Predictive Control of a Domestic Freezer for Real-Time Demand Response Applications

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***Abstract*--Demand side management and demand response aim to maximize the efficiency of the electricity delivery process by exploiting the flexibility of customers. At residential level, demand response can be applied only to a limited number of appliances, through load management, due to user intervention or dedicated automated actions. One category of appliances which concur well with demand response is the thermostatically controlled appliances. They operate in cycles and maintain the temperature of a process around a set-point and within certain temperature limits. When demand response is applied, the thermostatically controlled appliance is utilized as an energy buffer and a temporary increase or decrease in power and energy consumption is induced. This work focuses on the application of demand response to the operation of a typical domestic freezer. Real-time predictive control models are developed for this application and are validated during practical experiments.**

***Index Terms*—Power systems, supply and demand, demand response, home energy management, freezers, predictive control.**

I. Introduction

SUSTAINABILITY and economics are the main drivers of the electricity sector today, underlined by emissions reduction targets, energy efficiency goals and cost minimisation. The operators of electricity systems need to cope with critical periods when oversupplies of power or high peak demands of power occur. The former may cause a considerable unbalance to the system and can lead to unwanted disconnections, while the latter requires starting the reserve power plants, which entails high additional costs and significant emissions. Furthermore, the network might not be able to handle high demands. Consequently, in order to avoid the high additional expenditures and ensure the grid security, demand response is considered as an efficient mean that can provide solutions in real-time.

II. Residential Demand Response

Demand side management (DSM) refers to a series of policies and measures which are focused on controlling and reducing the electricity demand. It includes energy efficiency policies, smart energy tariffs or real-time control of distributed energy resources [1]. Demand response (DR) is one category of DSM and it focuses on altering the normal electricity usage of end-users in response to either changes in the price of electricity, or to changes in the timing, instantaneous load demand or overall electricity consumption and generation [2]. This study focuses on automated DR mechanisms that require minimum user intervention. That means that the end-user occasionally enters his/her preferences through a graphical user interface and then computer algorithms perform the load control automatically through integrated functions in appliances or home energy management systems. One class of appliances that can be suited for DR is that of thermostatically controlled appliances.

III. Research Objectives

This work focuses on the DR potential of a typical domestic freezer, namely on its ability to respond in real-time to a control signal received, while it remains under the influence of external factors such as user behaviour (i.e. door openings and thermal mass variation). The load profile and the energy consumption are assessed for different scenarios, firstly through experiments which focus on the real-time application of predictive control for the power management of one freezer and secondly through simulation studies for an aggregation of appliances.

Although the power demand of an individual freezer is relatively small, the aggregate effect of large numbers of them can have a significant impact on the total load of a distribution system.

IV. The Domestic Freezer

The household appliances can be distinguished into two categories with respect to energy management possibilities: controllable and non-controllable. The operation of controllable appliances can be scheduled within certain flexibility levels while most non-controllable appliances are used on demand. With respect to the average annual energy consumption at the residential level (in EU-27), the cold appliances (refrigerators and freezers) correspond to a share of 15.2%, thus being ranked second place after heating systems/electric boilers [17]. A further motivation for this research is that they have a 55% penetration rate among the Dutch households [3].

Freezers belong to the category of thermostatically controlled appliances together with refrigerators, heating,

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ventilation and space conditioning systems, as well as water heaters. The advantage of cold appliances (fridges and freezers) is that their operation is automatic and can thus be utilized for automated DR. A control strategy can determine a minimum or maximum operation within certain temperature limits, in order to provide the load shifting of the energy demand and bring benefits to the customer and/or to the power system [4].

Note that, in contrast to refrigerators, freezers are exposed to a less user actions; their electricity consumption is less affected by door openings or new food stored [5].

The utilized model of the operating process is based on the energy balance and has been presented in [6]. When the compressor is in an *off* state the active power term *P(t)* is 0; when the compressor is on, *P(t)*has the shape of an exponential decay function.

$$T(t+1) = \varepsilon \cdot T(t) + (1-\varepsilon)\left(T_{amb}(t) - \frac{\eta \cdot P(t)}{A}\right) \tag{1}$$

where $T(t)$ is the cooling compartment temperature (ºC) at discrete time instant *t*, ε is the factor of inertia, $P(t)$ is the instantaneous power at discrete time instant *t*, *A* is the overall thermal insulation (W/ºC), η is the coefficient of performance and $T_{amb}(t)$ is the ambient temperature (ºC) at discrete time instant *t*.

From this equation, a temperature evolution in the form of differential equations can be deduced (as presented in (2) and (4)), depending on whether the freezer compressor is switched *on* or *off* [6].

$$\dot{T}_1(t) = -\frac{A}{m_c}(T_1(t) - T_{ON}),\ when\ on, \tag{2}$$

$$where\ T_{ON} = T_{amb}(t) - \frac{\eta P(t)}{A} \tag{3}$$

$$\dot{T}_2(t) = -\frac{A}{m_c}(T_2(t) - T_{amb}(t)),\ when\ off \tag{4}$$

where m_c is the thermal mass (J/ºC).

The solutions of the differential equations are given by (5) and (6):

$$T_1(t) = a_1 \cdot e^{-\frac{A}{m_c}t} + T_{ON}(t) \tag{5}$$

$$T_2(t) = a_2 \cdot e^{-\frac{A}{m_c}t} + T_{amb}(t) \tag{6}$$

The coefficients a_1 and a_2 are obtained from solving the differential equations computed at the beginning of each *on* and *off* periods (at time $t = t_1$), according to (7) and (8):

$$a_1 = \frac{T_1(t_1) - T_{ON}(t_1)}{e^{-\frac{A}{m_c}t_1}} \tag{7}$$

$$a_2 = \frac{T_2(t_1) - T_{amb}(t_1)}{e^{-\frac{A}{m_c}t_1}} \tag{8}$$

The particular software model of the freezer developed in this research is tuned based on measurements obtained and on the computation of the equations parameters: the thermal insulation, the coefficient of performance and the thermal mass.

Firstly, the thermal insulation is estimated, from the physical characteristics of the freezer. Knowing the thermal conductivity coefficient ($k = 0.02\frac{W}{m^0C}$ [12]), the area of the freezer S and approximating the thickness of the freezer wall x, the thermal insulation parameter A is computed. It is assumed to be a constant parameter throughout the simulations since it strictly depends on the physical construction properties of the freezer:

$$A = \frac{k \cdot S}{x} = 1.06\frac{W}{°C} \tag{9}$$

Assuming that 60% of the heat loss is due to convection [12], the total heat loss Q_{tot} (cabinet heat loss) is computed. The convective heat loss Q_{conv} is calculated as a function of the thermal insulation A, the difference between the ambient temperature $T_{amb}(t)$, the average temperature of the freezer compartment T_{av} and the time duration of the *off* cycle Δt_{off} [14].

$$Q_{conv}(t) = A \cdot (T_{amb}(t) - T_{av}) \cdot \Delta t_{off} \tag{10}$$

$$Q_{tot}(t) = 0.6 \cdot Q_{conv}(t) \tag{11}$$

The coefficient of performance represents the ratio between the cabinet heat loss Q_{tot} and the energy consumption measured $W_{consumed}$.

$$\eta = \frac{Q_{tot}}{W_{consumed}} \tag{12}$$

The thermal mass is estimated from the previously computed parameters, the measurements recorded and the equations describing the temperature profile. Table 1 contains the parameters deduced for the freezer model:

TABLE I
ESTIMATION OF THE FREEZER PARAMETERS

Thermal insulation (W/ºC)	η	Thermal mass (J/ºC)
1.06	2.203	24590
	1.905	49140
	1.67	41900

The power consumption of the freezer is best modelled according to an exponential function, as presented in (13). The coefficients of the function have been calculated so that it highly correlates with the measured power consumption data.

$$P(i) = 16 \cdot \exp(-(t - t_1)/340) + 64 \tag{13}$$

V. MODEL-BASED PREDICTIVE CONTROL

Model-based predictive control (MPC) refers to a class of control algorithms which can be implemented in devices to guide their processes. The predictive controller has an internal model which is used to predict the behaviour of a process in a discrete time setting: it starts from the current time instant by taking into account the current state, and it proceeds over a future prediction horizon. At each control interval, the MPC algorithm attempts to optimize the future process behaviour by computing a sequence of future manipulated variable adjustments [7].

The linear first-order model developed in Matlab simulates the freezer operation based on (5) and (6) for the case when the temperature profile is simulated and on (13) for the representation of the power profile when the compressor is *on*.

As input, the optimisation algorithm takes the minimum and the maximum allowed temperatures in the freezer compartment, the ambient temperature, the thermal mass, the thermal insulation of the freezer, the standard *on* and *off* periods for a certain thermal mass value, as well as the initial time instant and temperature together with the duration of the simulation period. The parameter which varies during the simulations is the ambient temperature.

As a first step, the steady-state operation is simulated and a comparison is made between the simulated and measured temperature and power profiles. Subsequently, the user intervention is integrated and the impact of the door openings (through the determination of the heat loss) is analysed, together with the thermal mass variation based on experimental data. A higher thermal mass results in a higher buffer capacity for the freezer.

By predicting the door openings (based on measured user behaviour), the model can be utilized to create predictions about the temperature evolution and the power demand of the freezer. Thus the potential for demand response can be estimated and applied in real-time.

VI. EXPERIMENTAL SETUP

The experimental setup can be divided into three parts which are discussed in the following sections: conducting the measurements (sensing devices), communicating the necessary information among system entities and controlling the compressor.

The particular appliance used in the experiments is a typical domestic freezer with a nominal power consumption of 70 W, a volume of 91 liters and it is classified as energy class A, according to the EU energy label (EU Directive 92/75/EEC [8]), with an annual expected energy demand of 208 kWh.

A. The Sensing Infrastructure

The parameters permanently monitored are the internal air temperature of the freezer, the instantaneous power consumption and the room ambient temperature. Regarding the communication architecture, the experimental setup consists of different blocks, as shown in Fig. 1. The circuit board with the temperature sensor is placed inside the freezer which measures the internal air temperature every second. The temperature sensor is made of an integrated circuit with a high precision of 0.25°K and it is directly calibrated in degrees Kelvin (in order to easily perform negative temperature measurements). Moreover, the ambient temperature is monitored by a wall router, which has an integrated temperature sensor with an accuracy of 0.5°C. Furthermore, a plug meter, which contains an integrated metrology chip, records every second the active power demand of the freezer [9].

B. The Communication Infrastructure

The developed communication infrastructure is based on the Zigbee low-power wireless communication protocol [10]. The value of each parameter measured is transmitted through a transceiver device. The output of the temperature sensor placed inside the freezer is read by a microcontroller, which transmits it to the transceiver. The plug meter [9] is also connected to a transceiver, and the room temperature is monitored through a wall router, which has an incorporated transceiver. These transceivers transmit the measurements every second to a connect port (the main coordinator). The connect port stores the information on an external USB drive, which is accessible through a web-based interface on the server of the Electrical Engineering Department in TU/e.

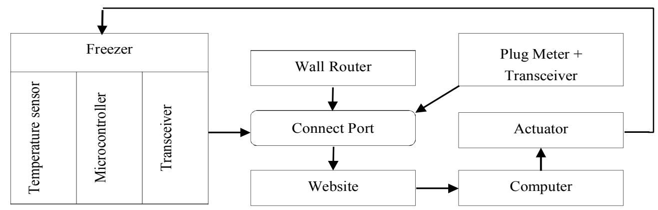

Fig. 1. The communication and data flow architecture

C. The Control Scheme

The actuator is composed of a solid state relay circuit which switches *on/off* the compressor of the freezer whenever a control signal is received from the computer. The computer is actually the physical accommodation of a software agent that processes the measured data and defines the future inputs for the actuator based on a local optimisation problem. Thus, at certain moments energy is stored in the form of cold and the freezer is kept at a lower temperature. At other moments the energy consumption is minimized and the freezer is kept on the upper temperature boundary. In this particular case of the domestic freezer, a minimum *on* time of five minutes has been assumed. This is due to the uncertainties related to the induced mechanical stress, which occurs when fast actuations are performed on the compressor's operation (*on*/*off*). A very short *on* time can have an impact on the maintenance costs. The software agent defines the future control signals for the freezer, by solving a local optimisation problem, which aims at maximizing an objective function (defined by the end-user) subject to the constraints related to the freezer operation. After the control input has been applied, the optimized power consumption is obtained. The control principle is illustrated in Fig. 2. In a real-life situation, at the household level and at the grid level the communication delays would add up to less than one second. Nonetheless, in the case of this experimental setup, there are several delays introduced by the limited capabilities of the communicating devices, adding up to one minute.

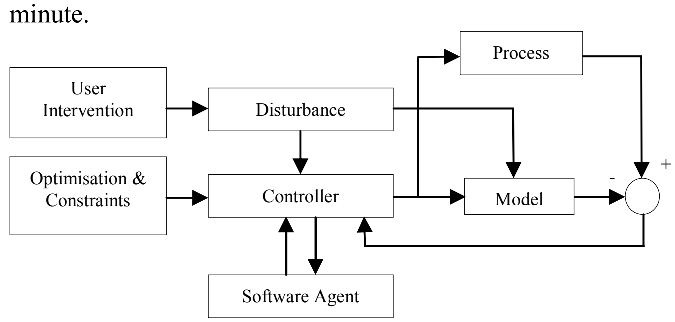

Fig. 2. The control strategy

VII. Modelling and Simulation of the Electrical Consumption of a Freezer

A. Normal freezer operation without user actions

In this case, the freezer operates without any external influencing factor (no user intervention), except for the variation of the ambient temperature. From the measurements recorded on a daily basis and the freezer construction characteristics, the parameter values of the freezer have been estimated and used in the simulations. Thus the simulated profiles representing the temperature evolution and the power are generated and then compared to the actual measurements. The prediction starts at current discrete time $t = 0$ *min.* and ends at $t = 150$ *min* (Fig. 3).

The differences can be attributed to hysteresis phenomena: the temperature of its compartments varies between certain temperature limits, but within a certain error. Moreover, the errors also arise from the fact that the temperature profile obtained from the measurements is assumed to represent an uniform temperature inside the freezer. Another source of error is due to the fact that in the Matlab model the freezer internal temperature decreases as long as the compressor is *on*, while in practice the measured temperature in the freezer continues to decrease or remains at a constant level for approximately one minute even after the compressor operation has been stopped, time period while the cold gets uniformly distributed.

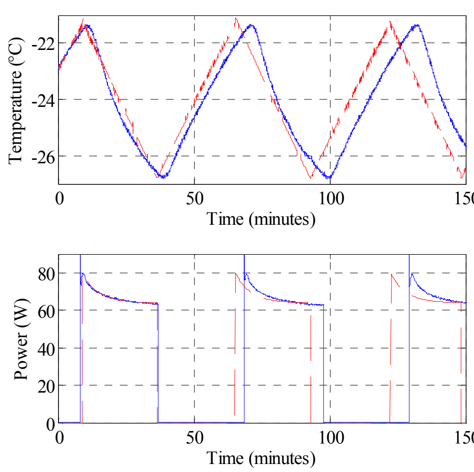

Fig. 3. The measured (continuous line) and simulated (interrupted line) temperature and power consumption of the freezer.

In order to evaluate the accuracy of the predictions made, the prediction errors are estimated. Fig. 4 presents the errors obtained by predicting the freezer operation for a future time horizon of 30 minutes, one hour, 1.5 hours, respectively 2 hours with respect to the current time. The errors are determined by evaluating the difference in energy consumption over the given time period and are computed for two main situations: when the prediction started during the *on* period, respectively during the *off* period. Moreover, during these experiments the thermal mass has a medium value (corresponding to the average freezer load). The value of the error is influenced by the total energy consumed in the respective time period, namely the number of *on* and off periods (in the case of minimum load, one *on* cycle lasts for approximately 26 minutes and the *off* cycle for approximately 40 minutes).

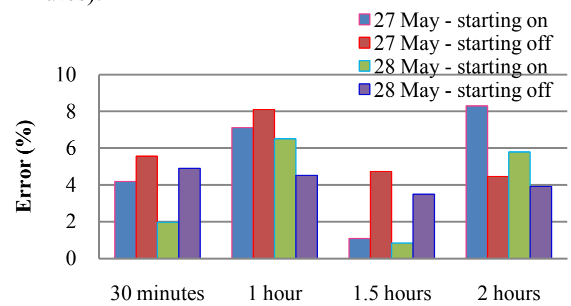

Fig. 4. The prediction errors in terms of energy content for several durations of forecasting horizons.

B. Door openings

When the door of the freezer is opened, a heat exchange occurs between the cold air inside the freezer and the warmer air in the room. In order to simulate the effect of door openings on the freezer operation, the heat loss during a door opening is estimated. This heat loss depends mainly on the temperature inside the freezer and the ambient temperature. Thus, a higher ambient temperature or a lower temperature inside the freezer results in a higher heat loss during a door opening. For the households included in the study, it is assumed that the temperature variation throughout the day is not higher than 2°C. Consequently, because this small variation does not have a significant impact on the operation of the freezer, it is assumed that the energy lost through one door opening is the same irrespective of the moment of the day.

The user behaviour is measured and integrated in the simulation studies. It is represented through a disturbance model that creates predictions about the future user actions (e.g. future schedule of door openings). The prediction of the user behaviour is derived from a fixed pattern: the average number of door openings during one day for a household. The door openings variation for each household is randomly generated so that the averages of their aggregated values correspond to the actual hourly pattern values.

In the case of the developed experimental setup, the temperature inside the freezer varies from -24°C to -18°C and the ambient temperature, throughout a day, varies from 21.5°C to 23.5°C. The duration of a single door opening is assumed to be 20 seconds. After performing several experiments, it was concluded that the average energy loss per door opening is approximately 13.6 Wh.

Fig. 5 presents the comparison between the measurement and simulation data of a single door opening. The prediction of the temperature profile starts at time $t = 0$ *min.* and it ends at $t = 130$ *min.* The thick line represents the measured temperature profile and the thin line represents the simulated temperature. The differences between the two graphs can be explained by the change in the thermal mass of the freezer after the door has been opened (due to the change of the air thermal mass), while the simulation assumes a constant value of the thermal mass during this experiment. Moreover, the temperature limits in the freezer are not reached, in contrast to the simulation.

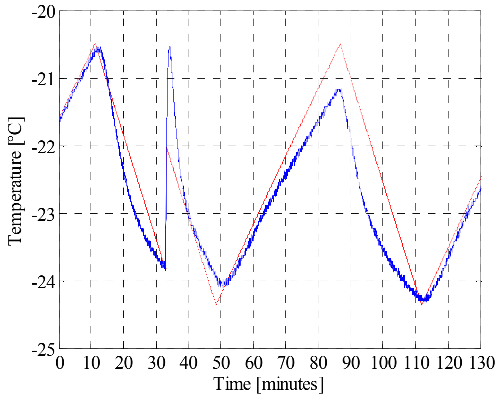

Fig. 5. The measured and simulated temperature profile during one door opening starting at $t = 32\ minutes$ and lasting for 20 seconds.

C. Thermal mass variation

The introduction of new food in the freezer is one parameter that influences its energy consumption significantly, starting the moment of its occurrence. While its frequency is reduced (approximately 2-3 times per week [11]), the experiments have shown that after its incidence, the operation of the freezer can be altered for a time period of up to 18 hours, after which it stabilizes. The magnitude of this effect is determined by the amount and type of food introduced, as well as by its initial temperature. The effect of introducing new items in the freezer can be physically described by Fourier's law by expressing the conductive heat transfer, phenomena through which the cooling of an item occurs. Moreover, by expressing the rate of the energy transfer to a certain object, an approximation of the temperature evolution of the item in time can be deduced.

When food is taken out of the freezer, a certain amount of energy loss occurs due to the door opening and the thermal mass of the freezer is modified.

During the experiments, water was chosen for the simulation of the load variation. The load introduction experiment consisted of the placing of one litre of water at room temperature, inside the freezer. After verifying the experimental results with the computer simulation algorithms, the prediction of the demand response potential for the next day is estimated, as well as the potential for real-time operation.

D. Demand response

The participation in a DR program consists of three main subsequent actions: the planning and scheduling of the next day's power demand (submitted by midday on the day-ahead market), the real-time operations (when load shifting is applied) and the financial settlement [16].

As part of the planning phase, the end-users inform the aggregator about their energy demand during the next day, in the form of energy schedules in kWh for each settlement period of 15 minutes. The aggregator builds up an aggregate order for the next day energy consumption and submits the bids to the operator of the day-ahead market [16].

During the real-time operational phase, the aggregator receives aggregate information from the end users. Due to the fact that in practice imbalances occur in this stage (leading to deviations from the original predicted schedules), the aggregator will initially try to solve them internally. Thus, it will send in real time a processed set-point trajectory which defines the way the end users should modify their energy consumption in order to compensate for imbalances. Consequently, the operation of the freezer will be optimally controlled in order for the conditions present in the control signal to be met. The optimization process integrates the freezer constraints and external influencing factors such as the door openings. The objective function that lies at the basis of the model predictive controller represents the maximization of the contribution of the freezer to the demand response program. Thus, the operation of the freezer is optimally controlled in order to comply with the request received from the aggregator, while dealing with system constraints, namely the external influencing factors such as ambient temperature and user behaviour [16].

After receiving the signal, the freezer establishes its control algorithm, performs a prediction of its energy consumption for the following requested period of time and submits this optimized profile to the aggregator, which either accepts it or rejects it. Fig. 6 portrays two possible cases for a freezer's optimized profile: from time instant $t = 0\ min.$ until time instant $t = 30\ min.$, the freezer performs its normal operation. At time instant $t = 30\ min.$, the freezer receives a request for up-regulation or down-regulation for the following time period of one hour. The freezer calculates and forwards the optimised power consumption forecast back to the aggregator and in case it is accepted, its operation will follow the profiles presented in Fig. 6 (the top figure for the case of a request to decrease the energy consumption and the lower figure for an increase in the energy consumption).

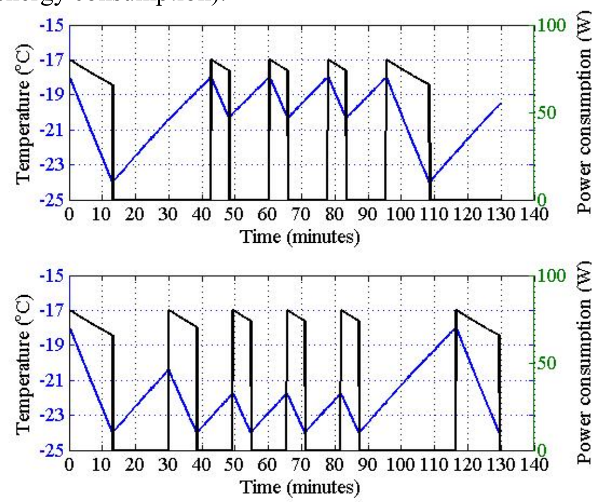

Fig. 6. Applying demand response to the operation of the freezer: the top figure represents the minimization of the energy consumption and the lower figure the maximization of the energy consumption.

VIII. The Day-Ahead Prediction of the Electrical Consumption for an Aggregation of Freezers

This section presents the prediction of the next day DR potential for the case study focusing on an aggregation of 1000 freezers. The day-ahead prediction of the energy consumption is submitted to the aggregator, for each settlement period of 15 minutes of the following day. The initial temperature, the initial *on/off* operation and the thermal mass loading (minimum, medium or maximum) of each freezer are set randomly by using a uniform distribution function for an aggregation of 1000 freezers. Due to the ratio between the *on* and the *off* periods, initially approximately one third of the freezers are *on* and the rest are *off*. The ambient temperature used in the predictions is the average temperature vector taken over the last several days. The door openings cases for the 1000 freezers are generated by adapting the data on the incidence of door openings for refrigerators [11] and knowing that the frequency of door openings for freezers is five times less than the one for refrigerators [12].

A. Normal freezer operation without user actions

The day-ahead prediction for the DR potential of an aggregation of freezers is firstly conducted for the case when there is no user behaviour affecting the operation of the freezer. The ambient temperature is the only external parameter which varies in time. The normal power consumption of the aggregation of freezers, averaged for every 4 seconds, would vary from 10 kW to 35 kW. If up-regulation is requested, the power consumption will be reduced to approximately 3-5 kW. If down-regulation is requested, the power consumption can be increased up to 60-65 kW. Consequently, according to the results obtained, if the freezer is not under the influence of the user behaviour, the energy consumption of the aggregation of 1000 freezers can be increased by up to 50 kW or decreased by up to 30 kW.

B. Door openings and load variation

A second analysis of the day-ahead prediction is done by incorporating the user behaviour through the freezer door openings and food load variation. Compared to the previous case, when the user behaviour was omitted, now the energy consumption is higher, as expected. The power consumption for the normal operation has an increasing trend during the day from 20-30 kW at the beginning of the day, to 60 kW at the end of the day when the door openings have the highest frequency. If maximization of energy consumption is requested, the response of the freezers leads to an average power of 68 kW available anytime during the day. For the case of minimization of energy consumption, the power demand can reach 10 kW during the first part of the day, in the middle of the day it increases to 30-40 kW, resulting in approximately 50-60 kW at the end of the day.

IX. Simulation of the Electrical Consumption of an Aggregation of Freezers in Real-Time

This section describes the response of an aggregation of freezers to the DR signal for up-regulation and down-regulation. At current time instant $t = 0$ *min.* the aggregator transmits to the agents of the freezers a set-point trajectory defined for a certain control horizon. Then for each freezer the demand response potential is computed and is sent back to the aggregator.

During the simulations, the control horizon is of one hour. When the freezer receives the control signal, it firstly checks whether it would need to prolong its current operation, in order to avoid damages to the appliance caused by mechanical stress. For the remaining control period, the operation of the freezer is optimized in a decentralized manner, so that it partially satisfies the request of the aggregator (through the set-point trajectory).

A. Normal freezer operation without user actions

During the first quarter of the hour, a significant reduction of the power consumption is obtained, of approximately 20 kW. Overall, an energy consumption reduction of 12.11 kWh is obtained. For the rest of the quarters, due to the fact that most freezers operate around the higher temperature limit, the energy reduction is not as significant as during the first quarter. This is driven by the fact that the operation of a large number of freezers has become synchronized due to temperature constraints.

For the case when down-regulation is requested, during the first quarter, the power consumption increase is significant, of about 40 kW, while for the rest of the time it is only slightly higher than the energy consumption during the normal operation. Overall, an increase in energy consumption of 18.24 kWh is obtained.

B. Door openings and load variation

Fig. 7 presents the real-time response of an aggregation of 1000 freezers when up-regulation, respectively down-regulation is requested for the control horizon of one hour: the power profile contains 4-second averages of the power demand. During the first quarter, the resulting energy reduction is significant (20 kW) compared to the usual energy use (Fig. 7, top plot). During the last quarter of the hour, the power reduction achieved is less, of approximately 10 kW, as most freezers operate in the upper region of the temperature variation interval. Overall, an energy consumption reduction of 12.85 kWh is obtained.

When the control signal of the aggregator requests down-regulation, the user behaviour favours an significant increase in the energy consumption for all periods, compared to the normal operation, with the highest increase during the first quarter, of about 40-50 kW (Fig. 7, lower plot). During the last quarter of the hour, the power increase is still achieved, but to a lower extent, of approximately 10-20 kW. Overall, an increase in energy consumption of 20.19 kWh is obtained.

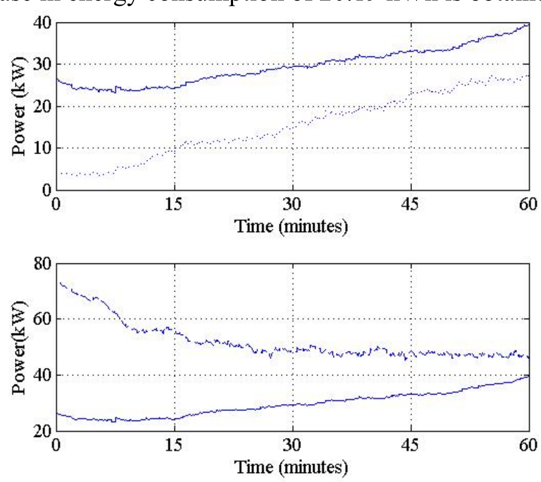

Fig. 7. The DR potential for minimum and maximum energy consumption: the interrupted line represents the power consumption in the case of minimum, respectively maximum operation and the continuous line represents the energy consumption in the case of a normal operation

If the control signal consists of a request for up-regulation during the first half hour and down-regulation during the second half hour, the contribution to DR becomes more significant (see Fig. 8). This is due to the fact that after the first half hour, all the freezers are operating in the upper temperature region (between -20ºC and -18ºC) and are afterwards brought to the lower temperature region (between -22ºC and -24ºC). Another factor that contributes to the significant result is length of the *on* periods (14 to 26 minutes), and of the *off* periods (30 to 40 minutes). Consequently, when the energy increase is requested, all the freezers will ideally reach the *on* state, leading to a power peak of 80 kW. In the first half hour an energy reduction of 69.1% is achieved, while during the second half hour an energy increase of 95.42% is reached.

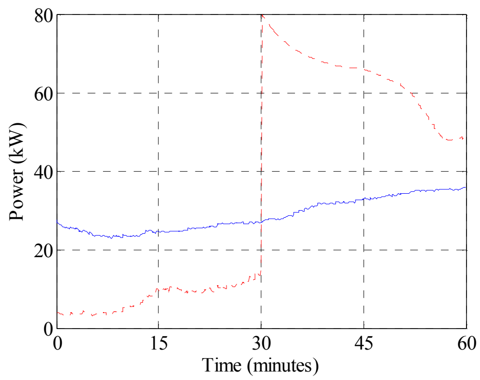

Fig. 8. The DR potential for firstly minimum and then maximum energy consumption: the blue continuous line represents the power consumption without DR and the red continuous line corresponds to the minimization and then maximization of the energy consumption.

When the control signal requests down-regulation during the first half hour and up-regulation during the second half hour, the contribution to DR is again significant (see Fig. 9). In the first half hour an energy increase of 110.37% is achieved, while during the second half hour an energy decrease of 48.82% is reached.

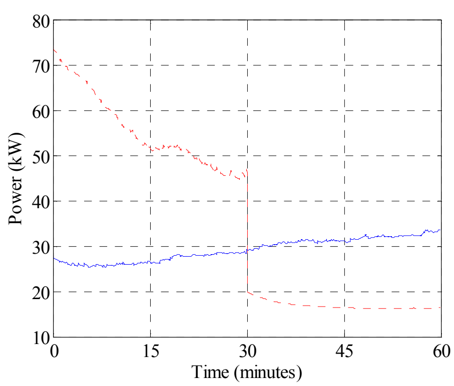

Fig. 9. The DR potential for maximum and then minimum energy consumption: the blue continuous line represents the power consumption without DR and the red interrupted line corresponds to the maximization and then minimization of the energy consumption

X. Results and Potential Applications

The developed software model generates predictions of the power demand over a receding horizon (the following day in the planning stage and the next hour in real-time), depending on the temperature evolution inside the freezer. The model-based predictive controller follows an objective function, in order to define the future inputs: maximization of the participation in the DR program. This objective function has been defined for four cases: when minimization of energy consumption is requested for the next hour, when maximization is requested and two more cases when a combination between the two is demanded.

The user behaviour is included in the simulations as an input in the disturbance model, which subsequently feeds the process model and the controller. The door openings cases for each freezer are simulated based on its average incidence data and are incorporated in the simulation through corresponding energy loss figures.

This type of control strategy can fit well in real-time operations, such as an optimisation over a finite period in the short-term future, while explicitly taking into account the constraints related to load-shifting actions.

XI. Conclusions

This paper has included an analysis on the domestic freezer capabilities for DR. The optimisation algorithm implemented is based on an objective function whose aim is to maximize the participation in the DR program subject to operational non-flexible constraints. The optimisation process integrates the effect of user behaviour through the presence of door openings.

The DR potential of the aggregation of freezers has been inspected for several scenarios. When a combination of up-regulation and down-regulation is requested, the change in energy demand of the aggregation of freezers is significant compared to the normal operation. More specifically, in both simulated cases the contribution to DR is not only achieved during the first half hour, but it is considerably higher during the third quarter. Thus, when down-regulation is requested during the second half hour, as a response all the freezers are expected to have their compressors *on*. Furthermore, when up-regulation is requested for the second half hour, most freezers will operate in the *off* state. Although a DR request to minimize or maximize the energy consumption during one hour does not lead to a significant contribution for the grid system operator, a combination between the two cases among the quarters of an hour will result in an important participation to the DR program.

In conclusion, freezers are more appropriate for short-term DR (of around 15 minutes) due to their low thermal inertia. After this time period, the aggregation of freezers becomes synchronized, leading to a higher consumption at certain moments compared to the usual operation.

The selected case study of the domestic freezer provides a closed system which is suitable for demonstration purposes in a laboratory environment. The ideas described in this paper can be extended to address other thermostatically controlled appliances, e.g. space-conditioning systems.

As the focus of this study was not on creating an accurate model for the operation of the freezer, the future research recommendations include the development of more detailed models in order to integrate with more precision the hysteresis phenomena and thus create more accurate predictions on the longer term. Moreover, the thermal mass study should include an insight into the thermodynamics concerning the freezing process of food with the scope of predicting with accuracy the energy consumption of the freezer after food is introduced in its compartments.

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XIII. Biographies

Nadina Baghină received a Bachelor Degree in Electrical Engineering and Computer Science from Jacobs University, Bremen, Germany in 2010.

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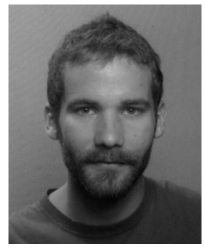

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Prof. Kling is involved in scientific organisations, such as CIGRE and the IEEE. As Netherlands’ representative, he is a member of CIGRE Study Committee C6 Distribution Systems and Dispersed Generation and the Administrative Council of CIGRE.

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