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Vinther, Kasper; Rasmussen, Henrik; Izadi-Zamanabadi, Roozbeh; Stoustrup, Jakob; G. Alleyne, Andrew

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Learning Based Precool Algorithms for Exploiting Foodstuff as Thermal Energy Reserve

Kasper Vinther, *Student Member, IEEE,* Henrik Rasmussen, Roozbeh Izadi-Zamanabadi, Jakob Stoustrup, *Senior Member, IEEE,* and Andrew G. Alleyne, *Senior Member, IEEE*

***Abstract*—Refrigeration is important to sustain high foodstuff quality and lifetime. Keeping the foodstuff within temperature thresholds in supermarkets is also important due to legislative requirements. Failure to do so can result in discarded foodstuff, a penalty fine to the shop owner, and health issues. However, the refrigeration system might not be dimensioned to cope with hot summer days or performance degradation over time. Two learning based algorithms are therefore proposed for thermostatically controlled loads, which precools the foodstuff in display cases in an anticipatory manner based on how saturated the system has been in recent days. A simulation model of a supermarket refrigeration system is provided and evaluation of the precool strategies shows that negative thermal energy can be stored in foodstuff to cope with saturation. A system model or additional hardware is not required, which makes the algorithms easy to implement in existing systems.**

***Index Terms*—Control systems, Temperature control, learning, precool, refrigeration, thermal storage.**

I. Introduction

SUPERMARKETS require refrigeration systems in order to maintain a high quality and lifetime of foodstuff, which is achieved by keeping the food at low temperatures. These refrigeration systems have multiple fridge and freezer display cases each equipped with local control of the air temperature inside the display case. A refrigerant is used to ensure transport of heat, which is achieved by proper control of pressures and mass flows inside the refrigeration system using compressors, valves, and fans. Further description of refrigeration systems is given later and examples of modeling of such systems can be found in [1]–[6].

Depending on the type of foodstuff there will be different legislative temperature thresholds, that must be maintained. In Denmark the Danish Veterinary and Food Administration (DVFA) conducts yearly checks of the supermarkets to ensure that regulations are met and that the legally required self-checks have been performed. The thresholds and inspection rules can be found in [7], [8] and depending on the type of food the fridges should typically be operated below $5°C$ and freezers should be operated below -18$°C$. If the DVFA inspects the supermarket and some of the foodstuff is maintained outside the limits, then that could result in discarded foodstuff and possibly a fine depending on the severity. Apart from regulatory requirements, proper temperature control avoids bacteria growth and resulting food safety risk, which is very important to the overall society.

The main contributors to changes in the load on supermarket refrigeration systems are the outside air temperature, which determines the high pressure set point for the condenser unit, and the daily opening and closing of the supermarket, which changes the load on the individual display cases. Refrigeration systems are therefore usually dimensioned to cope with all weather conditions and loads in order to guarantee that the foodstuff can be maintained within the prescribed temperature bounds independent of the ambient temperature. A negative aspect of over-dimensioning a system is higher peak power demand, which is costly and could require larger transformers or extensions of transmission lines for large systems such as warehouses and supermarkets. An interesting alternative to over-dimensioning the system is to store energy in terms of ”coldness” for later use. It is possible to use the refrigerated food to store energy during the lightly loaded hours of the day; e.g. at night or early morning. In other words, precooling of foodstuff can be used to temporally shift some of the load on the refrigeration system to reduce the peak loads. Precooling can also help if the refrigeration system capacity changes such as becoming less efficient due to component wear or changes in refrigerant charge. The number of display cases might also have increased since the commissioning phase which puts further stress on the system.

Installation of thermal energy storage tanks can help solve capacity problems and provides a way to shift loads to off peak hours with cheaper energy and to hours where the outside temperature is lower. Examples of utilization of thermal storage tanks and/or building thermal capacity is given in [9]–[11]. However, a considerable additional capital investment is also associated with installation of thermal storage tanks.

Research has been invested in the use of foodstuff as thermal storage. The authors in [12] showed significant cost savings in four low temperature warehouses using load shifting strategies, where the foodstuff and building was cooled more during the night and less during the day. Model Predictive Control (MPC) has also been investigated as control strategy for predicting when precooling of foodstuff in supermarkets is required. MPC was e.g. used in [13] to store energy in the display case

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K. Vinther, R. Izadi-Zamanabadi, H. Rasmussen, and J. Stoustrup are with the Department of Electronic Systems, Aalborg University, 9220 Aalborg, Denmark (kv@es.aau.dk; riz@es.aau.dk; hr@es.aau.dk; jakob@es.aau.dk).

R. Izadi-Zamanabadi is also with the Department of Electronic Control and Services, Danfoss A/S, 6430 Nordborg, Denmark (roozbeh@danfoss.com).

A. G. Alleyne is with the Department of Mechanical Science and Engineering, University of Illinois, Urbana, 61801 - IL, USA (alleyne@illinois.edu)

to cope with capacity problems during hot summer days and in [14]–[16] to provide ancillary services to the Smart Grid. Furthermore, thermal storage potential of different foodstuffs has been investigated in [17].

To the knowledge of the authors, previous work has used either a predefined precool schedule or a MPC approach, due to its constraint handling capabilities. In Denmark, with a population of 5.6 million, there are roughly 4500 supermarkets and the refrigeration systems in these supermarkets are seldom completely similar. This potentially gives thousands of different systems and, as with the heuristically chosen schedule, a model based MPC approach is often tailored to a specific system where deriving a suitable model can be cumbersome and costly. Changes in load patterns, operating conditions, and storage capacity will also occur during the year. Finally, system parameters also change due to e.g. reduction in refrigerant charge, faulty components, or component wear. These approaches therefore often lack flexibility, modularity and robustness towards changes.

Two alternative model free precool strategies are investigated in this paper in order to reduce the effect of system saturation on hot days. The first precool strategy was first introduced in [18], where precooling is applied individually to each fridge display case. The second strategy applies the precooling to the freezer section, since the freezers have slower dynamics and a wider dynamic range and thus higher storage potential. The strategies are inspired by learning based control methods, where Repetitive Control (RC) and Iterative Learning Control (ILC) are two examples of such methods. These methods are well covered in the literature (see e.g. [19]–[21]) and are often used in batch processes where a task is repeated. This makes it possible to learn a performance improving reference modifying signal (Serial ILC/RC) or a feedforward signal (parallel ILC/RC) for the next repetition of that task. Analysis of data from a Danish medium size supermarket system have shown that there is also a certain amount of daily repeatability in the operation of refrigeration systems. The proposed strategies are therefore devised to learn how much precool is needed and when it is needed based on data from previous days. The precooling can then be applied in the next day by temporarily lowering the air temperature thresholds within permissible bounds for the display cases controlled by on/off hysteretic control. The solutions do not require system model knowledge as MPC. They can be applied directly to existing lower level control without additional hardware, and they are tested on a realistic simulation model of a supermarket refrigeration system.

Data from a Danish supermarket is analyzed in Section II and a simulation model of a supermarket refrigeration system with typical control loops is provided in Section III. The precool strategies are then derived in Section IV and simulation results are presented in Section V. Finally, concluding remarks are given in Section VI.

II. Analysis of Medium Size Supermarket Refrigeration System Data

Data from a Danish medium size supermarket refrigeration system has been available through the ESO2 project [22].

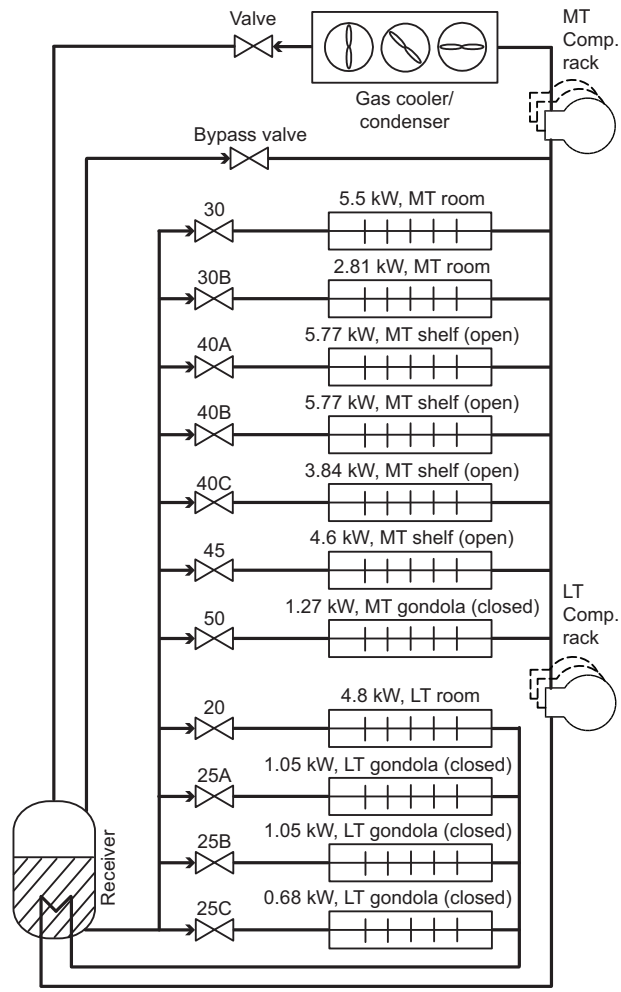

Fig. 1. Simplified schematic of the medium size supermarket refrigeration system. The numbers on the valves are used as reference.

The supermarket is open every day between 8 am and 9 pm and the main components of the refrigeration system are seven medium temperature (MT) storage evaporators, four low temperature (LT) storage evaporators, two compressors for the MT storages, two compressors for the LT storages, a bypass valve (BP), a gas cooler/condenser, and a receiver. The refrigerant in the system is CO_2 (R744) and data are logged with a sample time of 60 seconds. A schematic of the system is shown in Fig. 1. The work done by each of the two compressor racks can be estimated from the available data by

$$\dot{W}_{comp} = \frac{C_{cap}}{100} \dot{V}_{comp,max} \rho_{suc} \left(h_{ic} - h_{oe} \right), \tag{1}$$

where C_{cap} is the requested capacity in % and $\dot{V}_{comp,max}$ is the volumetric flow rate at maximum capacity, which is approximated by a constant value. The refrigerant density in the suction line ρ_{suc}, specific enthalpy out of the compressor rack h_{ic}, and the specific enthalpy into the compressor rack h_{oe} is determined based on temperature and pressure measurements and refrigerant property tables (Software package RefEqns is used [23]). The collected cooling loads from the MT section, the LT section, and the BP valve are estimated as

$$\dot{Q} = \dot{m}_r \Delta h, \tag{2}$$

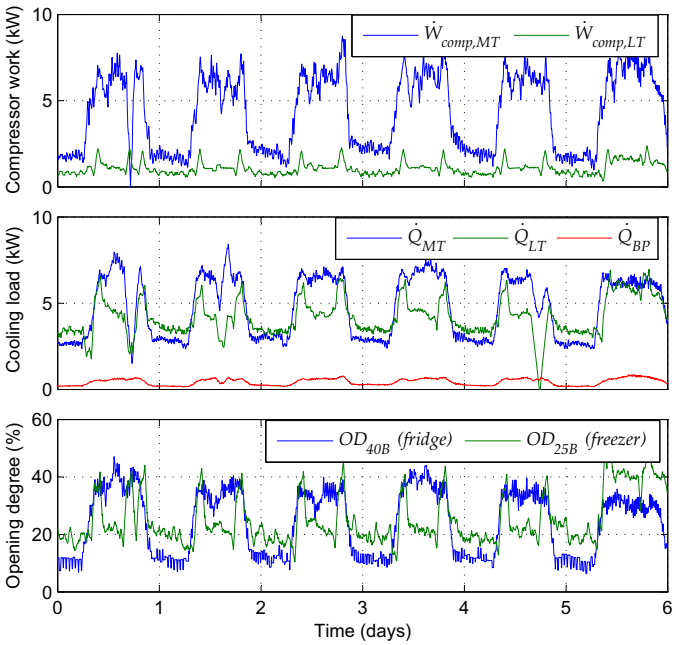

Fig. 2. Filtered supermarket data for six consecutive days in September 2011. The top graph shows the estimated work of the compressor racks. The middle graph shows the estimated cooling loads. The bottom graph shows the opening degree OD of a fridge and a freezer display case.

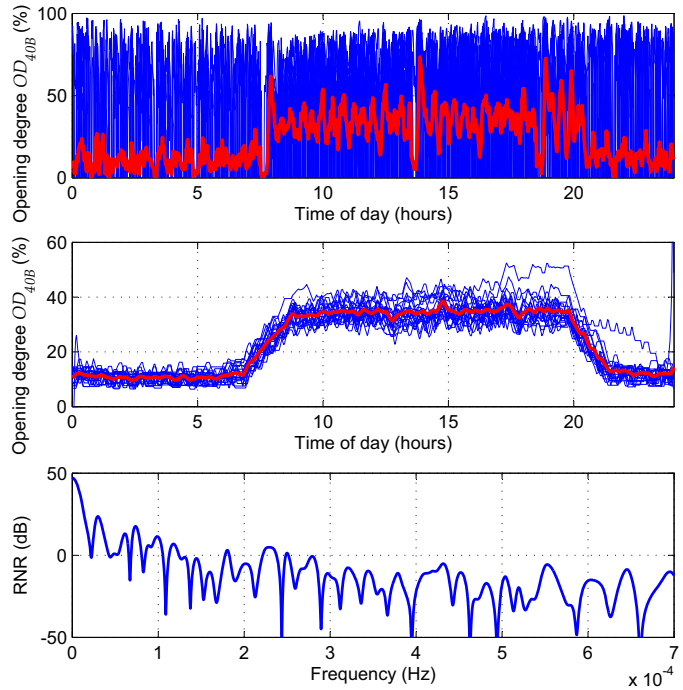

Fig. 3. Analysis of fridge valve signal based on 20 days of data from a supermarket. The top graph shows the 20 days of data in blue and the mean of this data in red. The middle graph shows the smoothed (low pass filtered) signal for each day in blue and the mean in red. The bottom graph shows the repeatable to non-repeatable ratio (RNR) for each frequency based on the data shown in the top graph.

where $\dot{Q}$ is the heat transfer rate (cooling load), $\dot{m}_r$ is the refrigerant mass flow rate (measured by mass flow meters individually for the MT section, the LT section, and the BP valve), and Δh is the specific enthalpy difference between the refrigerant at the receiver and either the outlet of the evaporators or the BP valve. The enthalpies are again based on temperature and pressure measurements.

The compressor works, cooling loads, and valve opening degrees OD for a fridge and a freezer display case are shown for six consecutive days from 18. of September 2011 in Fig. 2. The variation in the data is large and Matlab's `smooth` function has therefore been used to filter the data to reveal the average tendency during the day. 60 samples are used to filter the compressor work and 120 samples are used to filter the cooling loads and the valve opening degree. The short drop in the compressor work and the cooling loads around 0.7 days and the drop in cooling load around 4.7 days are due to short periods with missing samples. Further, the two daily peaks in the freezer valve signal around the supermarket opening and closing hours are caused by defrost cycles and is most visible in the freezers. A high degree of repeatability between the days is seen in terms of an increase in the load in the opening hours during the daytime, which is not surprising. The repeatability is mostly visible in the MT section and in open shelf type display cases. The refrigeration system does not saturate. However, if saturation would occur it would most likely be mid day, mid opening hours, and on hot summer days.

Fig. 3 shows further analysis of the fridge valve signal based on 20 days of data from September and November 2011. In [24], a way to calculate a Repeatable-to-Nonrepeatable Ratio (RNR) of a signal is proposed when the signal or system undergoes repetitions (e.g., each day). This can be done for all frequencies in the signal and a ratio above zero dB means that the power of the repeatable part of the signal is larger than the power of the nonrepeatable part. RNR is calculated as

$$RNR = 20log\left(\frac{|FFT\left[\bar{\mathbf{s}}\right]|^2}{\frac{1}{N_r}\sum_{j=1}^{N_r}|FFT\left[\bar{\mathbf{s}}-\mathbf{s}_j\right]|^2}\right), \quad (3)$$

where FFT denotes the Fast Fourier Transform, N_r is the number of repetitions/days used in the analysis, and the repeatable or mean part of the signal is

$$\bar{\mathbf{s}} = \frac{1}{N_r}\sum_{j=1}^{N_r}\mathbf{s}_j, \quad (4)$$

where $\mathbf{s}_j$ is a vector of the sampled signal in repetition j. The RNR calculation is applied on the valve data shown in the top graph in Fig. 3, where the red plot is the mean part of the 20 repetitions. The RNR result is shown in the bottom plot, which indicates that there is high repeatability for low frequencies. The second peak in RNR is located at a frequency with a period of approximately 9 hours, which corresponds to the third harmonic of a square signal generated by the opening hours of the supermarket, where the load is higher. This is also supported by the middle graph, which shows a relatively small day to day variation in the low pass filtered valve opening degree. Note that the variation in the unfiltered valve signal, shown in the top graph, is large due to on/off hysteretic control (see additional detail in Subsection III-D)

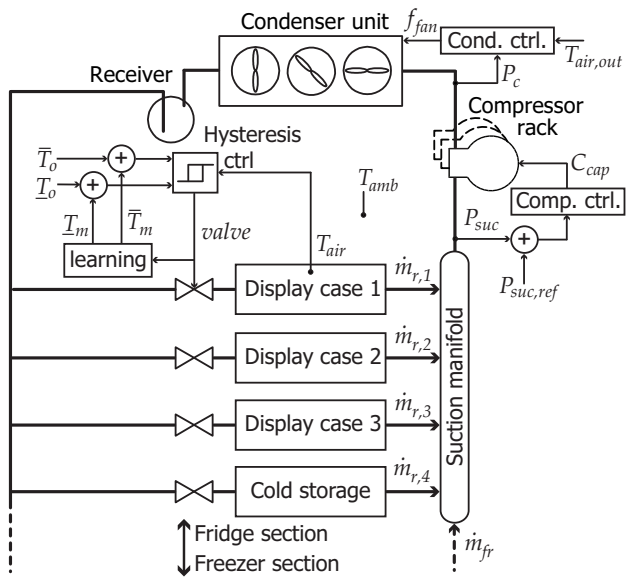

Fig. 4. Overview of supermarket refrigeration system model with multiple display cases and a cold storage room. The freezer section is simulated by an additional mass flow $\dot{m}_{fr}$ and controllers are used to regulate pressures and temperatures as indicated. Only one of the valve hysteresis controllers are shown in the figure.

and that low pass filtering the signal can give an indication of the load or capacity utilization in each evaporator. Further, note that the RNR calculation could, as a general tool, be applied on past data and used to evaluate if there is potential for a learning based control strategy and at which frequencies to apply it.

III. Supermarket Refrigeration System Model and a Standard Control Approach

Making yearlong tests and introducing saturation on the refrigeration system in an operating supermarket is not practically feasible. A benchmark model of a typical supermarket refrigeration system is therefore derived for simulation purposes with a focus on simulating air and foodstuff temperature. The typical control of such systems is also implemented and an overview of the simulation environment is provided in Fig. 4. This model makes it possible to evaluate the performance of different precool strategies and compare them under the same conditions, which would also not be possible with a real system. The model was first presented in [18] and represents a slightly modified version of a benchmark model widely studied in the literature, see [1], [2], [25], [26]. The major modification made is that the effect of changes in the outside air temperature can now result in saturation of the system on hot days due to a higher required compressor work. The model implemented in Matlab Simulink is available at www.es.aau.dk/projects/refrigeration/simulation-tools.

A. Fridge Display Case model

A model of an open shelf type display case with night cover is illustrated in Fig. 5 with indication of heat transfer paths. The heat transfer rates are between the evaporator wall and the refrigerant $\dot{Q}_e$, between the air that circulates over the

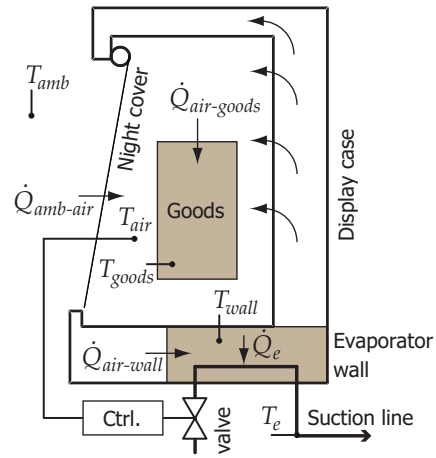

Fig. 5. Open shelf type display case model with night cover.

evaporator and the evaporator wall $\dot{Q}_{air-wall}$, between the air and the foodstuff $\dot{Q}_{air-goods}$, and between the ambient air and the air in the display case $\dot{Q}_{amb-air}$. Heat transfer caused by infiltration of air into the display case is assumed to be included in $\dot{Q}_{amb-air}$ and a lumped temperature model is used for simplicity. This gives the following differential equations for the temperatures:

$$\frac{dT_{goods}}{dt} = \frac{\dot{Q}_{air-goods}}{m_{goods}C_{p,goods}}, \tag{5}$$

$$\frac{dT_{wall}}{dt} = \frac{\dot{Q}_{air-wall} - \dot{Q}_e}{m_{wall}C_{p,wall}}, \tag{6}$$

$$\frac{dT_{air}}{dt} = \frac{\dot{Q}_{amb-air} - \dot{Q}_{air-goods} - \dot{Q}_{air-wall}}{m_{air}C_{p,air}}, \tag{7}$$

where m is mass, C_p is the specific heat capacity, and the heat transfer rates are given as

$$\dot{Q}_{air-goods} = UA_{air-goods}(T_{air} - T_{goods}), \tag{8}$$

$$\dot{Q}_{air-wall} = UA_{air-wall}(T_{air} - T_{wall}), \tag{9}$$

$$\dot{Q}_e = UA_{wall-r}(T_{wall} - T_e), \tag{10}$$

$$\dot{Q}_{amb-air} = UA_{amb-air}(T_{amb} - T_{air}). \tag{11}$$

Here, T_e is the evaporation temperature of the refrigerant and UA denotes the overall heat transfer coefficient.

The heat transfer coefficient UA_{wall-r}, between the evaporator wall and the refrigerant, is predominantly a function of the mass of liquid refrigerant m_r in the evaporator given as

$$UA_{wall-r} = \overline{UA}_{wall-r}\frac{m_r}{\overline{m}_r}, \tag{12}$$

where $\overline{m}_r$ is the maximum mass of liquid refrigerant and $\overline{UA}_{wall-r}$ is the heat transfer coefficient when the evaporator is fully filled and maintained at a superheat level of $T_{sh} = 10K$ (it is assumed that the superheat is controlled to this level when the valve is on). The rate of change of the mass of the refrigerant $\frac{dm_r}{dt}$ is simulated as

$$\frac{dm_r}{dt} = \begin{cases} \frac{\overline{m}_r - m_r}{\tau_{fill}} & \text{if } valve = 1, \\ -\frac{\dot{Q}_e}{\Delta h_{lg}} & \text{if } valve = 0 \text{ and } m_r > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{13}$$

where $valve$ is the control signal to the valve (either on or off), τ_{fill} is the time it takes to fill the evaporator from empty to full, and the specific latent heat of the remaining refrigerant is denoted Δh_{lg}.

B. Supermarket Refrigeration System Model

The mass flow from each display case, the suction pressure, and the compressor power is simulated to observe the effect of system saturation and precooling.

The dynamics of the condenser unit and the control on the condenser are assumed stable and fast compared to the rest of the system. A static relation is therefore used for the condensation temperature $T_c = T_{a,out} + 5$, where it is kept at a reference $5°C$ above the outside temperature $T_{a,out}$.

The mass flow of refrigerant from each display case i into the suction manifold can be formulated as

$$\dot{m}_{r,i} = \frac{\dot{Q}_e}{\Delta h_{lg}}. \tag{14}$$

The time derivative of the suction pressure is then defined as

$$\frac{dP_{suc}}{dt} = \frac{\sum_{i=1}^{n} \dot{m}_{r,i} + \dot{m}_{fr} - \dot{V}_{comp}\rho_{suc}}{V_{suc}\frac{d\rho_{suc}}{dP_{suc}}}, \tag{15}$$

where V_{suc} is the volume of the suction manifold, ρ_{suc} is the density, $\dot{V}_{comp}$ is the volume flow out of the manifold caused by the compressor work, and $\dot{m}_{fr}$ is additional mass flow from the freezer section.

The electrical power consumed by the compressor $\dot{W}_{comp}$ is finally approximated by

$$\dot{W}_{comp} = \frac{C_{cap}}{100}\dot{W}_{comp,max} = \frac{\dot{V}_{comp}\rho_{suc}\left(h_{is} - h_{oe}\right)}{\eta}, \tag{16}$$

where the controllable input C_{cap} is the requested capacity in %, $\dot{W}_{comp,max}$ is the power consumption at maximum capacity, h_{oe} and h_{is} are the specific enthalpies in and out of the compressor assuming an isentropic compression, and η is the efficiency from an isentropic process to the actual electrical power consumed.

A set of refrigerant specific relations are needed in order to solve the above equations. Software packages such as RefEqns [23] can be used for this purpose. However, to make the simulation independent of this package, a set of polynomial and regression fits to the refrigerant tables in RefEqns are provided here for refrigerant R404A (all-round refrigerant good for both fridges and freezers):

$$\rho_{suc} = 4.669P_{suc} + 0.3672, \tag{17}$$

$$\frac{d\rho_{suc}}{dP_{suc}} = 4.669, \tag{18}$$

$$\Delta h_{lg} = (0.00184P_{suc}^2 - 0.0683P_{suc} + 2.0339)10^5, \tag{19}$$

$$\begin{aligned} h_{is} =& (3.6436 - 0.00968P_{suc} + 0.0343P_c \\ & - 0.0000495P_{suc}P_c + 0.000373P_{suc}^2 \\ & - 0.000629P_c^2)10^5, \end{aligned} \tag{20}$$

$$\begin{aligned} h_{oe} =& (0.000332P_{suc}^3 - 0.00853P_{suc}^2 + 0.0953P_{suc} \\ & + 3.3467)10^5 + \Delta h_{T_{sh}}, \end{aligned} \tag{21}$$

$$\begin{aligned} \Delta h_{T_{sh}} =& 9 \ (T_{sh} = 10K \text{ assumption}), \\ P_c =& 0.00307T_c^2 + 0.1839T_c + 6.0826. \end{aligned} \tag{22}$$

The specific enthalpy $\Delta h_{T_{sh}}$ is the average increase in enthalpy when the refrigerant is superheated 10 degree and P_c is the condensation pressure. The fits are made for the operating ranges used in the simulations.

C. Suction Pressure Control

A PI controller with anti-windup is typically used to maintain the suction pressure at a specified reference $P_{suc,ref}$. This is achieved by changing the capacity C_{cap} of the compressor rack to meet the mass flow demand and a dead-band DB and a slow update time $t_{s,comp}$ is often used to reduce the mechanical stress on the compressors by reducing the number speed changes required. It is assumed that C_{cap} can be changed in a continuous fashion, i.e. the compressor rack has at least one variable speed compressor. The control equations are given in (23)-(28) and also provided in e.g. [2].

$$e(k) = P_{suc,ref} - P_{suc}(k), \tag{23}$$

$$e_{DB}(k) = \begin{cases} e(k) & \text{if } |e(k)| > DB, \\ 0 & \text{otherwise,} \end{cases} \tag{24}$$

$$I(k) = I(k-1) + \frac{K_{p,comp}t_{s,comp}}{\tau_{i,comp}}e_{DB}(k) + w(k), \tag{25}$$

$$C_{cap,s}(k) = K_{p,comp}e_{DB}(k) + I(k), \tag{26}$$

$$C_{cap}(k) = \begin{cases} \overline{C}_{cap} & \text{if } C_{cap,s}(k) > \overline{C}_{cap}, \\ \underline{C}_{cap} & \text{if } C_{cap,s}(k) < \underline{C}_{cap}, \\ C_{cap,s}(k) & \text{otherwise,} \end{cases} \tag{27}$$

$$w(k+1) = \frac{t_{s,comp}}{\tau_{i,comp}}(C_{cap}(k) - C_{cap,s}(k)). \tag{28}$$

The tunable PI control parameters are $K_{p,comp}$ and $\tau_{i,comp}$ and k is the discrete time index.

D. Relay Feedback Control of Display Case Air Temperature

Refrigerated air is circulated over the foodstuff to cool it down and the air temperature T_{air} in each display cases is controlled with an on/off valve and relay feedback control (hysteretic control) given as

$$valve(k) = \begin{cases} 1 & \text{if } T_{air}(k) > \overline{T}_{air}, \\ 0 & \text{if } T_{air}(k) < \underline{T}_{air}, \\ valve(k-1) & \text{otherwise,} \end{cases} \tag{29}$$

where $\overline{T}_{air}$ and $\underline{T}_{air}$ define the upper and lower thresholds for the temperature and 0 and 1 corresponds to a fully closed or fully open valve, respectively. This type of control is very simple and a commonly used control method for regulating the temperature of a medium within bounds. The foodstuff temperature is usually not measured in supermarkets.

E. Representative Weather Data

A weather file for Phoenix, Arizona is used to simulate realistic high outdoor temperatures and load profiles on the refrigeration system. This data is based on typical meteorological year 2 (TMY2) weather data and shown in Fig. 6 for a year, which reveals the seasonal changes in temperature. The higher outdoor temperature during the summer period will also result in a higher load on the refrigeration system as the difference in condenser and suction pressure needs to be higher.

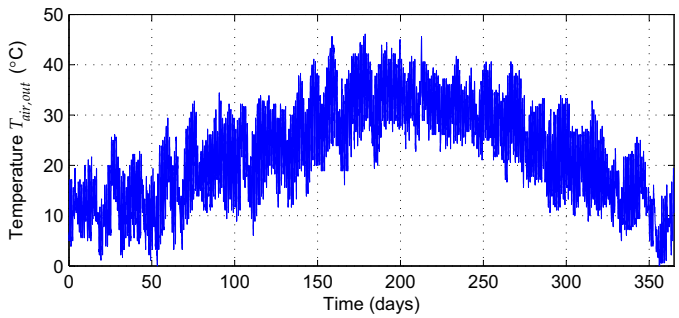

Fig. 6. Outdoor air temperature $T_{air,out}$ in Phoenix Arizona based on TMY2 weather data from 1st of January to 31st of December.

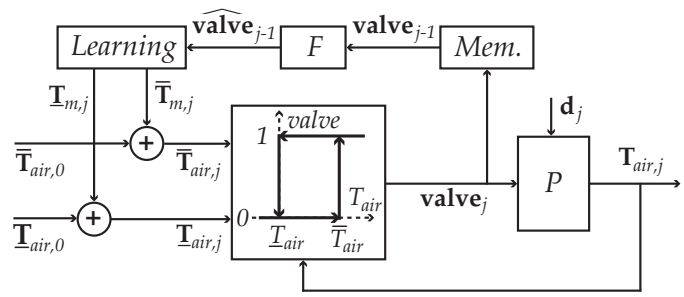

Fig. 7. Relay feedback controlled system P with adaption of the thresholds using a learning based approach. The trial domain is denoted j.

IV. Precool of Refrigerated Foodstuff

The potential for precooling of refrigerated foodstuff in supermarkets is investigated in this section, to be able to handle capacity saturation problems better. As stated in Subsection III-D, relay feedback (hysteretic control) is used as temperature control. In the following it is assumed that the thresholds on the output T_{air} can be shifted up or down within some legislative hard constraints. This is also the only possible way to apply precooling, if assuming that the foodstuff temperature T_{goods} is unknown and that the precool control should not change the original setup, but only modify the references/thresholds to the lower level controllers. Two precool algorithms are outlined at the end of the section, which are both based on a general learning based precool concept.

A. Learning Based Precool

A general way to apply precooling to thermostatically controlled systems is shown in Fig. 7, which illustrates the proposed solution using a trial domain notation, where the input and output vectors contain all the discrete samples in one trial j (for trial domain notation see e.g. [20]). The system is denoted P and it is disturbed by unknown disturbances $\mathbf{d}_j$ during trial j. These disturbances have some repeatable part from trial to trial (e.g. day to day). This repeatability was also presented in Section II. A memory block is used to save previous valve input signals $\mathbf{valve}_{j-1}$ and an estimate of the load on the system is obtained by filtering this signal giving the vector $\widehat{\mathbf{valve}}_{j-1}$. The idea is then to use this data to modify the initial air temperature threshold vectors $\overline{\mathbf{T}}_{air,0}$ and $\underline{\mathbf{T}}_{air,0}$ with the reference modifying vectors $\overline{\mathbf{T}}_{m,j}$ and $\underline{\mathbf{T}}_{m,j}$;

$$\overline{\mathbf{T}}_{air,j} = \overline{\mathbf{T}}_{air,0} + \overline{\mathbf{T}}_{m,j} \tag{30}$$

$$\underline{\mathbf{T}}_{air,j} = \underline{\mathbf{T}}_{air,0} + \underline{\mathbf{T}}_{m,j}. \tag{31}$$

By lowering the thresholds for a period of time it is possible to precool the foodstuff, since the air flowing across the foodstuff is colder in this period. Note that F can have zero phase shift properties and by low pass filtering the on/off signal a mean value or duty cycle is obtained. If this duty cycle reaches an upper limit during the trial $j-1$ it is likely to assume that it will happen again in trial j and preemptive action is taken by precooling in advance.

The reference modifying vectors are recalculated each trial and contain zeros except for the precool period where the values are set to $\overline{T}_m$ or $\underline{T}_m$, which are the allowed modification of the upper and lower thresholds. The precool period is determined by a length Δ and an end time t_{end}. The end time could either be based on when the duty cycle went into saturation in the previous trial, when it came out of saturation, or based on some known schedule like the opening hours of the supermarket. The length of the precool period is determined based on a serial ILC inspired learning algorithm;

$$\Delta_j = \Delta_{j-1} + \delta_{j-1} \tag{32}$$

$$\delta_{j-1} = \begin{cases} k_1\overline{\Delta} & \text{if } \left\|\widehat{\mathbf{valve}}_{j-1}\right\|_\infty \geq \overline{\widehat{valve}} \\ k_2\overline{\Delta} & \text{otherwise,} \end{cases} \tag{33}$$

where δ_{j-1} is the update and $\overline{\widehat{valve}}$ is the upper threshold on the duty cycle, which indicates if the system was saturated in the previous trial and if more or less precooling is required. The gains $k_1 \in]0,1]$ and $k_2 \in [-1,0[$ are the learning and delearning gains, where e.g. $k_1 = 1$ means that the maximum allowed precool time $\overline{\Delta}$ is reached in one trial and lower values mean slower convergence.

The upper limit on the precool time $\overline{\Delta}$ should approximately correspond with the time it takes to precool the foodstuff, since a longer precool time only results in an increase in power consumption. The precool time is therefore limited as

$$\Delta_j = \begin{cases} \overline{\Delta} & \text{if } \Delta_j > \overline{\Delta} \\ 0 & \text{if } \Delta_j < 0 \\ \Delta_j & \text{otherwise.} \end{cases} \tag{34}$$

Potential ways of determining a suitable maximum precool time is further discussed in Subsection IV-E.

Remark that the reference update is based on the error in the previous trial in serial ILC, whereas it is based on the saturation of the input in previous trials in the proposed solution. This strategy is chosen, because it does not help to change the reference signal to force precooling in the refrigeration system when the system is already saturated. Note also that $valve$ and T_{air} could be replaced by other inputs and outputs in other types of storage control problems, e.g. buffer tank level control or building indoor temperature control.

B. Simple Thermal Storage Example

A simple thermal storage example is presented in the following, to demonstrate the precool algorithm under perfect repeatability in load pattern and without multiple display cases.

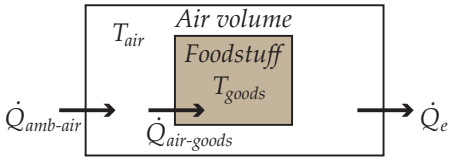

Fig. 8. Simple thermal example system model. The load disturbance is the heat transfer from the surroundings $\dot{Q}_{amb-air}$ and the controllable input is the heat transfer $\dot{Q}_e$.

TABLE I
PARAMETER VALUES USED IN THE SIMPLE THERMAL STORAGE EXAMPLE.

System par.	Value	Ctrl par.	Value
$UA_{air-goods}$	300 $(\frac{W}{K})$	$\overline{\Delta}$	4 $(hours)$
m_{air}	50 (kg)	k_1	$\frac{1}{4}$ (-)
$C_{p,air}$	1 $(\frac{kJ}{kg \cdot K})$	k_2	$-\frac{1}{12}$ (-)
m_{goods}	500 (kg)	ω_F	$8.7E^{-4}$ $(\frac{rad}{s})$
$C_{p,goods}$	4 $(\frac{kJ}{kg \cdot K})$	$\overline{\widehat{\dot{Q}}}_e$	$0.99\overline{\dot{Q}}_e$ (W)
$\overline{\dot{Q}}_e$	2850 (W)	t_{end}	9 $(hours)$
$\underline{\dot{Q}}_e$	0 (W)	$\overline{T}_m$	-3 $(°C)$
		$\underline{T}_m$	-2 $(°C)$

Fig. 8 shows a model of the system, which is essentially a very simplified refrigeration system. Relay feedback control was applied on the air temperature T_{air} with the heat transfer going out of the system $\dot{Q}_e$ as an on/off type input with $\overline{\dot{Q}}_e$ and $\underline{\dot{Q}}_e$ as the on and off signals, respectively (note that the heat transfer is controlled directly instead of the valve signal). The load on the system $\dot{Q}_{amb-air}$ was simulated as a square signal that repeats itself daily. The upper value is higher than the possible cooling $\overline{\dot{Q}}_e$, which will result in input saturation and thus temperature deviation. The objective is to keep the foodstuff temperature T_{goods} below $5°C$.

A state space representation of the system illustrated in Fig. 8 can be derived from (5), (7), and (8) giving

$$\begin{bmatrix} \dot{T}_{air} \\ \dot{T}_{goods} \end{bmatrix} = \begin{bmatrix} \frac{-UA_{air-goods}}{m_{air}C_{p,air}} & \frac{UA_{air-goods}}{m_{air}C_{p,air}} \\ \frac{UA_{air-goods}}{m_{goods}C_{p,goods}} & \frac{-UA_{air-goods}}{m_{goods}C_{p,goods}} \end{bmatrix} \begin{bmatrix} T_{air} \\ T_{goods} \end{bmatrix} + \begin{bmatrix} \frac{-1}{m_{air}C_{p,air}} \\ 0 \end{bmatrix} \dot{Q}_e + \begin{bmatrix} \frac{1}{m_{air}C_{p,air}} \\ 0 \end{bmatrix} \dot{Q}_{amb-air}, \quad (35)$$

and system and control parameters used in the simulation are collected in Table I. The low pass filter F is implemented using the Matlab command `butter` with a cutoff frequency $\omega_F = 8.7E^{-4}$ radians/s. Furthermore, `filtfilt` is used to make the filter have zero phase shift properties and this gives a good estimate of the average load $\widehat{\dot{Q}}_e$. The precool time is then increased if $\widehat{\dot{Q}}_e > 0.99\overline{\dot{Q}}_e$ (99% of maximum capacity).

The results using a maximum load of 3 kW is shown in Fig. 9. The foodstuff temperature increased to $6.6°C$ without precooling, because the load became too large at 9 in the morning each day. This was lowered to $4.5°C$ after four days, when precooling was applied with the chosen learning gain.

A similar simulation was performed with a maximum load on the air of 2.8 kW and the results are shown in Fig. 10. The algorithm cycled between different values of

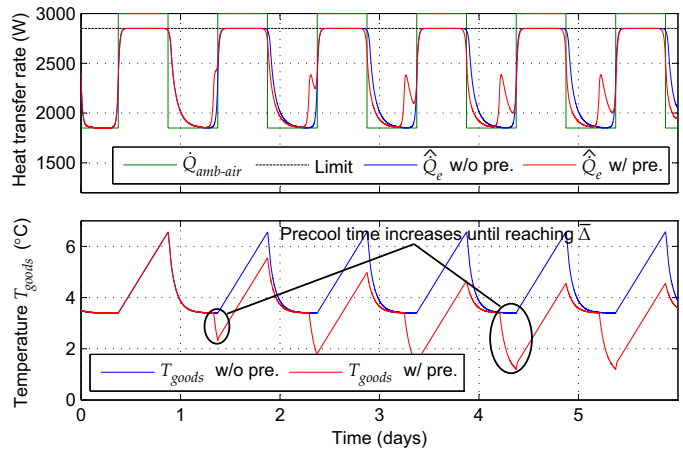

Fig. 9. Simulation results with and without precool using the simple example model with a max load of 3 kW and an upper limit on $\dot{Q}_e$ of 2.85 kW.

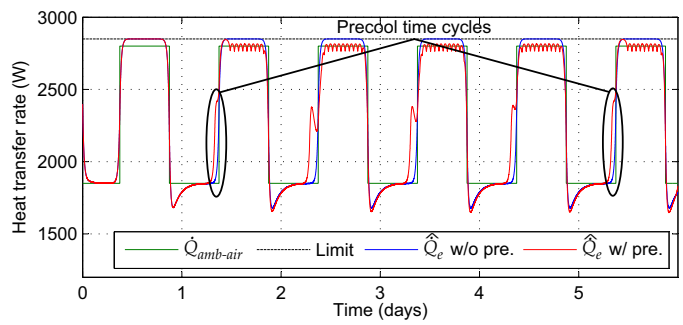

Fig. 10. Simulation results with and without precool using the simple example model with a max load of 2.8 kW and an upper limit on $\dot{Q}_e$ of 2.85 kW.

precool time on a four day basis. The precool times are $\Delta_j = \{0, 60, 120, 100, 80, 60, 120, 100, 80, 60, ...\}$ minutes of precool and the required precool time that just exactly removes the saturation is approximately 70 minutes. This value can not be reached with the chosen learning gains, since the they discretize the obtainable precool times.

C. Convergence of the Precool Time in the Trial Domain

The precool period will cycle between levels of precool time as indicated in Fig. 10 and the levels are determined by k_1 and k_2. The jump between levels can be made smaller by decreasing the learning and de-learning rates (k_1 and k_2), but that will also result in slower convergence.

If there is total repeatability between trials and if Δ^* denotes the smallest possible precool time that avoids input saturation, i.e. $\Delta^* = \inf\left\{\Delta : \left|\left|\widehat{\textbf{valve}}\right|\right|_\infty < \overline{\widehat{valve}}\right\}$, then the precool time Δ_j will converge to the interval

$$\Delta^* + k_2\overline{\Delta} < \Delta_j \leq \Delta^* + k_1\overline{\Delta}, \quad (36)$$

when $\Delta^* + k_2\overline{\Delta} \geq 0$ and $\Delta^* + k_1\overline{\Delta} \leq \overline{\Delta}$. Furthermore, if no precooling is required ($\Delta^* \leq 0$) then $\Delta_j \to 0$ and if maximum precooling is required ($\Delta^* > \overline{\Delta}$) then $\Delta_j \to \overline{\Delta}$.

Since no precool is cheapest in terms of energy, then k_1 should be small and k_2 should be large numerically (removes precool quickly again). However, if robustness towards hot days is more important, then it should be the opposite.

D. Foodstuff Storage Potential Considerations

The time it takes to precool the foodstuff should be reflected in the choice of $\overline{\Delta}$. The temporal thermal storage potential of different refrigerated foodstuffs is predominantly determined by the foods total surface area, mass, overall heat transfer coefficient, and specific heat capacity. The Biot number B is also an important factor and it is the ratio of internal temperature difference required to move energy within a product compared to the difference required at the surface to add or remove the same energy. The Biot number therefore gives an indication of the appropriateness of a lumped versus a non-lumped temperature analysis and defined as [27]

$$B = \frac{U\frac{V}{A}}{k}, \tag{37}$$

where A is the exposed surface area of the product, V is the volume, U is the surface heat transfer coefficient, and k is the thermal conductivity. A lumped analysis can be applied if the Biot number is small ($B < 0.1$), which means that the temperature will not vary significantly inside the product and a non-lumped analysis is more appropriate if B is large.

[17] provides experimentally obtained Biot numbers for different type of foods, which indicate that they are generally above 0.1. However, a lumped analysis is often performed despite of this, because it does not involve solving complex multidimensional partial differential equations. The lumped approach is also taken here for two additional reasons; because the entire mass of the foodstuff can be activated during precooling and because the system only gradually becomes more saturated, due to a slowly changing average air temperature, caused by the increasing outside temperature, which changes slowly over several hours.

A large increase is seen, in the overall heat transfer coefficient between the air in the store and the air inside the display case, when the supermarket is open, since the insulating night cover in open shelf type display cases has to be removed in this period. This also coincides with customer activity, which gives an increased heat load and the behavior is included in the simulations presented in Section V. The constant flow of foodstuff from store to display cases to the customers (out of the store) is therefore included in the behavior of the overall heat transfer coefficient, since no specific data was available on how much food is moved during the day due to confidentiality. Additionally, since foods have different thermal storage potential, different combinations of UA values and mass times specific heat mC_p is used in each display case. This gives different time constants and a step in the air temperature from 3.5 to $1°C$ using (5) is performed in order to determine how long it takes to precool the food. The time is measured as the time from the step to when 90% of the step is reached and the result is shown in Fig. 11. This gives 166 minutes for Display case 1, 250 minutes for Display Case 2, 500 minutes for Display Case 3, and 300 minutes for the cold storage room. They therefore represent different time constants and storing potentials.

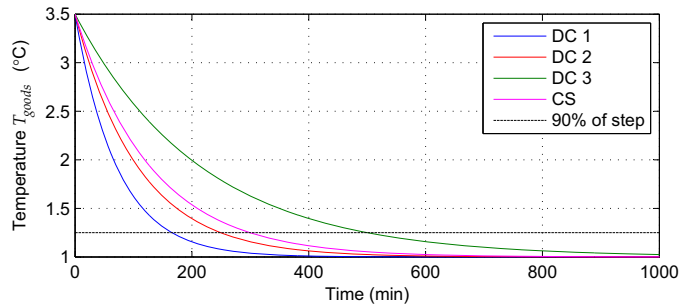

Fig. 11. Food temperature during a step in the air temperature.

E. Precool Algorithms and Tuning Guideline

Ad hoc tuning guidelines are provided here based on simulations and experience with supermarket refrigeration systems. The parameters can also be tuned after installation if needed.

1) Learning gains k_1 and k_2: Tuning of these parameters was discussed in Subsection IV-C and they should have a value in the intervals $k_1 \in]0, 1]$ and $k_2 \in [-1, 0[$. Setting $k_1 = 1$ and k_2 small gives the safest option, but will often result in more precooling than necessary. The choice should reflect how changeable the weather can be expected to be. Simulations with the weather data presented in Fig. 6 have shown that $k_1 = \frac{1}{4}$ and $k_2 = -\frac{1}{12}$ gives a good tradeoff between ensuring precooling when needed and energy consumption.

2) Filter parameters ω_F and $\overline{\widehat{valve}}$: A zero phase shift low pass filter is used to convert the valve on/off signal to a duty cycle (utilized capacity). The filter therefore depends on the approximate switching period of the valves, which is usually between 5-15 minutes in display cases. A cutoff frequency of $\omega_F = 5.82E^{-4}$ rad/s is used in the following, which corresponds to a period of three hours. The duty cycle threshold $\overline{\widehat{valve}}$ is set to 0.99. Precooling is thus activated when the utilized capacity reaches 99% of maximum on previous days.

3) Maximum precool time $\overline{\Delta}$: The maximum precool time is individual for each display case and could either be based on experiments or experience. It should approximately be the time it takes to cool the foodstuff down from the normal steady state temperature to the steady state value using the precool thresholds, see also Subsection IV-D. A potential way to reveal the time constant of the foodstuff temperature, when this temperature is not measured, could be to make a step down in the air temperature thresholds and then monitor how long it takes the valve duty cycle to settle after the step. This is possible because the valve duty cycle settles when the foodstuff temperature has settled. The test could either be performed during initial startup, as part of an automatic night procedure, or it could be based on the previous precool cycle.

4) Precool end time t_{end}: The placement of the precool period could be based on supermarket opening hours, energy tariffs if they are known in advance, experience, etc. An alternative is to update it automatically, since the estimated duty cycle also gives an indication of when the system was saturated on the previous day. The precool period should then be placed before this period and should be extended into the

saturation period to ensure that the stored thermal energy is kept for as long as possible in the local fridges. The automatic approach is used in the simulation in Subsection V-A and a fixed t_{end} corresponding to the opening of the supermarket is used in the simulation in Subsection V-B. However, note that both strategies for choosing t_{end} could have been used in the two simulated case studies.

The two precool strategies are outlined in the pseudocode denoted algorithm 1 and 2. The first algorithm applies precool individually in each fridge display case and finds t_{end} automatically. An algorithm is needed for each of the fridges:

Initialize $\Delta = 0$, $n = 0$, $\overline{\mathbf{T}}_m = \mathbf{0}$, $\underline{\mathbf{T}}_m = \mathbf{0}$, $t_{end} = 0$
Wait until midnight (start of new trial)
function ALGORITHM_1($valve$)
  if n has reached 24 hours of data **then**
    Reset n
    Filter **valve** to get $\widehat{\mathbf{valve}}$
    Find longest saturation period in $\widehat{\mathbf{valve}}$
    if system is saturated **then**
      Set t_{end} at start of long saturation period
    end if
    Update Δ according to (32), (33), and (34)
    Set $\overline{\mathbf{T}}_m = \mathbf{0}$ and $\underline{\mathbf{T}}_m = \mathbf{0}$
    Insert precool in $\overline{\mathbf{T}}_m$, $\underline{\mathbf{T}}_m$ using Δ, t_{end}, $\overline{T}_m$, $\underline{T}_m$
    Extend precool to include saturation period
  else
    Increment n
  end if
  Set new temperature thresholds in fridge display case: $\overline{T}_{air} = \overline{\mathbf{T}}_{air,o}(n) + \overline{\mathbf{T}}_m(n)$, $\overline{T}_{air} = \overline{\mathbf{T}}_{air,o}(n) + \overline{\mathbf{T}}_m(n)$
  Save **valve**$(n) = valve$
end function

The second algorithm determines if any of the m number of fridges are saturated and then applies precooling in the freezer section instead and uses a fixed t_{end}. An algorithm is needed for each individual freezer display case or room:

Initialize $\Delta = 0$, $n = 0$, $\overline{\mathbf{T}}_m = \mathbf{0}$, $\underline{\mathbf{T}}_m = \mathbf{0}$, $t_{end} = 0$
Wait until midnight (start of new trial)
function ALGORITHM_2($valve_1$,$valve_2$,...,$valve_m$)
  if n has reached 24 hours of data **then**
    Reset n
    for $i = 1, m$ **do**
      Filter $\mathbf{valve}_i$ to get $\widehat{\mathbf{valve}}_i$
    end for
    Update Δ according to (32), (33), and (34)
    Set $\overline{\mathbf{T}}_m = \mathbf{0}$ and $\underline{\mathbf{T}}_m = \mathbf{0}$
    Insert precool in $\overline{\mathbf{T}}_m$, $\underline{\mathbf{T}}_m$ using Δ, t_{end}, $\overline{T}_m$, $\underline{T}_m$
  else
    Increment n
  end if
  Set new temperature thresholds in freezer: $\overline{T}_{air} = \overline{\mathbf{T}}_{air,o}(n) + \overline{\mathbf{T}}_m(n)$, $\overline{T}_{air} = \overline{\mathbf{T}}_{air,o}(n) + \overline{\mathbf{T}}_m(n)$
  Save **valve**$(n) = valve$
end function

Both Algorithm 1 and 2 should run with the same sample time as the $valve$ signal being updated.

V. Simulation Results

First, Algorithm 1 is simulated, for an entire year starting from 1st of January using the weather data shown in Fig. 6. The size of the compressor is dimensioned so that the temperature of the foodstuff stays below $5°C$ in all display cases and in the cold storage room even during the hottest day in the year, if the air temperature thresholds are kept on the low settings constantly (constant precool). This is the most costly scenario in terms of energy and if there is no precool, then there will be some days where the temperature of the foodstuff exceeds $5°C$. The precool algorithm is therefore compared with these two extremes in terms of both keeping the energy consumption and the temperature low.

Algorithm 2 is also simulated for a year. The difference here is that precooling is applied to the freezer section. A small extension of the model presented in Section III-B is therefore required. All freezer section foodstuff is lumped together and represented by the temperature of the foodstuff $T_{goods,fr}$ and simulated using (5). The load heat transfer rate is calculated as in (8) and the cooling heat transfer rate is calculated using (14), where the change in enthalpy Δh_{fr} is approximated with a constant, since it is assumed that the low temperature pressure can be maintained at a constant level. The controllable input is the mass flow from the freezer section, which is allowed to vary $\pm 30\%$ around the nominal value $\dot{m}_{fr} = 0.05$ kg/s. The nominal value is the value used in the first simulation and corresponds to the required mass flow for keeping $T_{goods,fr}$ at the setpoint -18$°C$ in steady state. This makes the simulations comparable and does not require modeling and simulation of multiple freezer display cases and an additional compressor rack. A simple PI temperature controller is used to control the mass flow to make the freezer food temperature follow the set point reference and has control parameters $K_{p,fr}$ and $T_{i,fr}$.

All simulation parameters are shown in Table II and the system parameters are in the same range as values used in the benchmark models presented in [1], [2], [25], [26]. The supermarket is assumed to be open from 9 am to 9 pm all days in the year and the customer load is evenly distributed during the day. Although not incorporated here, individual learning algorithms could be activated for weekdays and weekends, if there is a discrepancy in loading patterns. $UA_{amb-air,h}$ is used in the open period and $UA_{amb-air,l}$ is used when the night cover is down during the closed hours. The factor two variation includes the extra load due to exchange of foodstuff during the day and correspond to the supermarket data shown in Section II. Gaussian noise is also added to $UA_{amb-air,l}$, $UA_{amb-air,h}$, and $UA_{amb-air,cs}$ with a standard deviation of 5 W/K during the opening hours and 1 W/K during the closed hours, which gives realistic variations in the load disturbances. Furthermore, noise with a standard deviation of 0.0032 kg/s is added to the freezer mass flow, the precool algorithm sample time $t_{s,ilc}$ is set to 5 seconds (sampling of the valve signal), and $\overline{\Delta}$ is extended by one hour to account for uncertainties.

A. Local Precool Control in Fridge Display Cases

Simulation results without and with the precool algorithm are shown for four summer days in Fig. 12. The compressor

TABLE II
PARAMETER VALUES USED IN SUPERMARKET SYSTEM SIMULATIONS. SUBSCRIPT $1-3$ DENOTES DISPLAY CASES, cs IS COLD STORAGE, AND fr IS FREEZER SECTION.

System par.	Value	Ctrl par.	Value
$UA_{amb-air,l}$	75 ($\frac{W}{K}$)	$\overline{\Delta}_1$	226 (min)
$UA_{amb-air,h}$	150 ($\frac{W}{K}$)	$\overline{\Delta}_2$	310 (min)
$UA_{amb-air,cs}$	110 ($\frac{W}{K}$)	$\overline{\Delta}_3$	560 (min)
$UA_{air-goods,1}$	450 ($\frac{W}{K}$)	$\overline{\Delta}_{cs}$	360 (min)
$UA_{air-goods,2}$	300 ($\frac{W}{K}$)	$\overline{\Delta}_{fr}$	480 (min)
$UA_{air-goods,3}$	150 ($\frac{W}{K}$)	ω_F	$5.82E^{-4}$ ($\frac{rad}{s}$)
$UA_{air-goods,cs}$	600 ($\frac{W}{K}$)	$\overline{\widehat{valve}}$	0.99 ($-$)
$UA_{air-wall}$	500 ($\frac{W}{K}$)	k_1	$\frac{1}{4}$ ($-$)
$\overline{UA}_{wall-r}$	900 ($\frac{W}{K}$)	k_2	$-\frac{1}{12}$ ($-$)
UA_{fr}	137.5 ($\frac{W}{K}$)	$\overline{T}_m$	-3 ($^\circ C$)
$C_{p,goods}$	3917 ($\frac{J}{kg \cdot K}$)	$\underline{T}_m$	-2 ($^\circ C$)
$C_{p,air}$	1000 ($\frac{J}{kg \cdot K}$)	$\overline{T}_o$	5 ($^\circ C$)
$C_{p,wall}$	385 ($\frac{J}{kg \cdot K}$)	$\underline{T}_o$	2 ($^\circ C$)
$C_{p,fr}$	2000 ($\frac{J}{kg \cdot K}$)	$P_{suc,ref,l}$	4.4 (bar)
m_{wall}	180 (kg)	$P_{suc,ref,h}$	4.1 (bar)
$m_{air,1-3}$	50 (kg)	DB	0.1 (bar)
$m_{air,cs}$	125 (kg)	$K_{p,comp}$	-10 ($-$)
$\overline{m}_r$	0.6 (kg)	$T_{i,comp}$	220 (s)
$m_{goods,1-3}$	500 (kg)	$t_{s,comp}$	60 (s)
$m_{goods,cs}$	1200 (kg)	$t_{s,ilc}$	5 (s)
$m_{goods,fr}$	4000 (kg)	$K_{p,fr}$	-0.2 ($-$)
τ_{fill}	40 (s)	$T_{i,fr}$	1800 (s)
T_{amb}	22 ($^\circ C$)		
η	0.5 ($-$)		
$\overline{\dot{W}}_{comp}$	7985 (W)		
$\overline{\dot{m}}_{fr}$	0.065 ($\frac{kg}{s}$)		
$\underline{\dot{m}}_{fr}$	0.035 ($\frac{kg}{s}$)		
Δh_{fr}	110 ($\frac{kJ}{kg}$)		

capacity goes into saturation when the supermarket is open due to the high condenser pressure (hot outside temperature). The result is that the suction pressure control can not keep the suction pressure at the reference and the largest deviation is during the hottest hours of the day. This also means that the valve duty cycle for the display cases saturates at 100%, which gives an increase in the average air temperature $\widehat{T}_{air}$ (low pass filtered). Finally, this makes the foodstuff temperature exceed $5^\circ C$ during day 177 and 178 without precooling. The precool time is shown in Fig. 13. Precooling is mostly applied in the hot summer months as expected and limited by the individual $\overline{\Delta}$ for the storages.

The total energy charge can be calculated based on the simulated compressor power combined with an energy tariff. Here a 2010 time-of-use tariff [28] is applied for Phoenix, Arizona, which corresponds with the weather data file.

The simulation results are compared in Table III. Display cases 1 and 2 violate the $5^\circ C$ threshold in five and four days, respectively, if precooling is not applied. The precool algorithm increases the energy charge cost by only 1.21% compared to 4.24% if the display cases are precooled all the time, showing the advantage of the precool learning algorithm.

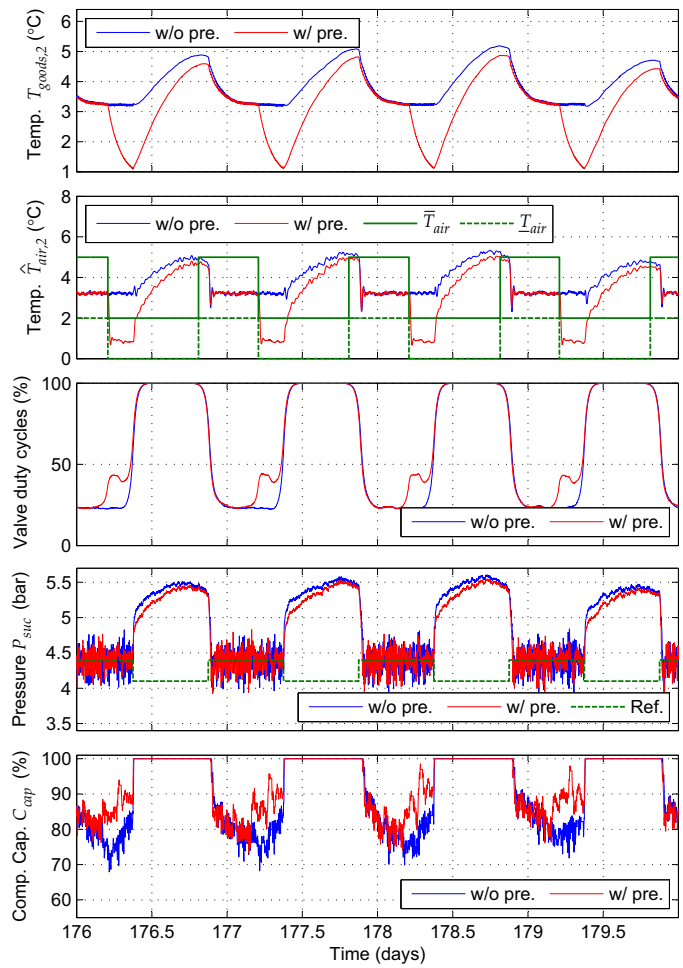

Fig. 12. Simulation results without and with variable precool in each fridge for selected days during the summer period. The air temperature (filtered) and foodstuff temperature are shown for display case 2.

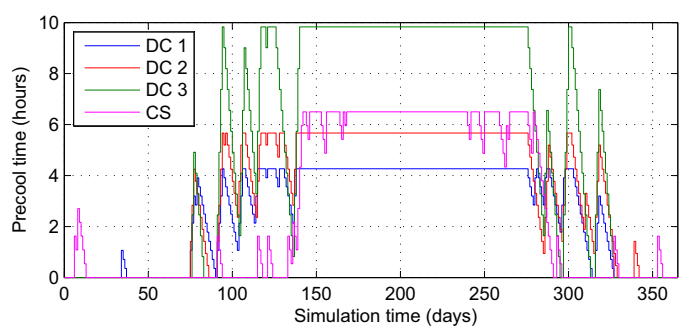

Fig. 13. Precool time used in the three display cases and in the cold storage room for each day in the simulation starting from 1st of January.

Note that the proposed algorithm does not guarantee the temperatures will be held within the constraints, but only keeps the foodstuff temperatures as low as possible when the system saturates and thus increases the robustness of the system. The limit of $5^\circ C$ for some fridge products might be different elsewhere, but most bacterial growth stops below this temperature [7].

TABLE III
SUMMARY OF CASE STUDY RESULTS FOR SIMULATION FROM 1ST OF JANUARY TO THE 31ST OF DECEMBER WITH AND WITHOUT PRECOOL LOCALLY IN EACH FRIDGE.

Quantity	No precool	Variable precool	Constant precool
$T_{goods,1}$ above lim. (days)	5	0	0
$T_{goods,2}$ above lim. (days)	4	0	0
$T_{goods,3}$ above lim. (days)	0	0	0
$T_{goods,cs}$ above lim. (days)	0	0	0
Total energy (kWh)	54742	55401	57235
Energy charge (U.S. $)	3089	3126	3220

B. Precool in the Freezer Section

Simulation results without and with variable precool in the freezer section are shown for four summer days in Fig. 14. The saturation in the display case valve duty cycle is much less when compared with the result presented in Fig. 12. The suction pressure is also kept at the reference much longer and the compressor works more during the non-saturated period resulting in an overall higher power consumption. This is due to the increased refrigerant mass flow in the freezer section during the precool period until 9 am, where the foodstuff temperature $T_{goods,fr}$ reaches the lower reference at $-23°C$ and the lower mass flow after when the temperature increases to $-18°C$ again. The freezer section parameters used in the simulation gives a relatively fast time constant compared to an average freezer display case. However, approximately the same performance is achieved in terms of keeping the maximum foodstuff temperature in the fridge display cases below $5°C$ and no days went above the limit. This indicates that there could be a high potential in placing the precool in the freezers instead. The precool time applied to the freezer section is shown in Fig. 15. The daily defrost cycles, which mostly affect the display case air temperatures, are not included in the simulation. However, defrost cycles could potentially benefit from precool as the temperature in the display cases are lowered leading to less likelihood of exceeding the upper temperature thresholds. Further, if the valve saturates after defrost cycles in previous days then a precool algorithm could also be used to precool the foodstuff before these cycles.

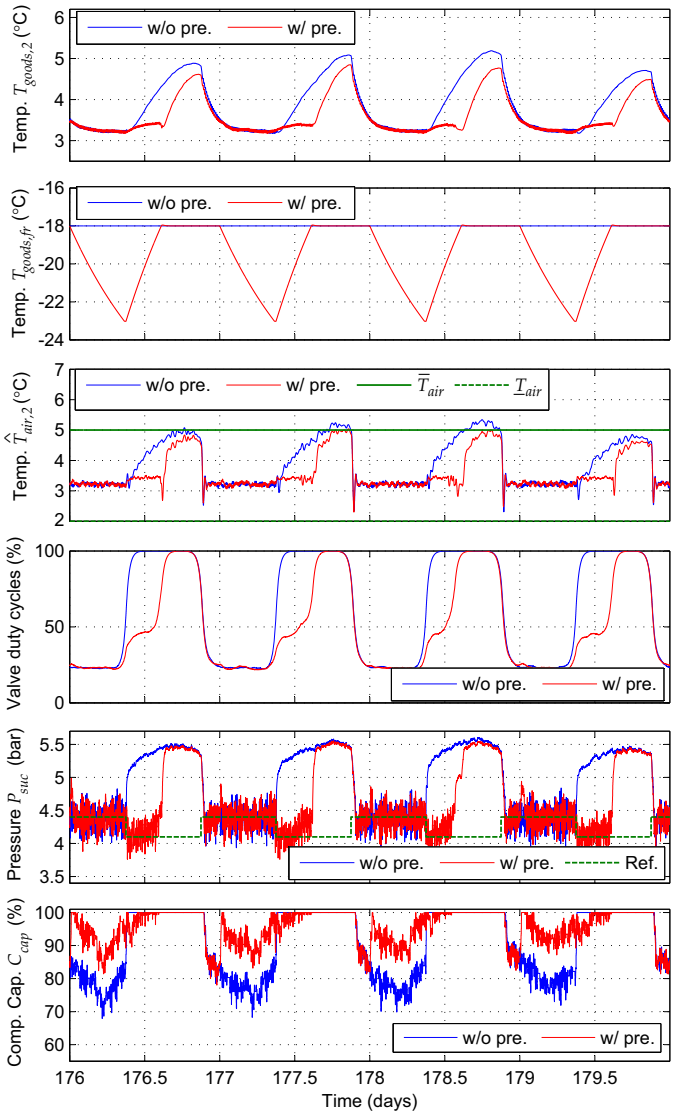

Fig. 14. Simulation results without and with variable precool in the freezer section for selected days during the summer period. The air temperature (filtered) and foodstuff temperature are shown for display case 2 along with the freezer foodstuff temperature $T_{goods,fr}$.

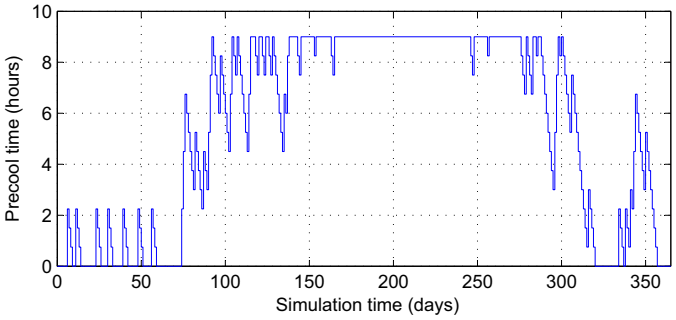

Fig. 15. Precool time used in the freezer section for each day in the simulation.

VI. CONCLUSION

Two learning based algorithms have been proposed for storage of thermal energy in foodstuff. They automatically find the appropriate amount of precool time to be applied and when the precooling should be started in the current day. The first method applies the precooling directly to the individual fridge display cases and the second method instead applies it to the freezer section to lower the total system load later in the day. A supermarket refrigeration system model with multiple display cases has been derived and yearlong simulations showed that precooling of the foodstuff could prevent upper temperature thresholds from being violated during the hottest days of the year with both algorithms. Precooling the fridge display cases constantly demonstrated that intelligent precooling was less costly. Additionally, there could be a high potential in combining precooling in fridges with precooling in freezers, if coordinated correctly. Finally, the methodology presented could easily be extended to handle operation of ice storages

for supermarkets, which is currently being introduced in some larger supermarket chains.

The proposed precool algorithms provide interesting alternatives to MPC and fixed precool schedules, since no system model is required and because the learning based approach ensures adaption to changes in load patterns. Furthermore, no additional hardware is required and the algorithms can easily be plugged into existing systems. The primary additional effort would be tuning but good initial guidelines are given in Section IV. Potential uses of this approach could also extend to ice production, warehouses, refrigerated transports, building air conditioning, etc. The primary requirement is that there is sufficient repeatability in the load pattern.

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Kasper Vinther was born in Denmark in 1984. He received his M.Sc. degree in control engineering with specialization in intelligent autonomous systems from the Department of Electronic Systems at Aalborg University, Denmark, in 2010.

He was a visiting researcher with the Department of Mechanical Science and Engineering at the University of Illinois at Urbana Champaign, USA, in 2012. He has been a Ph.D. student at the Department of Electronic Systems at Aalborg University since 2010, where he has been working with modeling and control of refrigeration systems in collaboration with Danfoss A/S.

His current research interests include control engineering in general with applications to refrigeration, heating, and Smart Grids.

Henrik Rasmussen was born in Denmark in 1944. He received his M.Sc. degree from Danish Technical University in 1970 with specialization in Electro Physics. He received his Ph.D. degree from the Department of Electronic Systems at Aalborg University in 1996. He has been employed as Associate Professor at Aalborg University until 2012 where he retired.

Roozbeh Izadi-Zamanabadi was born in Iran in 1963. He received his M.Sc. in control engineering from DTU, Denmark, in 1993 and his Ph.D. in fault tolerant control from the Department of Electronic Systems in Aalborg University, Denmark, in 1999.

His academic track includes assistant - and associate professor positions in Aalborg University. Currently, he is Lead Expert in Control Technology at the Department of Electronics and Services at Danfoss A/S, Nordborg, Denmark. He is also part-time lecturer at Aalborg University.

His current research interests include Fault diagnosis, Fault Tolerant Control, model-based and model-free control system design with applications to refrigeration, air conditioning, and Smart Grids.

Jakob Stoustrup received his M.Sc. (EE) in 1987, and his Ph.D. (Applied Mathematics) in 1991 from the Department of Mathematics, Technical University of Denmark, where he held several positions.

He held visiting Professorships at the University of Strathclyde, U.K., and the Mittag-Leffler Institute, Sweden. Since 1997 Professor at Automation & Control, Aalborg University, Denmark, and since 2006 Head of Research for the Department of Electronic Systems. Acted as Associate Editor, Guest Editor, and Editorial Board Member of several international journals. Stoustrup is an IEEE SM, and past Chair of IEEE Chapter. Since 2008 Chairman for the IFAC Technical Committee SAFEPROCESS. Since 2011 member of IFAC Technical Board. Member of the Danish and Swedish Research Councils, and the European Research Council. Board Member of The Danish Academy of Technical Sciences.

His main contributions are to robust control, fault tolerant control, and plug-and-play control, with 250+ peer-reviewed papers. Stoustrup has carried out industrial cooperation with approximately 100 companies.

Andrew G. Alleyne received his B.S. in Engineering Degree from Princeton University in 1989 in Mechanical and Aerospace Engineering. He received his M.S. and Ph.D. degrees in Mechanical Engineering in 1992 and 1994, respectively, from The University of California at Berkeley.

He joined the the University of Illinois, Urbana-Champaign in 1994 and currently holds the Ralph M. and Catherine V. Fisher Professorship in the College of Engineering. He was awarded the ASME Dynamics Systems and Control Division's Outstanding Young Investigator Award and was a Fulbright Fellow to the Netherlands where he held a Visiting Professorship in Vehicle Mechatronics at TU Delft. He is the recipient of the 2008 ASME Gustus L. Larson Memorial Award and is also a Fellow of ASME. His research interests are a mix of theory and implementation with a broad application focus. In addition to research he has a keen interest in education and has earned the College of Engineering's Teaching Excellence Award and the UIUC Campus Award for Excellence in Undergraduate Education. He has been active in the ASME, the IEEE, and several other societies. Additionally, he serves on several boards including the Scientific Advisory Board for the U.S. Air Force.