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Aggregation and Control of Supermarket Refrigeration Systems in a Smart Grid

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Abstract: In this work, control strategies for aggregation of a portfolio of supermarkets towards the electricity balancing market, is investigated. The supermarkets are able to shift the power consumption in time by pre-cooling the contained foodstuff. It is shown how the flexibility of an individual supermarket can be modeled and how this model can be used by an aggregator to manage the portfolio to deliver upward and downward regulation. Two control strategies for managing the portfolio to follow a power reference are presented and compared. The first strategy is a non-convex predictive control strategy while the second strategy consists of a PI controller and a dispatch algorithm. The predictive controller has a high performance but is computationally heavy. In contrast the PI/dispatch strategy has lower performance, but requires little computational effort and scales well with the number of supermarkets. Two simulations are conducted based on high-fidelity supermarket models: a small-scale simulation with 20 supermarkets where the performance of the two strategies are compared and a large-scale simulation with 400 supermarkets which only the PI/dispatch controller is able to handle. The large-scale simulation shows how a portfolio of 400 supermarkets successfully can be used for upward regulation of 900 kW for a two hour period.

Keywords: Smart Grid, Supermarket refrigeration system, Control strategies.

1. INTRODUCTION

The growing demand on fossil fuel independence and focus on climate related issues is leading to a larger penetration of renewable energy sources throughout the developed world (Department of Energy (2008)). The European Commission has set a target of 20 % renewables by 2030 (European Commision (2010)) and China has doubled its share of wind power production every year since 2004 (Yan et al. (2010)), while Denmark has set a goal of 50 % wind power in the energy sector by 2020 and 100 % by 2050 (Danish Ministry for Climate and Buildings (2012)).

One of the challenges arising when relying on renewable sources is a destabilization of the power grid as production from e.g., wind turbines or photovoltaics can vary greatly according to the weather. In traditional setups the grid is balanced by central power plants, which not only deliver power, but also ancillary services such as upward- and downward regulation, primary frequency reserve, etc. When these conventional power plants are replaced by renewables, the ability to provide such services will disappear, as these systems typically will utilize all the available power. It should be mentioned that recent research into how wind turbines can offer certain type of services has been investigated in (Juelsgaard et al. (2012)).

It is therefore evident that to ensure a reliable future power grid, new methods and alternative ways of delivering these services must be found. One of the main approaches for doing this is known as *smart grid*, where the flexible consumption of demand side devices is utilized in the balancing effort (Palensky and Dietrich (2011)). In this balancing effort, different technologies such as controlling flexible devices by informing them of future power prices, have been investigated in (Hovgaard (2013)). Further, Biegel et al. (2013b) details how flexible devices can be modeled and aggregated such that their accumulated response can enter into the markets on same terms as conventional generators. Biegel et al. (2013a) describes how a portfolio of ON/OFF demand side devices can be controlled to offer upwards and downwards regulation. Moreover, Biegel et al. (2013c) investigates how the flexible consumption of demand side devices in cooperation with production units can be used to stabilize the grid.

This work presents a method for harnessing significant volumes of consumption flexibility of supermarket systems in a simplistic manner. The basic concept is to construct a simple interface between the supermarkets and an aggregator. This is achieved by characterizing each supermarket by two distinct operation modes denoted *ON* and *OFF*, or collectively as the storage mode state (SMS). In the OFF mode, the supermarket can run in its default operation mode which for example could be to minimize power consumption. However, in the ON mode, the supermarket is asked to increase the overall power consumption, which is effectively done by lowering the temperatures in the display cases. This simple interface is chosen for a number of reasons. First of all, the supermarket is still in full control of its primary process and there is no risk the aggregator will cause the foodstuff to exceed the maximum allowed temperature. Secondly, the method is easy to implement and requires no additional hardware. Furthermore, the proposed method does not require any complex modeling or adaption of each supermarket, no complex interface is needed, only an ON/OFF signal received from the aggregator and a feedback of power consumption. This makes it possible to implement the method on already existing supermarket refrigeration systems and use them as providers of regulating services. With properties that to some extent can be compared to the current secondary and tertiary reserves. Finally, this method makes the contracting of flexibility simple and transparent without need for consumption baselines etc; the aggregator could for example provide compensation simply based on the duration and number of ON-activations which significantly simplifies the contractual setup (Harbo and Biegel (2012)).

The paper structure is as follows. In Sec. 2, the system architecture is presented. Following, in Sec. 3 the role of the local supermarket supervisor is explained. In Sec. 4 the flexibility and power response of a supermarket is modeled. Next, Sec. 5 shortly explains how the aggregator interfaces the portfolio to the electricity markets, followed by Sec. 6 on how a virtual power plant (VPP) controls the portfolio to ensure that a power reference is followed. Simulation examples demonstrating the strategies is presented in Sec. 7. Finally, Sec. 8 concludes the work and the results are discussed in Sec. 9.

2. SYSTEM ARCHITECTURE

In this section, an overview of the general system architecture is given and the relation from supermarket through aggregator to electricity markets is explained. The setup is depicted in Fig. 1 and illustrates the basic idea in the Danish smart grid setup, where the aggregator manages a portfolio of flexible demand-side devices and utilizes the accumulated flexibility in the unbundled electricity markets on equal terms with conventional generators (Energinet.dk and Danish Energy Association (2012)). In the following, the main players of this architecture are introduced.

2.1 Regulating Power Markets

Suppliers can place bids of upward regulation (increasing production or lowering consumption) or downward regulation (lowering production or increasing consumption) in the regulating power market. The transmission system operator (TSO) utilizes these reserves for grid stabilization by activating upward/downward regulation according to the system imbalances in the delivery hour (Energinet.dk (2007)).

In this paper the focus is on the technical aspects of how a portfolio of supermarkets can be managed to deliver

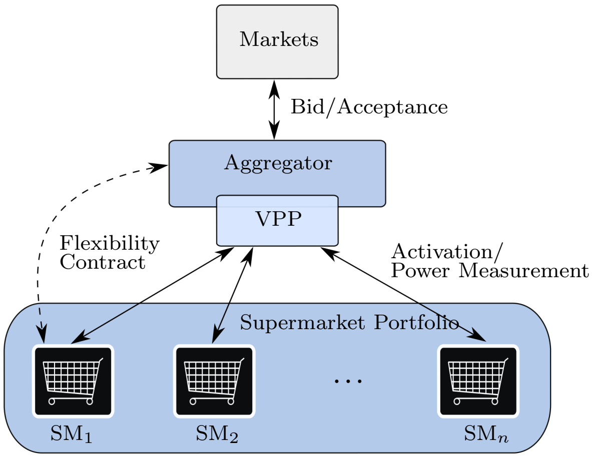

Fig. 1. Illustration of the interconnection between electricity markets and supermarket portfolio. The aggregator is bidding into the markets by managing n supermarkets through a VPP and an ON/OFF interface.

such upward or downward regulation services. Therefore, topics such as bidding strategies, flexibility contracts, or the economical aspects for the supermarkets for delivering these services, are not considered – these issues are outside the scope of this paper.

2.2 Aggregator & VPP

The aggregator is a legal entity in charge of contracting flexibility from the flexible consumers, in this case the supermarkets. By these contracts, the aggregator is allowed to utilize the flexibility of each device, thus enabling the aggregator to accumulate and utilize the flexibility of an entire portfolio of devices. The devices are managed through what is known as a virtual power plant (VPP). The objective of the VPP is to ensure that the services sold by the aggregator to the regulating power market are indeed delivered.

2.3 Supermarket Portfolio

The supermarket is capable of offering flexible consumption by utilizing the thermal mass contained in its display cases. Decreasing display case temperatures will automatically result in an increase in power consumption. When the temperatures are below the upper bound it is thus possible to decrease the power consumption until the temperatures again reach this upper bound.

By utilizing this ability of numerous supermarkets and aggregating them, the collected power consumption profile can be used for bidding into the regulating power markets.

3. LOCAL SUPERMARKET SMART GRID CONTROL

A local supervisor controller must be implemented at the supermarket refrigeration system. The controller ensures that the supermarket reacts to the VPP ON/OFF signal and feeds back the total power consumption, as illustrated in Fig. 1. The functionality of this supervisor controller is illustrated in Fig. 2 and described in the following.

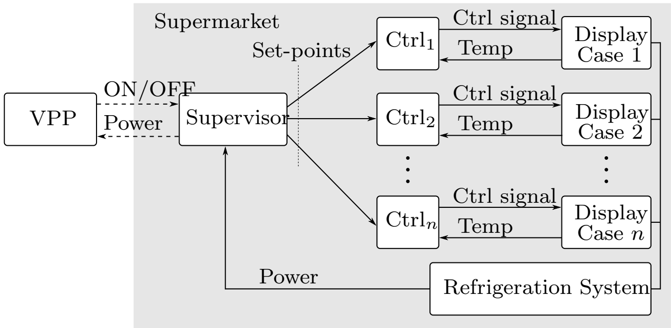

Fig. 2. Placement of the supermarket supervisor according to the local display case controllers and the refrigerations system, for one supermarket in the portfolio.

When the SMS of a supermarket for example is switched from OFF to ON, the strategy is to store energy quickly by changing the temperature references of all local display case controllers to their lower bounds, thus activating the system, and thereby increasing the power consumption, as much as possible. This will offer the largest amount of flexibility within a smaller time span. When the SMS is switched from ON to OFF the strategy is reversed and all temperature references are changed to their upper bounds. By offering flexibility in this way, and under the assumption of well tuned local temperature controllers, it is possible to manage a significant volume of the flexibility, without jeopardizing foodstuff safety; further, there is no need for new hardware on the individual display cases. As previously described, these are some of the reasons for choosing this simple ON/OFF interface.

4. MODELING

In order for the aggregator to use the flexibility of the portfolio in its bidding strategy, a model of the flexibility of each supermarket is needed. Furthermore, a model of the power profile of each supermarket, is required to enable the VPP to deliver the required upward or downward regulating power.

4.1 Flexibility

To describe flexibility, a subset of the power node modeling framework introduced by Heussen et al. (2011) is used to construct a bucket model, see e.g., Pedersen et al. (2013) for an example of this bucket model fitted to a refrigeration system. The relation between energy storage and power consumption is described by the following constrained discrete time equation

$$E(k+1) = a_d E(k) + T_s P(k) \tag{1}$$

$$\underline{E} \leq E(k) \leq \overline{E} \tag{2}$$

$$\underline{P} \leq P(k) \leq \overline{P}, \tag{3}$$

where $E(k) \in \mathbb{R}_+$ is the energy stored at sample k, $P(k) \in \mathbb{R}_+$ is the power consumed at sample k, $a_d \in \mathbb{R}$ is the discrete time drain rate, $T_s \in \mathbb{R}_+$ is the sampling time, $\overline{E}$ and $\underline{E} \in \mathbb{R}_+$ are constraints on energy level, $\overline{P}$ and $\underline{P} \in \mathbb{R}_+$ are constraints on power consumption.

The objective is to fit this model to a supermarket system only based on knowledge of the SMS and power consumption measurements. This means that the size of the supermarket refrigeration system and specific setup are unknown factors. However the assumption of a known coefficient of performance (COP) is made in order to normalize the power and thereby decouple the disturbance of outdoor temperature from the following model. The COP describes the amount of electrical energy converted to cooling energy by the refrigeration system. There are ways to estimate this value, e.g., (Hovgaard et al. (2013)), and an affine approximation can be made (Shafiei et al. (2013a)). Fig. 3 illustrates a sketch of the evolution of

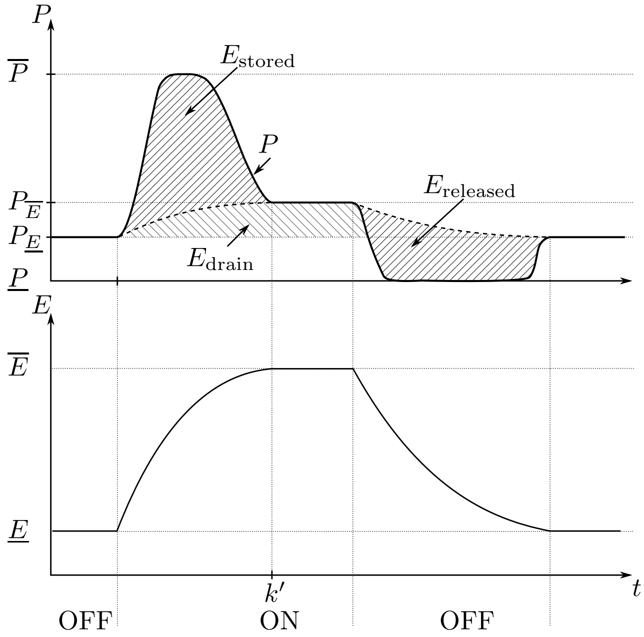

Fig. 3. Sketch of the power response when supermarket is switched between ON and OFF. E_{stored} denotes the stored energy, which is equal to the released energy E_{released} and E_{drain} denotes the increased energy drainage from increasing the energy level.

power consumption and energy level when the SMS is switched between ON and OFF. The SMS is started in OFF and the energy level is at its lower bound, $E(k) = \underline{E}$. Let $P(k) = P_{\underline{E}}$ denote the steady state power required to keep the energy level at $\underline{E}$. When the SMS is switched to ON, $P(k)$ rapidly increases to $\overline{P}$. As the energy level rises to $\overline{E}$, $P(k)$ will decrease until steady state where $P(k) = P_{\overline{E}}$. Similar reasoning applies when switching the SMS from ON to OFF. It should be noted that the model also accounts for the increased loss that occur, due to the increased temperature difference, when the energy level is increased. Furthermore, the notion of storing energy in refrigeration systems by lowering temperatures is technically incorrect, as decreasing temperatures is the same as lowering energy level. However, the ability to shift consumption in this manner is effectively the same as storing energy from an aggregator point of view.

To describe such a model, the parameters a_d, $\overline{P}$, $\underline{P}$, $\overline{E}$ and $\underline{E}$ must be identified. This can be accomplished directly via measurements. To find the constraints on energy, Eq. (1) can be rewritten into Eq. (4) and (5), given that the system is in steady state running at its energy bounds, i.e. $E(k) = \underline{E}$ or $E(k) = \overline{E}$.

$$\underline{E} = a_d\underline{E} + T_s P_{\underline{E}} \Rightarrow \underline{E} = \frac{T_s P_{\underline{E}}}{1 - a_d} \quad (4)$$

$$\overline{E} = a_d\overline{E} + T_s P_{\overline{E}} \Rightarrow \overline{E} = \frac{T_s P_{\overline{E}}}{1 - a_d}. \quad (5)$$

Knowing that $E(k') = \overline{E}$, see Fig. 3, the sequence of equations starting from sample k' and back to the sample where the switch to ON occurred, $E(1) = \underline{E}$, $k = 1, \ldots, k'$, can be written as

$$\overline{E} = a_d E(k' - 1) + T_s P(k' - 1) \Rightarrow \quad (6)$$

$$E(k' - 1) = \frac{\overline{E} - T_s P(k' - 1)}{a_d} \Rightarrow \quad (7)$$

$$E(k' - 2) = \frac{E(k' - 1) - T_s P(k' - 2)}{a_d} \quad (8)$$

$$\vdots$$

$$E(1) = \underline{E} = [((\overline{E} - T_s P(k' - 1))/a_d - T_s P(k' - 2))/a_d \cdots - T_s P(0)]/a_d. \quad (9)$$

Assuming that T_s is known as well as the time sequence of measurements $P(0), \ldots, P(k')$, Eqs. (4)-(5) can be inserted into Eq. (9), thereby reducing the problem to one equation in one unknown, namely a_d, which can be solved in a deterministic way. In the following the continuous time model of energy is used to describe the power profile, where the continuous counterpart of a_d is easily found as $a_c = \ln(a_d)/T_s$. The continuous time model is given as

$$\frac{dE(t)}{dt} = a_c E(t) + P(t). \quad (10)$$

4.2 Power Profile

The high fidelity supermarket model developed by Shafiei et al. (2013b) is utilized to examine an actual power response from a supermarket system when switching the SMS between ON and OFF. Such a response is depicted in Fig. 4.

The fluctuations in power consumption are caused by several factors such as: hysteresis control of the display case temperatures and the compressors occasionally switching. It is thus evident that the simulated power consumption of the model does not look exactly like the sketch in Fig. 3. However, the zero phase filtered version resembles the general behavior. Furthermore, notice that when the number of supermarkets in the portfolio increases, these fluctuations in the individual supermarket's power consumption will have less impact on the collective power response. Therefore, it is only the general behavior of each supermarket's power response which is of interest, i.e. the filtered version.

To describe this behavior the power profile is split into two parts. One part handles the power consumption due to drain from increasing the energy level, indicated by the slowly ascending/descending dashed lines in Fig. 3. The second part describes the extra consumption from storing energy. Given that the behavior when switching between the two modes are similar, they are modeled in the same way. The power consumption at time t, can thus be expressed as

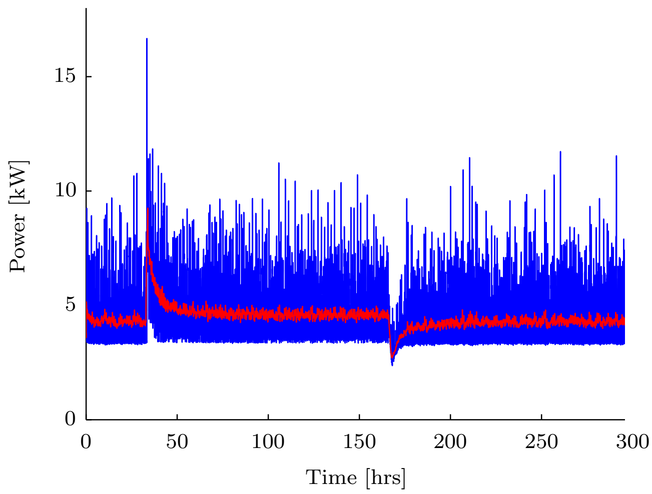

Fig. 4. Power response of high fidelity supermarket refrigeration system model. (Blue) is simulated power consumption and (Red) is a zero phase filtering over 60 minutes of it.

$$P(t) = \widetilde{P}(t) + \widehat{P}(t), \quad (11)$$

where $\widetilde{P}(t) \in \mathbb{R}$ describes the power consumption due to loss and $\widehat{P}(t) \in \mathbb{R}$ describes the power consumption due to storing/releasing energy. Due to conservation of energy, $\frac{dE(t)}{dt} = 0$; thus, the power loss is modeled as

$$\widetilde{P}(t) = -a_c E(t). \quad (12)$$

To evaluate how $\widetilde{P}(t)$ evolves, Eq. (12) is differentiated with respect to t

$$\frac{d\widetilde{P}(t)}{dt} = -a_c \frac{dE(t)}{dt} \quad (13)$$

$$= -a_c^2 E(t) - a_c \widetilde{P}(t) - a_c \widehat{P}(t). \quad (14)$$

The power storage is modeled by a system of linear equations describing both the steep ascent/descent and slow ascent/descent. Furthermore, the input, $u(t)$, to the system is binary. The system is as follows

$$\widehat{P}(t) = \frac{dx_1(t)}{dt} \quad (15)$$

$$\frac{dx_1(t)}{dt} = b_1 x_1(t) + c_1 x_2(t) \quad (16)$$

$$\frac{dx_2(t)}{dt} = b_2 x_2(t) + c_2 u(t), \quad (17)$$

where $x_1(t) \in \mathbb{R}$ describes the slow ascent/descent, $x_2(t) \in \mathbb{R}$ describes the fast ascent/descent, i.e. $|b_2| >> |b_1|$, $b_i \in \mathbb{R}_-$, $c_i \in \mathbb{R}_+$ are parameters of the model and $u(t) \in \{0, 1\}$ is the binary ON/OFF control input. To model the dynamic behavior of $\widehat{P}$, its derivative with respect to t is found

$$\frac{d\widehat{P}(t)}{dt} = \frac{d^2 x_1(t)}{dt^2} \quad (18)$$

$$= b_1^2 x_1(t) + (b_1 c_1 + b_2 c_1) x_2(t) + c_1 c_2 u(t). \quad (19)$$

4.3 Combined Model

The flexibility and power profile model is collected to form the following state space system, representing a supermarket:

$$\frac{dx(t)}{dt} = Ax(t) + Bu(t) \tag{20}$$

$$y(t) = P(t) = Cx(t), \tag{21}$$

where

$$x(t) = \begin{bmatrix} E(t) \\ \widetilde{P}(t) \\ \widehat{P}(t) \\ x_1(t) \\ x_2(t) \end{bmatrix}, \; A = \begin{bmatrix} a_c & 1 & 1 & 0 & 0 \\ -a_c^2 & -a_c & -a_c & 0 & 0 \\ 0 & 0 & 0 & b_1^2 & b_1c_1 + b_2c_1 \\ 0 & 0 & 0 & b_1 & c_1 \\ 0 & 0 & 0 & 0 & b_2 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 \\ 0 \\ c_1c_2 \\ 0 \\ c_2 \end{bmatrix}, \; C = [0 \; 1 \; 1 \; 0 \; 0],$$

and with parameter a_c known from the flexibility modeling and the parameters b_i, c_i are found using prediction error method (PEM) (Ljung (1999)). The results of fitting the model to the response depicted in Fig. 4, is seen in Fig. 5. The model can not describe the high peak when

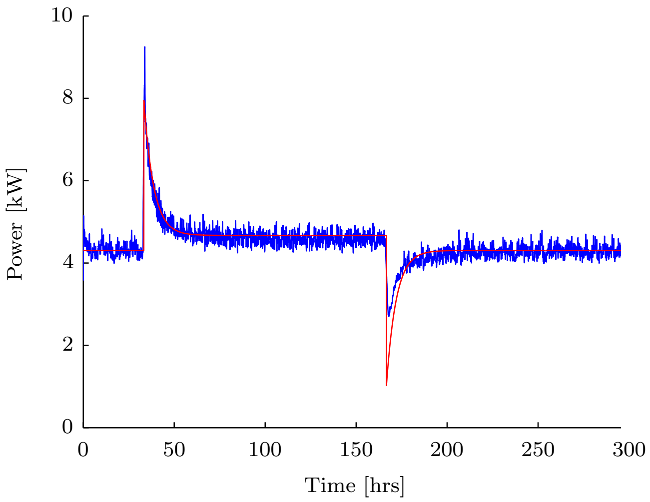

Fig. 5. Comparison between filtered power response (blue) and linear model (red).

switching the SMS from OFF to ON and the lower peak when switching the SMS from ON to OFF. However, it describes the general behavior between switches well. The discrepancies could be handled by a more complex model, but as this model is intended for large scale VPP control it is kept simple, leaving these discrepancies to be handled by the VPP control algorithm.

4.4 Portfolio Model

To obtain a model for the entire portfolio, the individual systems are concatenated as:

$$A_{\text{smp}} = \mathtt{diag}(A_1, \ldots, A_n) \tag{22}$$

$$B_{\text{smp}} = \mathtt{diag}(B_1, \ldots, B_n) \tag{23}$$

$$C_{\text{smp}} = \mathtt{diag}(C_1, \ldots, C_n), \tag{24}$$

where $A_{\text{smp}} \in \mathbb{R}^{5n \times 5n}$, $B_{\text{smp}} \in \mathbb{R}^{5n \times n}$, $C_{\text{smp}} \in \mathbb{R}^{n \times 5n}$, n is the number of supermarkets in the portfolio, and `diag(X,Y,...)` is a block diagonal matrix with $X, Y, \ldots$ as diagonal blocks.

5. AGGREGATOR

The purpose of the aggregator is to interface the portfolio of supermarkets to the various electricity markets and through knowledge of flexibility be able to plan power consumption according to these markets. This makes the aggregator responsible for providing the power reference for the VPP to track. In this setup the aggregator can use the supermarket portfolio model describing the power profile and energy flexibility to form the optimal daily power reference, based on e.g. estimates of future power prices. For such a day ahead cost optimization, the objective will be very similar to the economic MPC approach suggested by Hovgaard et al. (2011) scaled to multiple supermarkets.

The setup is, however, different when offering regulating services. Because of the ON/OFF interface the regulating services offered by a single supermarket have specific characteristics. When the SMS of the supermarket is set to ON for downward regulation; upward regulation will immediately follow upon switching to OFF. For the aggregated portfolio though, this behavior can be compensated by the large number of supermarkets and thus the ability to track a reference is achieved. Therefore, the following sections will focus on a generic notion of load shifting applicable in many different setups.

6. VIRTUAL POWER PLANT

The VPP must ensure that the power reference created by the aggregator is tracked. This section, presents two methods for doing this; following, the performance of the two methods is compared.

6.1 Predictive Solution

The first method follows directly from the supermarket portfolio model and the objective previously described. This can be reformulated in a receding horizon fashion leading to the following optimization problem which must be solved at each sample k.

$$\begin{aligned} \text{min.} \quad & \sum_{\kappa=k}^{k+N-1} (P_{\text{ref}}(\kappa) - \sum_{i=1}^{n} P_i(\kappa))^2 \\ \text{s.t.} \quad & x(\kappa+1) = A_{\text{smp}}x(\kappa) + B_{\text{smp}}u(\kappa) \\ & P(\kappa) = C_{\text{smp}}x(\kappa) \\ & u(\kappa) \in \{0,1\}^n, \\ & \kappa = k, \ldots, k+N-1, \end{aligned}$$

with variables $x(k+1), \ldots, x(k+N)$, $P(k), \ldots, P(k+N-1)$, $u(k), \ldots, u(k+N-1)$ and data $x(k)$, A_{smp}, B_{smp}, C_{smp}, $P_{\text{ref}}(k), \ldots, P_{\text{ref}}(k+N-1)$ and $P_i(\kappa)$ denotes the i'th entry in the $P(\kappa)$ vector, $P(\kappa) \in \mathbb{R}^n$. It can be seen that the decision variables in the vector $u(\kappa)$ are binary.

While it is possible to solve this problem for few supermarkets and a small horizon, it grows exponentially with the length of the horizon and the number of supermarkets in the portfolio. As a result, it is not practical to find the solution for hundreds of supermarkets over a horizon of even just tens of samples.

Therefore, a dispatch solution is introduced in the following.

6.2 Dispatch Algorithm

In this section an algorithm is designed, inspired by Petersen et al. (2013), that decides on activation by means of sorting the set of supermarkets in the portfolio denoted $\mathcal{S}$.

The control structure is depicted in Fig. 6 and is comprised of a standard PI controller with a dispatcher inserted between controller and plant to handle the conversion of a continuous scalar to a vector of binary variables.

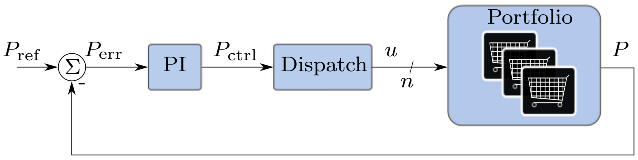

Fig. 6. Illustration of the dispatch strategy. The PI controller acts on the error P_{err} to form the control signal P_{ctrl} for the Dispatcher. The Dispatcher translates the control signal P_{ctrl} to ON/OFF signals for the portfolio.

The dispatch algorithm is summarized below, where ε is a tolerance band, the subsets of available supermarkets to switch ON, $\mathcal{S}_{\text{ON}} \subseteq \mathcal{S}$, or OFF, $\mathcal{S}_{\text{OFF}} \subseteq \mathcal{S}$, can be obtained in different ways, see e.g., Biegel et al. (2013a) for an example with ON/OFF time constraints. Here, the subsets are sorted by *best power response first*, meaning that the supermarket capable of offering a response closest to the error, e, is (de)activated first.

(1) Initialize by obtaining $P_{\text{ctrl}}(k)$.
(2) **if** $P_{\text{ctrl}}(k) > 0$.
  (a) Generate $\mathcal{S}_{\text{ON}}$.
  (b) Simulate response of $\mathcal{S}_{\text{ON}}$ according to (22)-(24).
  (c) Set $e = P_{\text{ctrl}}(k)$.
  (d) **while** $\mathcal{S}_{\text{ON}} \neq \emptyset$ **and** $|e| > \varepsilon$
    - Choose S_i from $\mathcal{S}_{\text{ON}}$ to switch ON, according to *best response first*.
    - Update $\mathcal{S}_{\text{ON}}$ by removing S_i.
    - Update $e = e - P_i$.
    - Switch supermarket ON: $u_i(k) = 1$.
  (e) Apply $u(k)$ to portfolio.
(3) **else if** $P_{\text{ctrl}}(k) \leq 0$.
  (a) Generate $\mathcal{S}_{\text{OFF}}$.
  (b) Simulate response of $\mathcal{S}_{\text{OFF}}$ according to (22)-(24).
  (c) Set $e = P_{\text{ctrl}}(k)$.
  (d) **while** $\mathcal{S}_{\text{OFF}} \neq \emptyset$ **and** $|e| > \varepsilon$
    - Choose S_i from $\mathcal{S}_{\text{OFF}}$ to switch OFF, according to *best response first*.
    - Update $\mathcal{S}_{\text{OFF}}$ by removing S_i.
    - Update $e = e - P_i$.
    - Switch supermarket OFF: $u_i(k) = 0$.
  (e) Apply $u(k)$ to portfolio.
(4) Increase k by one and go to step 1.

7. SIMULATION EXAMPLES

Two simulations are presented in this section: a small-scale example where the predictive strategy and the dispatch strategy are compared and a large scale example where only the dispatch solution is applicable. A sampling time $T_s = 5$ minutes is used.

Method	Tracking Error (RMSE)		Computation	
	Power [kW]	%	Time [sec]	%
Predictive	2.15	100	5051	100
Dispatch	3.5	163	$24{\cdot}10^{-3}$	$47{\cdot}10^{-3}$

Table 1. Comparison between the different VPP control methods, both simulated on a portfolio of 20 supermarkets.

7.1 Small-Scale Example

The two different approaches are compared on a scenario consisting of $n = 20$ linear supermarket models following a power reference. For now, the linear models are used to examine the two methods performance under idealized circumstances. The Predictive solution is implemented with a horizon of 12 hours. The results are summarized in Table 1 and can be seen in Fig. 7. This simulation example is carried out to evaluate the tracking abilities of the dispatch solution when compared to the predictive solution.

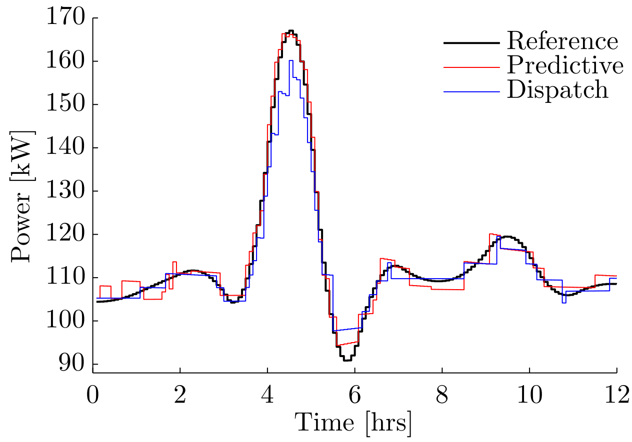

Fig. 7. Plot of the two different controlled methods ability to follow a power reference, when controlling a portfolio of 20 linear supermarket models.

A number of interesting results is observed. As expected, the predictive solution performs best with regards to RMSE because of its ability to reach the peaks, however with the cost being a high computation time. The dispatch solution on the other hand is capable of tracking the same power reference, with an increase in RMSE of 63 %. Furthermore, the computation time is reduced with a factor $210 \cdot 10^3$. This further motivates the dispatch strategy for large scale implementation.

7.2 Large-Scale Example

This simulation is based on $n = 400$ supermarkets. Only the dispatch algorithm is examined as the predictive controller cannot handle this large number of devices. To enhance the reliability of the results, the simulations are based on the nonlinear, high-fidelity supermarket model presented by Shafiei et al. (2013b). Further, a heterogeneous portfolio with between 5 and 10 medium temperature cabinets and between 2 and 6 low temperature cabinets corresponding to typical Danish supermarkets, is considered. Additionally, the parameters of the model is uniformly distributed between ± 20 % of the original parameter values to mimic different types of foodstuff, length of piping and different display case models. To further increase the credibility of the simulation, 30-minute run-time and stop-time constraints, are imposed. Hereby the SMS of each supermarket cannot be switched between ON and OFF more often than each 30 minutes. This constraint is included as rapid switching may cause excessive wear on the refrigeration components, in particular the compressor.

The result of the performed simulation is illustrated in Fig. 8, where also the uncontrolled consumption of the portfolio is shown to illustrate the potential of shifting consumption. First the power reference is constructed, based on a strategy of increasing the overall consumption of the portfolio during the low cost night hours and keeping this level in order to offer upward regulation, during two afternoon peak hours. First, the consumption of the portfolio is brought up to a level of 2800 kW. This is not optimal with respect to minimizing the power consumption of the supermarkets, however it enables the activation of 900 kW upward regulation for a two hour period during the afternoon peak hours. After the regulation period the consumption is regulated to a level of first 2100 kW and then down to 2050 kW. When the upward regulation is activated, it has 15 minutes to reach the new level and the transitions after the regulation period can be chosen freely.

This simulation shows the behavior of the controlled portfolio where supermarkets first are switched between modes to maintain a mean consumption close to the referenced 2800 kW; following, when activated for the upward regulation period, the SMS of many supermarkets are switched to the OFF mode lowering the mean consumption with 900 kW. This is followed by an increase in activation of supermarkets to again reach the higher reference of first 2100 kW and then 2050 kW. Controlling the portfolio in this manner will result in an overall increased consumption of 7018 kWh, which is a 13.5 % increase. However, the peak consumption during the two hours of upward regulation has been lowered by 985 kWh, which is a 24.7 % decrease. Furthermore, when activated for upward regulation, the system reaches the new level within the specified 15 minutes.

8. CONCLUSION

In this work, a simple interface that allowed an aggregator to access a large share of the consumption flexibility in supermarket systems, was presented. The presented method allowed for simple flexibility contracts between supermarket owners and aggregator; moreover, the interface ensured that the primary process of the supermarkets was ensured such that foodstuff safety was guaranteed. Based on this interface, a method for modeling the supermarket flexibility was proposed along with two control strategies for regulating the accumulated power consumption of a portfolio of supermarkets towards a power reference. The first control strategy was based on solving a mixed integer problem (MIP) to find the optimal solution within a given control horizon. The second approach was based on a PI controller combined with a dispatch algorithm, leaving out explicit optimization completely.

While the predictive control strategy showed the best tracking abilities, its complexity grew exponentially with

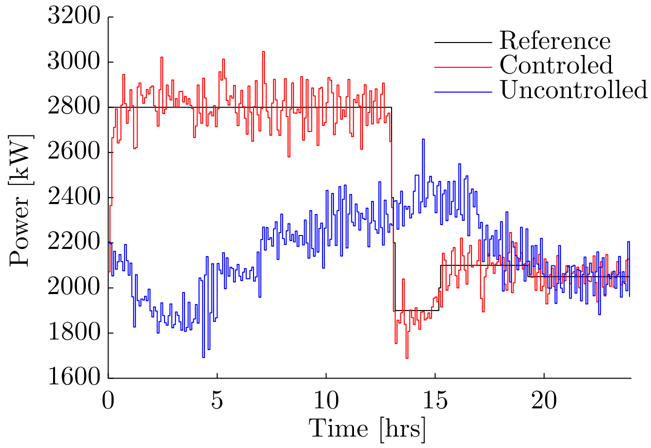

Fig. 8. 24 hour simulation of a portfolio of 400 supermarkets activated for 2 hours of upward regulation and the same portfolios power consumption when uncontrolled. The variations in uncontrolled consumption is caused by a disturbance in form of varying outdoor temperature.

portfolio size and was therefore computationally infeasible for larger portfolios. Moreover, it was shown that the dispatch solution had a decrease in tracking ability of 63 % with regards to RMSE, but reduced computation time with a factor $210 \cdot 10^3$, even for a small portfolio size.

The dispatch strategy was able to follow a power reference simulating an upward regulation of 900 kW for two afternoon peak hours, where the new reference level was reached within 15 minutes. The simulation was carried out on a large portfolio of supermarkets based on a high fidelity nonlinear model. The simulation results was compared with the uncontrolled consumption of the same portfolio. The controlled portfolio showed an overall increase in consumption of 13.5 %, whereas the peak consumption was decreased by 24.7 % for the two hours of upwards regulation.

9. DISCUSSION

The large-scale simulation result should be seen in a broader perspective, where e.g., a large number of supermarkets and other consumers are uncontrolled and will all have peak consumption in the same time period. By controlling a subset of these supermarkets, it is thus possible to lower the overall peak consumption and by offering such regulating service generate additional revenue.

The high fluctuations in power consumption of each supermarket, makes it difficult for the portfolio to follow the power reference precisely, however the mean evolves closely around the reference. It is expected that an even larger portfolio size would increase the overall systems tracking abilities.

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