

Improving Demand Response Potential of a Supermarket Refrigeration System: A Food Temperature Estimation Approach

Rasmus Pedersen, John Schwensen, Benjamin Biegel, Torben Green, and Jakob Stoustrup.

Abstract—In a smart grid the load shifting capabilities of demand-side devices such as supermarkets are of high interest. In supermarkets this potential is represented by the ability to store energy in the thermal mass of refrigerated foodstuff. To harness the full load shifting potential we propose a method for estimating food temperature based on measurements of evaporator expansion valve opening degree. This method requires no additional hardware or system modeling. We demonstrate the estimation method on a real supermarket display case and the applicability of knowing food temperature is shown through tests on a full scale supermarket refrigeration system made available by Danfoss A/S. The conducted application test shows that feedback based on food temperature can increase the demand flexibility during a step by approx. 60 % the first 70 minutes and up to 100 % over the first 150 minutes - thereby strengthening the demand response potential of supermarket refrigeration systems.

Index Terms—Supermarket Refrigeration Systems, Temperature Estimation, Data Driven, Demand Response, Smart Grid.

I. INTRODUCTION

THE recent interest and research in the field of smart grid technologies has yielded many suggestions for possible flexible consumers [1]–[3]. Supermarket refrigeration systems represent one such class of flexible consumers due to the inherent thermal mass of the foodstuff. Hence, it is believed, that supermarkets represent a potential for effectively storing energy and thereby shifting consumption in time, see e.g. [4], [5]. The overall concept is that by allowing the foodstuff temperature to vary within predefined limits, it is possible to shift consumption temporally. However, without an estimate of the food temperature, the system is restricted to keeping the temperature of the air surrounding the foodstuff within these predefined limits, thus limiting the possible control action due to the much smaller thermal mass of air compared to the foodstuff. As a result, the possible load shift is reduced.

Currently, foodstuff temperature is rarely considered in commercial systems because air temperature is much more practical to measure. Air temperature is also the parameter

which for example the Danish legislation is based on [6]. That is despite the fact that inspections conducted by the food administration are performed with infrared thermometers measuring the surface temperature of food items, and only in case of suspected violation is the core and air temperature noted [7]. The main reason for this procedure is that food quality depends on food temperature and not on the current temperature of air surrounding it. This demonstrates that if the food temperature was known, the control action could be based on keeping food temperature within bounds, instead of air temperature. Furthermore, there is in general a broad acceptance that for refrigeration systems to offer increased flexibility, it must utilize the thermal mass of the contained goods and it is therefore evident that a means of obtaining food temperature, or estimates of it, is crucial for fully harnessing the load shifting potential of these systems.

Knowledge of foodstuff temperature can be used for several applications such as in [8] where it is used to plan daily operation and defrost cycles for ensuring foodstuff quality and safety. There, the foodstuff temperature is obtained through extensive knowledge and complex modeling of system dynamics. In [9] and [10] knowledge of foodstuff temperature is used to effectively shift refrigeration system power consumption according to economic aspects of the individual systems, by predictive control techniques. It is characterized by assuming knowledge of foodstuff temperature in the predictive control formulation.

Recently, means to measure the thermodynamical behavior of refrigerated foodstuff have been introduced by Danfoss A/S [11]. This sensor, besides adding an extra cost to the system, is however also fixed to a specific dynamical behavior, leaving it incapable to adapt to differences in display cases. In [12] a method of estimating food temperature in closed cabinets is presented. This method however can not handle the disturbances an open supermarket display case is exposed to. Further, in [13] a model based technique using an extended Kalman filter was proposed for estimating the cold room temperatures in supermarkets. This method allows not only for temperature estimation but also prediction of future temperatures, which could be used for planning demand response events. However, for the method to be applicable, a model for each individual supermarket setup needs to be derived and verified. This quickly becomes a complex and time consuming task.

In this paper we propose a data driven method for estimating foodstuff temperature, where excitations such as defrost cycles

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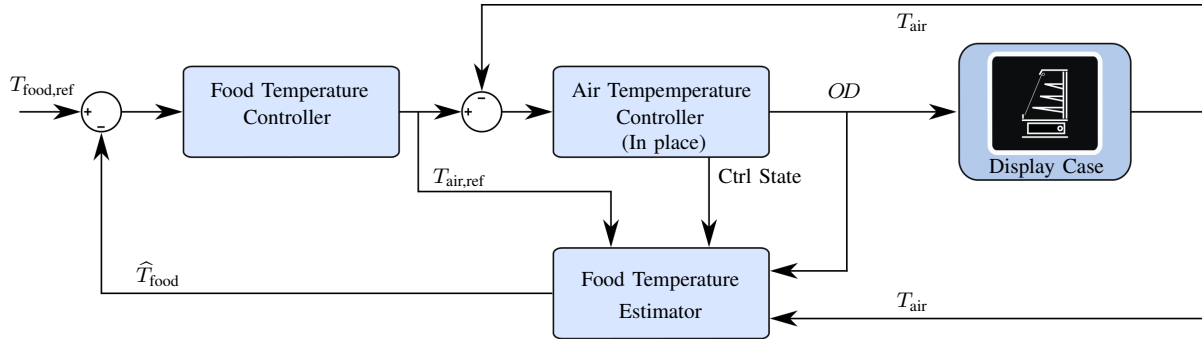


Fig. 1. Illustration of the estimator and two feedback control loops consisting of: an inner loop controlling display case air temperature and an outer loop controlling food temperature.

and step in air temperature reference are actively used. The basic concept is to low-pass filter the measured air temperature and estimate the filter's time constant based on opening degree of the display case expansion valve and system identification techniques. This time constant is shown to be highly correlated with the opening degree after each excitation. The estimated time constant is then updated adaptively, where robustness has been added by letting the estimated time constant be a function of how well it fits with the opening degree data. The proposed method requires no additional hardware as air temperature is already measured and expansion valve opening degree is a known computed controller output. No system modeling effort is required as the method is purely data driven [14]. To further strengthen the results, the method is validated on data from a real display case.

The paper structure is as follows. In Sec. II, the system architecture is presented. Following, in Sec. III the refrigeration system used for testing the proposed method is introduced. In Sec. IV we present the main result: that food temperature can be estimated, based on opening degree of evaporator expansion valve. Next, Sec. V describes the food temperature estimation algorithm, followed by Sec. VI describing test results verifying the proposed method. An application test and a simulation example showing the potential benefits of knowing foodstuff temperature, is given in Sec. VII. Finally, Sec. VIII concludes the work.

II. SYSTEM ARCHITECTURE

In this section, an overview of the system architecture is given and the interconnection between control loops and estimator is explained. The setup consist of a food temperature estimator and two feedback control loops: an inner loop controlling the display case *air temperature* and an outer loop controlling the *food temperature*. This setup is depicted in Fig. 1 and in the following we briefly explain the role of the control loops and the estimator.

A. Inner Control Loop

In a typical commercial supermarket setup, only the inner control loop for each display case is present; this controller is in charge of keeping the air temperature at given references. In this setup, the existing air temperature controller is exploited in

the process of food temperature estimation, by examining the variation in control signal once air temperature is in steady state but food temperature is not. The inner loop controller receives set-points from the outer control loop in a typical cascade coupling.

B. Outer Control Loop

The outer control loop is used to ensure a referenced food temperature. The outer loop controls the temperature by applying set-points to the inner controller. Both the inner and outer controllers are implemented as PI controllers.

C. Estimator

Knowledge of food temperature can be obtained by adding sensory equipment such as the sensor described in [11]. There are, however, several disadvantages of using add-on sensory equipment: besides adding an extra cost to the system, the sensor has a predefined fixed dynamical behavior thus not capable of capturing differences in display case content. Therefore, we propose a food temperature estimation method that doesn't rely on additional sensors or modeling.

III. EXPERIMENTAL SETUP

The system used for gathering data and conducting tests is a full scale supermarket refrigeration system made available by Danfoss A/S. It consists of 6 display cases of which 4 are medium temperature (MT) and 2 are low temperature (LT); hence, the total setup mimics an ordinary smaller supermarket.

In addition to all the measurements obtainable through the default commercial controllers, sensors are present for both surface and core temperature of simulated foodstuff. Each display case is equipped with one package of simulated foodstuff, placed in the center forefront to capture the region most exposed to thermal load from the surroundings i.e., the region with the potential highest foodstuff temperature. The thermal mass is largely provided by numerous containers of ethylene- and propylene-glycol while the foodstuff sensors are attached to blocks of foodstuff replicas made from tylose, a type of cellulose gel, simulating meat [15], [16].

The controllers and display cases are commercially available units typical for a supermarket. The operating mode of the



Fig. 2. The medium temperature section of the supermarket refrigeration system with foodstuff replicas.

controllers is set to modulating control, a mode where a continuous variable valve opening degree is approximated by a PWM signal. Further, the sensors used for data acquisition are used in commercial systems to document that temperatures are within bounds, thus they are seen as being highly reliable.

The medium temperature cabinets of the laboratory setup can be seen in Fig. 2 and the estimation procedure is applied to the vertical shelving unit on the far left.

A. Defrost Cycles

The temperature of refrigerant in the display case evaporator is typically subzero in order to absorb enough heat from the air. This will cause moisture to not only condense when air passes over the surface of the evaporator, but subsequently freeze and over time build up a layer of ice covering the evaporator. This will ultimately block the air flow and drastically reduce the cooling capacity. To counter this problem, regular defrost cycles are run, where the flow of refrigerant is stopped and the continuing recirculation of hotter air will melt the ice. For low temperature display cases an additional heating element is turned on to actively melt this ice.

IV. CORRELATION BETWEEN FOOD TEMPERATURE AND DISPLAY CASE DYNAMICS

In this section the main contribution of this paper is presented: that foodstuff temperature can be estimated based on how the opening degree of the evaporator expansion valve evolves over time. The proposed method is inspired by the common approach to modeling a display case, see e.g. [17], [18] or [19]. We will illustrate the theoretical correlation between food temperature and opening degree, through this common model; further, actual supermarket laboratory experiments will support the theory by demonstrating this behavior.

In Fig. 3 a generic display case is shown from which the energy balance equations in (1) and (2) are derived. This is done under the assumptions that the air is perfectly mixed and that heat loss is purely conductive. Further, we assume that the food temperature is invariant across all food items,

i.e., we only find one food temperature. The energy balance equations are given as follows

$$MCp_{\text{air}} \frac{dT_{\text{air}}}{dt} = \dot{Q}_{\text{load}} + \dot{Q}_{\text{food/air}} - \dot{Q}_e, \quad (1)$$

$$MCp_{\text{food}} \frac{dT_{\text{food}}}{dt} = -\dot{Q}_{\text{food/air}}, \quad (2)$$

with

$$\begin{aligned} \dot{Q}_{\text{load}} &= UA_{\text{load}}(T_{\text{amb}} - T_{\text{air}}), \\ \dot{Q}_{\text{food/air}} &= UA_{\text{food}}(T_{\text{food}} - T_{\text{air}}), \\ \dot{Q}_e &= OD \cdot \overbrace{K_v \sqrt{\rho_{\text{suc}}(P_{\text{rec}} - P_{\text{suc}})}(h_{\text{oe}} - h_{\text{ie}})}^{c_1}, \end{aligned}$$

where MCp_{air} and MCp_{food} are the product of mass and specific heat capacity for the air and foodstuff inside the display case, T_{air} and T_{food} are temperatures of the air and foodstuff, \dot{Q}_{load} is the heat flux (thermal load) to the display case, $\dot{Q}_{\text{food/air}}$ is the heat flux from foodstuff to air, \dot{Q}_e is the heat flux (cooling capacity) of the evaporator, UA_{load} and UA_{food} are the heat transfer coefficients from ambient air to display case air and from foodstuff to display case air respectively, K_v is a valve specific constant, ρ_{suc} is the density of the refrigerant on the suction side, P_{suc} is the suction pressure, P_{rec} is the receiver pressure, h_{ie} and h_{oe} are the enthalpies at the inlet and outlet of the evaporator respectively, and finally OD is the opening degree of the expansion valve.

This model is used to establish the relation between opening degree and food temperature i.e., the parameter values are assumed constant throughout the estimation period, and frost buildup happens on a much slower time scale. Notice that the mass changes as food items are removed from the display case, and restocked, however this happens at a rate much slower than the estimation period (also during peak opening hours). Therefore, these parameters are not considered further, see e.g. [17] for a thorough explanation of them.

Further, the assumption of heat loss being purely conductive, might affect the proposed estimation approach, when applied to low temperature display cases, where the radiation heat transfer is dominant. However, the main result of food temperature being correlated with evaporator expansion valve

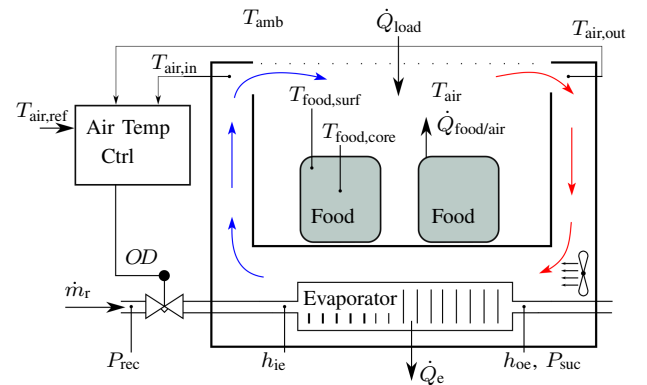


Fig. 3. Generic model of open horizontal display case, with air temperature controller. The controller uses a linear combination of the inflow air temperature and the outflow air temperature for feedback, i.e. $T_{\text{air}} = \beta T_{\text{air,in}} + (1 - \beta) T_{\text{air,out}}$.

opening degree should still be true. The evaluation of this has been left for future work.

Due to the active control present for T_{air} , the steady state set-point temperature is reached quickly and can therefore be neglected, while T_{food} has much slower dynamics, thus reaching the set-point later. Focusing in this area of operation Eq. (1) can be rewritten as

$$\begin{aligned} MCp_{\text{air}} \frac{dT_{\text{air}}}{dt} &= \dot{Q}_{\text{load}} + \dot{Q}_{\text{food/air}} - \dot{Q}_e = 0 \\ \Rightarrow \dot{Q}_e &= UA_{\text{food}}(T_{\text{food}} - T_{\text{air}}) + UA_{\text{load}}(T_{\text{amb}} - T_{\text{air}}) \\ \Rightarrow OD &= \frac{1}{c_1} (UA_{\text{food}}T_{\text{food}} + UA_{\text{load}}T_{\text{amb}} \\ &\quad - (UA_{\text{load}} + UA_{\text{food}})T_{\text{air}}). \end{aligned} \quad (3)$$

The applied OD required to keep T_{air} constant is thus an affine function of T_{food} dependent on the current operating point. Hence, OD and T_{food} must exhibit similar dynamic behavior. The assumption on load being purely conductive, could be omitted as long as the air temperature reaches steady state much faster than the food temperature, making the method applicable to all kinds of cold storage.

To verify the theoretical results in a real life environment, we conduct an experiment on one of the supermarket display cases in the experimental setup. The results are seen in Fig. 4 where the air temperature is plotted along with both surface and core temperature of foodstuff replicas and an estimate of food temperature, which will be explained further in the following section.

First, we apply a step down in air temperature reference, where it is seen that air temperature overshoots and therefore does not reach steady state much faster than the food temperature. This is followed by three defrost perturbations, seen as the sudden peaks in air temperature, where it is clear that air temperature reaches steady state long before food temperature. Lastly, a step up in air temperature reference is applied, where the air temperature only shows a little overshoot and therefore reaches steady state quickly compared to the food temperature. However, what is clear from steps and defrost perturbations is that we observe exactly the behavior outlined in the above concept.

V. ESTIMATION OF FOOD TEMPERATURE

In this section we establish a method to automate food temperature estimation, as shown in Fig. 4, without using any measurements of food temperature. The concept is to use a first order low-pass filtering of the air and find the time constant of available opening degree data and use this as the filters time constant. The structure of the designed food temperature estimator is depicted in Fig. 5.

In Eq. (2) it is seen that the only variable affecting T_{food} is T_{air} and in steady state they would obviously have to be equal. So food temperature is just a low-pass filtered version of air temperature through a filter of unity gain and a time constant found by measurements of OD , i.e. we utilize the relationship between OD and T_{food} established.

We denote the estimate seen in Fig. 4 the *optimal first order fit*, which is obtained by using both measured air and food

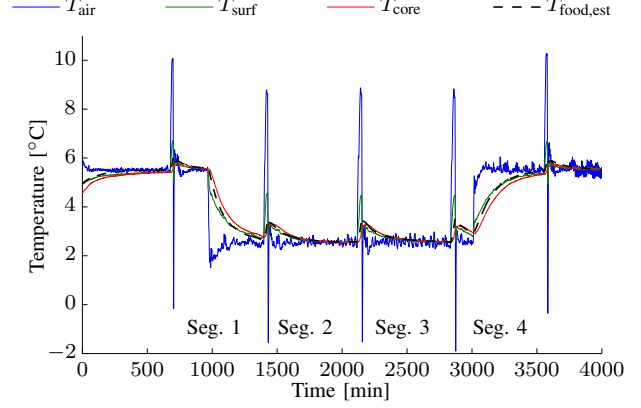


Fig. 4. Measured temperatures including first order optimal estimation of food temperature for the chosen structure, $\tau_{\text{opt}} = 144$ minutes. Data is segmented according to the defrost cycles, seen where the air temperature changes abruptly.

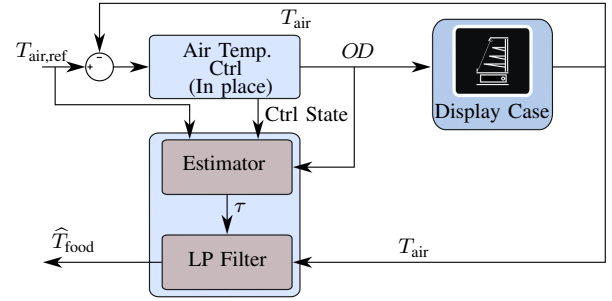


Fig. 5. Structure of the designed food temperature estimator and how it interacts with the display case and air temperature controller.

temperature and finding the optimal time constant in the least squares error sense. In this presented example it results in a time constant, $\tau_{\text{opt}} = 144$ min. and a RMSE of 0.39 °C. This gives the best possible result for the given structure and will therefore be the benchmark which the following estimation algorithm is evaluated against, i.e. it can be seen as the best case scenario. It should be noted that the optimal first order fit has been found from a much larger data set, where only a subset is shown here to ease illustration. The challenge is to approach this level of fit in a more realistic setup without the measured food temperature.

In Fig. 4 there are four marked segments of data, each between a pair of defrost cycles. To verify that the expected correlation is indeed present, and to ease illustration, the opening degree and measured food temperatures are normalized, see Fig. 6. Notice it is only the transient behavior which is of interest, as the filter has unity gain. Furthermore, the figure shows the estimated time constants. The estimation is performed using the Prediction Error Method (PEM) and fitting a first order system to the scaled opening degree data in order to obtain the time constant.

There is a clear difference in the accuracy of each of these fits as expressed by the noted percentage of fit in Table I. The poor fit from segment 1 is caused by air temperature not reaching steady state sufficiently fast compared to food

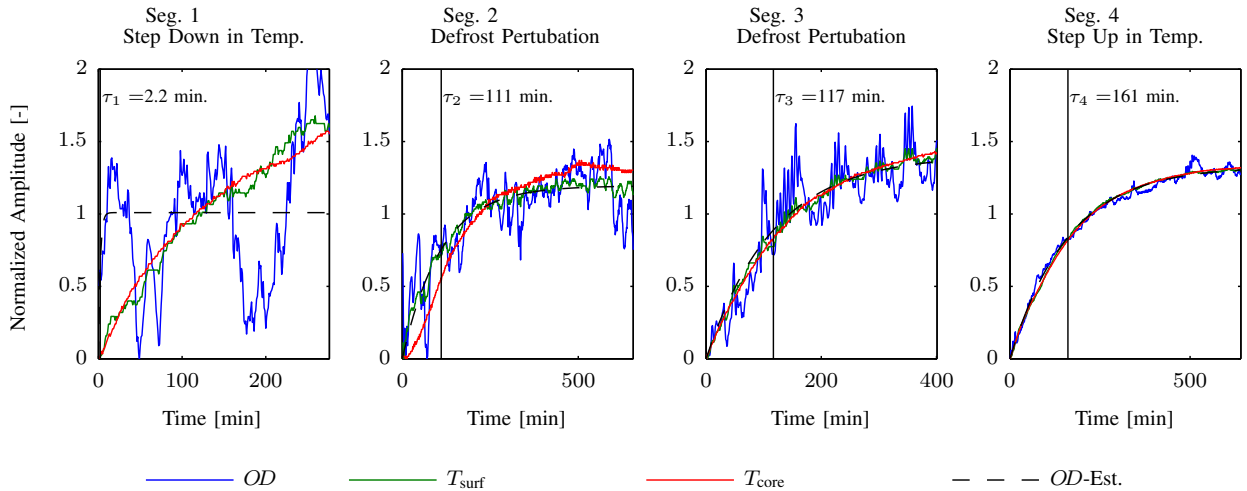


Fig. 6. Normalized data for each of the four segments. The transient behavior of OD is used to fit a first order system from which the time constant is obtained. The vertical lines show the identified time constants for each segment. Data for each of the four segments has been normalized according to $\text{norm}(T) = 1 - (T - \mu) / \max(T - \mu)$, with μ being the mean, in order to resemble a unit step and enable easy comparison of time constants.

TABLE I
TABLE OF THE FOUR SEGMENTS, THEIR ESTIMATED TIME CONSTANTS,
AND MODEL TO OD DATA FIT. THIS DATA IS BASED ON FIG. 6.

Segment	Estimated Time Constant [min]	Model to OD Data Fit [%]
Best Fit	144	-
Seg. 1	2.2	0.6
Seg. 2	111	43
Seg. 3	117	62
Seg. 4	161	90

temperature, as seen in Fig. 4.

The estimation algorithm is based on updating the time constant of the filter with the most recently calculated one. The measure of fit, associated with each estimation can be used to recursively update the time constant as

$$\tau(n+1) = (1 - \alpha)\tau(n) + \alpha\tau_{\text{new}}(n), \quad (4)$$

where τ is the adaptively updated time constant, τ_{new} is the newly obtained estimate of the time constant and n is the segment number. Here, α will be a function of the measure of fit (it can be seen as a confidence parameter, how much do we believe in the newest estimation) and $\tau(n)$ will thus be a weighted linear combination of all previous $\tau(n-i)$, $i = 1, \dots, n$. The initial guess of time constant could be based on display case type and content of it, or simply by obtaining multiple sets of opening degree data and train the algorithm before deployment.

VI. RESULTS

We now test the presented algorithm on the Danfoss supermarket refrigeration system; that is, food temperature is estimated exclusively based on OD data. The algorithm is initiated with a value of $\tau = 129$ min. corresponding to a

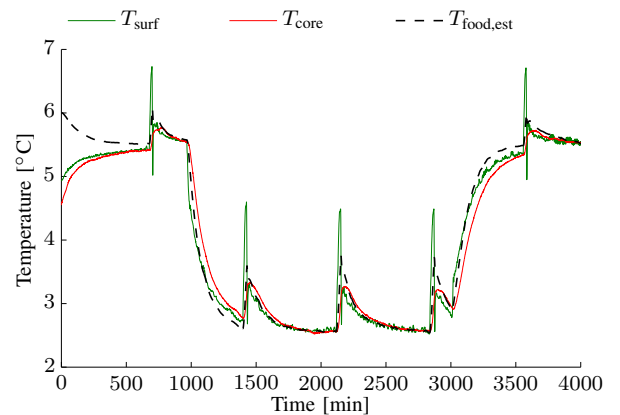


Fig. 7. Result of implementing the proposed algorithm on a single open vertical display case described in Sec. III. The estimation filter time constant is updated once during each defrost cycle and the initial guess is set to $\tau = 129$ [min].

rise time of 9.9 hrs for 500 g ground beef found in [4], a foodstuff very similar to the 500 g packs of meat replicas used. It should be noted that if the food items are closely packed the time constant will increase significantly [4]. The confidence parameter α is set according to the model fits seen in Table I, i.e. for seg. 1: $\alpha = 0.006$, seg. 2: $\alpha = 0.43$, etc. The result of updating the food temperature at each defrost cycle, after each segment is seen in Fig. 7.

The initial estimated food temperature was set to the measured air temperature resulting in the large discrepancy seen at the beginning of the plot. It is observed that the initial guess of time constant is close to the actual time constant, resulting in very little improvement to be seen over the entire data set. To demonstrate the adaptive capabilities of the algorithm,

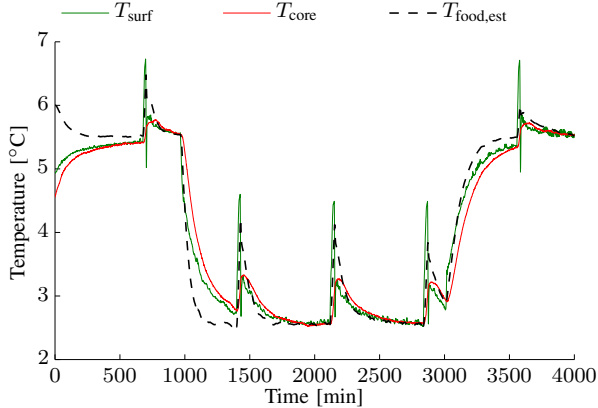


Fig. 8. Repeated experiment with an initial guess of time constant to be $\tau = 70$ [min].

TABLE II

ESTIMATION OF THE TIME CONSTANT AFTER EACH ITERATION AND THE RESULTING RMSE FROM APPLYING THE TIME CONSTANT TO THE ENTIRE DATASET. THE RMSE FOR THE OPTIMAL FIRST ORDER FIT IS 0.39 °C.

Iteration	Test 1		Test 2	
	τ [min]	RMSE [°C]	τ [min]	RMSE [°C]
Init.	129	0.41	70	0.67
1	128	0.41	69	0.67
2	121	0.42	87	0.56
3	118	0.43	105	0.47
4	156	0.40	155	0.40

the experiment is repeated with a worse initial guess of $\tau = 70$ minutes. This is shown in Fig. 8 where the response of the estimated temperature is clearly too fast in the first segment, but after a few iterations the algorithm has converged to approximately the same time constant as seen in Fig. 7.

The results of the two tests are collected in Table II, where also the resulting root mean square error (RMSE) between estimate and measured surface temperature of food, is shown. The RMSE is calculated based on letting the estimated time constant from each iteration be applied to the entire dataset. The reason for including RMSE is to illustrate that even a poor estimate will result in very little temperature deviation. What should also be noted is the robustness of the algorithm, towards poor estimates; i.e. the estimate from segment 1 has almost no influence on the adaptively update estimate of τ .

VII. APPLICATION EXAMPLES

The following examples should serve to illustrate the potential that lies in explicitly using the concept of food temperature for refrigeration system control. In the first example, tests have been performed on the entire setup described in Sec. III, that illustrates the increase in load shifting potential when using food temperature as feedback. Secondly, a simulation have been performed, using the high fidelity model developed in [17], to further motivate using foodstuff temperature in the control strategy.

A. Test Scenario

The example considers two separate tests which are performed to show the difference in load shifting abilities: First, a baseline test where only the inner control loop in Fig. 1 is present and no knowledge of food temperature is used. Second, a test with food temperature estimation applied, i.e. the outer loop is implemented in order to feed back food temperature.

One advantage of controlling food temperature is the ability of storing energy faster through larger control action of the actuator. It is important to note that while energy is in fact removed from the display case system, through the evaporator, it can effectively been seen as stored; in the sense that by preemptively increasing power consumption above nominal, allows for later decreasing below nominal without violating capacity limits (in this case a maximum temperature).

Fig. 9 shows the power response, for both tests, resulting from stepping the temperature reference 4°C to 1°C for all MT-cases and -19°C to -24°C for all LT-cases. While the use of food temperature feedback does appear to increase consumption it is further clarified in Fig. 10 showing the energy consumed relative to baseline. The relative consumption has increased approximately 60 % during the first 70 minutes, rising to a 100 % increase over the first 150 minutes.

This increased consumption will inevitably increase losses in the system. Mainly to the surrounding environment, previously noted as \dot{Q}_{load} in Fig. 3 due to the larger temperature difference. But potentially also through reduced coefficient of performance (COP) of the system, depending on the control methodology of the inner loop, since the temperature difference over which heat has to be transferred may need to be increased. While these losses are not insignificant, and will reduce the efficiency of the storage, they do not prevent the concept of storing energy in refrigeration systems. Further, the increasing amount of renewables in the Western electricity markets cause a higher occurrence of extreme prices and at the same time lower electricity prices - which is the ideal scenario for the refrigeration storage system described in this paper. For example, the Nordic system base price for 2016 (ENOYR16) [20] has dropped from 50 EUR/MWh in 2011 to around 17 EUR/MWh in end 2015, while the occurrences of extreme imbalance prices, in for example Germany, has increased so that prices higher than 500 EUR/MWh (and lower than -500 EUR/MWh) happens every month. This indicates that flexibility, e.g. from thermal storage solutions, may become of very high value; further, the drawback of increased electrical consumption may have a very limited cost due to the low electricity prices.

B. Control Scenario

To further illustrate the increase in load shifting potential, a simulation is carried out on the supermarket refrigeration system model presented in [17], consisting of seven MT display cases and four LT display cases. We consider the setup depicted in Fig. 11, where a supermarket supervisor receives a power reference signal from e.g., an aggregator [21]. In this example the reference signal is similar to the one demonstrated

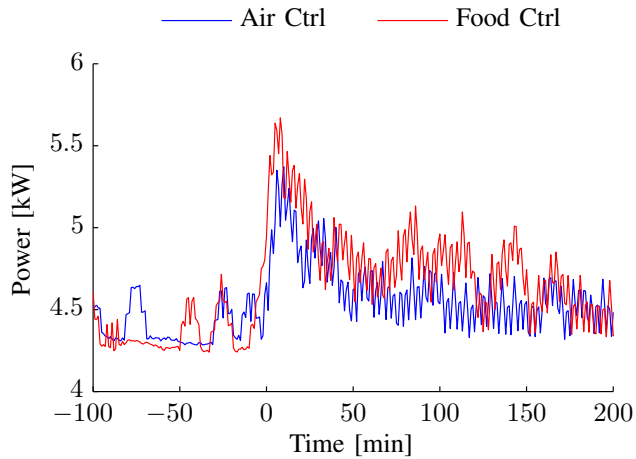


Fig. 9. Power response of supermarket refrigeration system to step in both air and food temperature reference. The data is filtered with a ± 5 minute moving average.

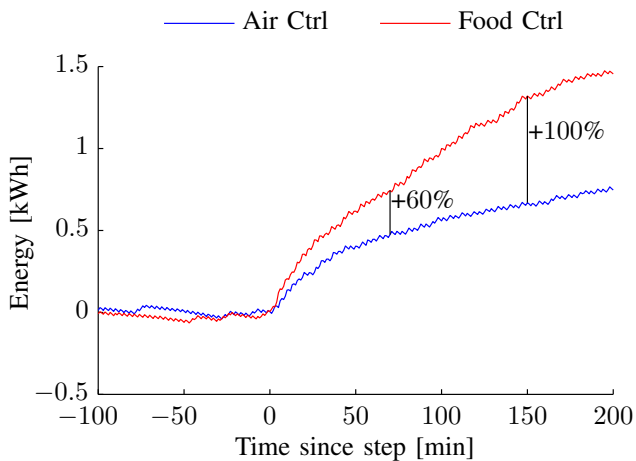


Fig. 10. Consumed energy relative to the baseline of 4.4 kW. Calculated as the cumulative power deviation from this baseline.

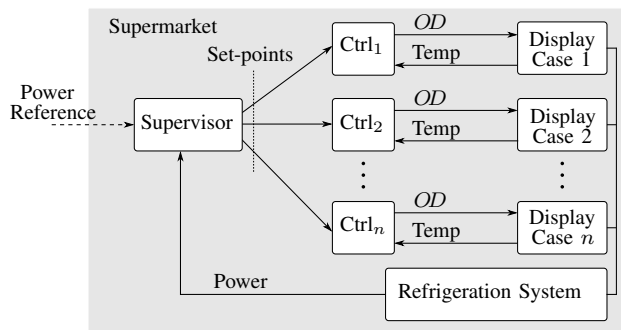


Fig. 11. Control system setup for the supermarket refrigeration system. The supervisor dispatches temperature references to the n display case controllers.

in [22], where the supermarket is set to follow a demand curve used for secondary reserve.

The supervisor is implemented as a PI controller followed

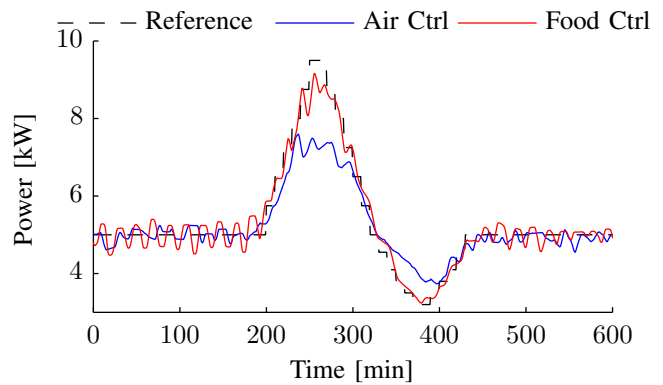


Fig. 12. The control systems reference tracking ability.

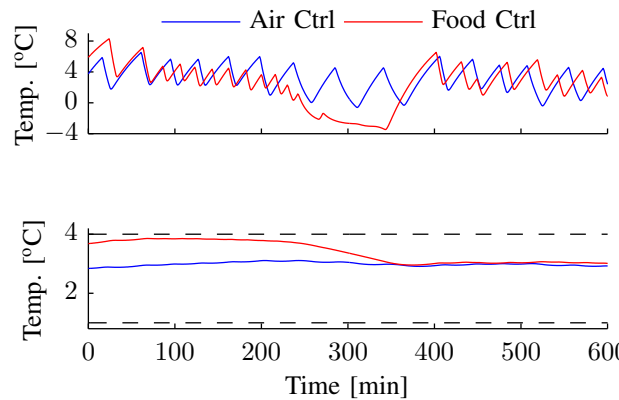


Fig. 13. Top: Air temperature of a medium temperature display case. Bottom: Food temperature of the same display case. In both cases the food temperature had the same initial condition. However, only a subset of the data is shown here to illustrate the delivery period.

by a dispatcher where the temperature references for the individual display cases are weighted so they reach constraints on temperature at the same time. This ensures that the overall system dynamics are maintained for a much broader operating range. The reference following capabilities are shown in Fig. 12, for a system utilizing foodstuff temperature and for one using only air temperature. For this proof-of-concept example an additional 1.49 kWh (10.8 %) is consumed during the storage period (200-320 min.) relative to air temperature control. Likewise, a reduction in consumption of 0.74 kWh (10.5 %) is made during the release period (330-430 min.). The air and food temperatures of a single display case are shown in Fig. 13.

As expected, when using food temperature as feedback instead of air temperature, the system is capable of following a reference with a higher amplitude, thus potentially increasing the value of a supermarket when offering flexibility to an aggregator. The difference in behavior is clearly seen from the food temperature in Fig. 13, where in the case of only using air temperature the system utilizes almost none of the foodstuff's thermal mass. When actively utilizing this mass, the air temperatures are allowed to vary much more enabling the system to follow the power reference.

The actual value of this increased flexibility is difficult to estimate in a market that has not yet generally adopted the use of smaller flexible users. As is the increased potential that comes with an increasing market share of, often renewable, highly varying power plants of different sizes. The value of the proposed method of using estimated food temperature is, that for many systems it requires little more than a software update, when compared to only using air temperature. In return a significant increase in available flexibility is achieved. Although utilizing this added flexibility will likely have a higher cost, it is also an additional product previously not available at all. Thus the supermarket may choose to sell it only when the extra costs are covered. Since the hardware is exactly the same it should still be possible to deliver the previously available amount with the same efficiency.

VIII. CONCLUSION

In this work, we established a method for estimating food temperature in supermarket display cases based on measurements of air temperature and knowledge of the evaporator expansion valve opening degree. The benefits of the proposed method were shown to be: no add-on sensory equipment needed, no modeling of the underlying refrigeration system, and a robust updating algorithm for handling poor estimates. Moreover, the developed estimation method was verified through test on a real supermarket display case and showed that even poor estimates of the filter time constant resulted in an RMSE below 0.7 °C. The demonstration clearly indicated that the proposed method was able to capture the main dynamics of the thermal mass in the supermarket display cases.

To illustrate the benefits of having knowledge of food temperature available, tests on a full scale supermarket refrigeration system were performed. These showed a significant increase in added consumption from the start of the step, reaching its maximum at 150 minutes into the step. Hereby these tests verified the significantly larger flexibility potential when limiting the allowable foodstuff temperatures instead of putting these restrictions on the air temperature, as is currently done.

To further motivate the proposed estimation method, a simulation on a high fidelity supermarket model verified the increased flexibility potential from knowing food temperature.

The work documented in this paper has resulted in the patent described in [14].

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