, angle and frequency that the doors are operated at during weekdays and weekends, for both MT and LT RDCs. Both the findings and the presented methodology act as an important stepping-stone towards creation of predictive algorithms for refrigeration control systems.

By adapting the Co-heating test, originally developed for building applications, an accurate and resource-efficient method for the thermal characterisation of RDCs has been developed, as presented in Article 4. The method evaluates infiltration rates within the 10% limit compared with the condensate collection method. In addition, data on thermal performance, such as the heat transfer coefficient for the envelope and its thermal inertia, can be measured in a systematic way.

The hygrothermal model (Article 2) together with the methodology for generation of thermal performance parameters (Article 4) and the in-depth analysis of customer interaction with RDCs in operational supermarkets (Article 3), together assembles a suite of studies that further enables a more in-depth understanding of demand response by supermarkets, aligned with the scope of this thesis.

Thus, this suite could be used to enable and further evaluate demand response capacity by RDCs, and potentially included in control systems and large scale MPC for the demand response optimisation problem for the grid.

Future work

To improve the generated predictions, more comprehensive studies on door operations and customer interactions should be conducted, possibly utilising the methodology presented in Article 3 to gather data on the interactions with the RDCs, thereafter translating the variations in customer interaction to thermal load by utilising the Co-heating method, as presented in Article 4.

Future research on the actual aggregated capacity of supermarkets contributing to demand-side management by demand response, with top-down models following the constraints of RDCs by the inclusion of the hygrothermal model presented in Article 2 would provide more accurate insights in actual capacity. Thus, adapting the model for inclusion in such a large scale setting would be necessary.

Another interesting direction of development and research is the integration of thermal energy storage, e.g. PCM, in the refrigeration systems, possibly allowing extending the demand response capacity.

As briefly discussed above, another aspect of interest for future research would be to evaluate alternative control strategies, both on how the conditions in the RDC are monitored and how the control system responds to adjust it.

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Appendix