Direct Control Implementation of a Refrigeration System in Smart Grid

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Abstract— The thermal capacity of the content in a cold storage room renders it possible to shift the governing refrigeration system's power consumption in time, without compromising temperature constraints. In this paper we introduce a method of implementing such a cold storage room into a directly controlled smart grid, by use of a predictive control strategy. In this application the shift in consumption is used to stabilize a small grid by utilizing excess renewable energy to minimize the need for fossil fueled production sources. In order for the centralized grid controller to handle such a node, its flexibility is communicated in form of a simple generic bucket model. Finally, the provided experiments verify the effectiveness of the proposed method.

I. Introduction

The growing demand of fossil fuel independent energy is leading to a larger penetration of renewable energy sources throughout Europe [1]. Power production from energy sources, like wind turbines, solar panels, etc., can vary greatly according to the weather, leading to an increased fluctuation in generated power. It is therefore required to maintain an online power reserve to prevent shortages (e.g. fossil fueled power plants where hydro plants are not feasible). Increasing the overall coverage of renewable energy will either require to greatly oversize production capabilities as reaching the rated power outputs are inherently dependent on the power source. This means that when the rated power is reached it is not possible to fully utilize it. Alternatively, the consumption could be controlled and thereby match the fluctuating power source. The concept of connecting several flexible nodes in an attempt to optimize the power grid is often described as Smart Grid.

In this paper we investigate one possible solution for storing excess energy from the electrical grid. This can help stabilize the grid as consumption is essentially shifted in time, although at a cost. With the ability to shift consumption it can be shaped to fit the fluctuations in power production arising from an increased penetration of wind and solar power. The proposed solution is focusing on utilizing the slow dynamics of refrigeration systems to store energy by decreasing the operating temperature, within constraints, thus power consumption is increased. The energy can thereby later be released, as the lower temperature allows for below nominal power consumption until temperature reaches the upper constraint. These constraints of course depends on the contents of the specific refrigeration system.

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The high-level control for both smart grid and refrigeration system is designed using model predictive control (MPC), although the individual refrigeration processes are controlled by a number of simpler distributed PI controllers. The use of MPC enables estimates of future inputs to be considered when optimizing the usage of available storage.

Analysis of the refrigeration system used is done similarly to [2] in which the goal was to optimize the system itself initially from a set-point perspective.

On the grid side, possible advantages of utilizing storage capabilities of certain nodes have been investigated in [3] in addition to describing a method of describing nodes by a bucket analogy. The limited capacity of the distribution net is considered and using predictions of future consumption the storage is controlled to optimally distribute power in the grid. A more detailed proposal of the bucket model is seen in [4].

Many previous publications address the problem of indirectly controlling a node in the grid through the price of power. In [5]-[6] an indirect method for controlling a display case connected to a smart grid, by use of MPC, is investigated. The objective is however to reduce the financial cost of operating the display case, resulting in an optimization of the local system. In [6] it shows that savings of up to 9-32% are possible using predictions of energy prices. Additionally, potential for participating in the balancing market is also shown.

Air conditioning systems provide similar opportunities to supermarket display cases as in [7]. Here a Thermal Energy Storage unit is used to shift power consumption to off-peak hours and shows significant savings in cost power despite an overall increase in consumption. Through changes in power prices on the grid the system can be indirectly controlled from the grid point of view.

In [8] a setup similar to this paper is used to investigate the potential of such direct control through simulations.

In this paper, a direct control method is investigated, focusing on stabilizing the grid instead of maximizing financial benefits for the individual node. The main control is centralized and computes set-points for multiple refrigeration systems while at the same time obeying the constraints for each of them. For the central controller to be able to monitor and predict flexibility of each node, the previously noted bucket analogy is expanded to create a leaking bucket model that can be applied to general refrigeration systems. The proposed solution has been implemented on a test facility.

The paper will first describe the modeling of the refriger-

ation system in Section II followed by controller design in Section III. Once the test setup is described, the actual test will be discussed in Section IV before presenting the results in Section VI. Finally, Section VII will conclude the paper and discuss suggestions for potential future work.

II. Modeling

In Fig. 1 the direct, centralized smart grid controller structure is depicted. The nodes can be categorized as being either an intelligent producer, consumer or both. Focus of this paper will be on the grayed areas (A cold storage connected to a Virtual Power Plant) and therefore the node can be seen solely as a consumer. In order for the Virtual Power Plant (VPP) to utilize the MPC framework a model of each node is needed. It should be noted, that a VPP is an entity that can balance a local grid, based on flexibility information provided by the connected nodes, by controlling power consumption and production. It is clear that complex models of the nodes will simply be cumbersome to both obtain and solve optimization problems for, since several nodes may be connected to the VPP. Therefore, a simple generic model of each node is needed. First, this generic model will be introduced. Followed by a simple model of a cold storage room. Lastly, how the cold storage is fitted to the generic model is explained.
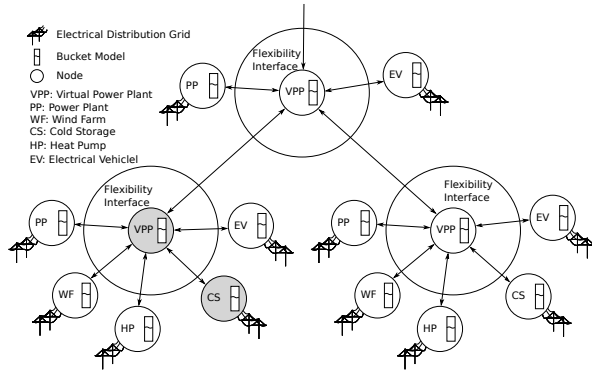

Fig. 1. General idea of a direct, centralized smart grid control setup. Each node communicates its flexibility to a local VPP, which in return provides the nodes with production and/or consumption demand. The lower level VPP's then communicates their flexibility to an upper level VPP, thereby obtaining a hierarchical structure.

A. Grid-Node

To model each node, from VPP point of view, the generic "bucket" model, described in [4], has been adopted. The model can be further simplified when the node is treated as a consumer, see *e.g.* [3]. The consumer "bucket" model is illustrated in Fig. 2, where the model consists of a consumption P, a storage rate b, a drain rate a, also the energy stored is denoted by E.

The storage rate, b, describes how much of the consumed power will be stored, *e.g.* for a cold storage it is the refrigeration systems coefficient of performance (COP). The drain rate, a describes how much of the stored energy will be lost, *e.g.* for a cold storage it is due to heat exchange
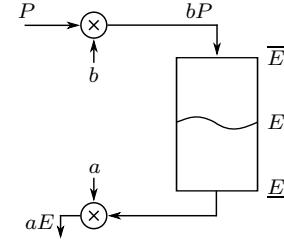

Fig. 2. Generic "bucket" model of smart grid consumer node.

with the surroundings. The energy stored, E, can take many different forms, *e.g.* for a cold storage it could be in form of sub cooled foodstuff. By subcooling foodstuff, energy is not actually stored, instead consumption is shifted. However, this shift in consumption can be seen as energy storage, from a smart grid point of view. The change in energy level can be described by the following equation:

$$\frac{dE(t)}{dt} = -aE(t) + bP(t) \qquad (1)$$

From Eq. (1) it can be seen that whenever $bP(t) > aE(t)$ the energy level will increase and vice versa, given that a and b are positive semi-definite. Furthermore, the model also takes into account that when the energy level increases so does energy loss, thereby this increase comes with a cost, *i.e.* as E increase so does aE. The idea is then, that the grid can freely regulate the energy level under limitations on both power consumption and energy capacity:

$$\underline{P} \le P(t) \le \overline{P} \qquad (2)$$
$$\underline{E} \le E(t) \le \overline{E} \qquad (3)$$

where $\underline{P}$ and $\overline{P}$ for *e.g.* a cold storage describes the lower and upper bound on refrigeration system power consumption and $\underline{E}$ and $\overline{E}$ for a cold storage describes the temperature limits set by the contents of it. This simple first order model gives an approximation of fare more complex systems, which is deemed valid under the assumption that each node is governed by a local controller.

B. Cold Storage

To model the refrigeration system governing the cold storage, a simple static modeling approach has been adopted from [2], to describe the AAU refrigeration facility [9]. It is deemed valid to develop a static model for the refrigeration system because of its considerable faster dynamics, compared to the dynamics of the attached cold storage. A complete system setup including distributed controllers is illustrated in Fig. 3.

It is assumed that the temperature of the refrigerated goods is the same as the cold storage temperature in this setup, thereby not taking the heat transfer between evaporator-air and air-goods into consideration. To describe the amount of energy in the cold storage an energy balance equation is
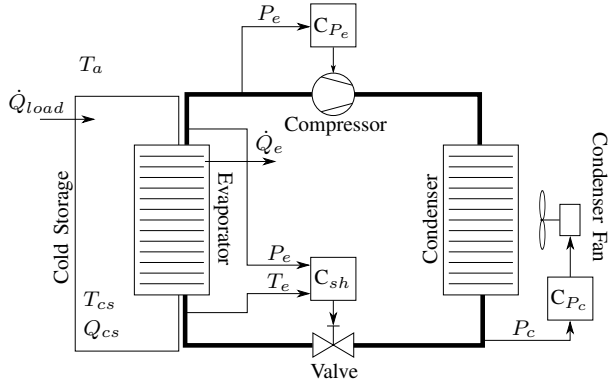
Fig. 3. Schematic of a generic refrigeration system and cold storage with distributed controllers handling states of the vapor compression cycle. Where P_e is the evaporation pressure, P_c is the condensation pressure, T_e is the temperature in the evaporator, T_{cs} is the cold storage temperature, T_a is the ambient temperature, $\dot{Q}_{load}$ is the heat load on the cold storage, $\dot{Q}_e$ is the heat energy taken out of the cold storage and Q_{cs} is energy in the cold storage.

formulated as

$$\frac{dQ_{cs}(t)}{dt} = \dot{Q}_{load}(t) - \dot{Q}_e(t), \qquad (4)$$

with

$$Q_{cs} = m_{cs} c_{cs} \, T_{cs} \qquad (5)$$

$$\dot{Q}_{load} = \mathrm{UA}_{cs}(T_a - T_{cs}) \qquad (6)$$

$$\dot{Q}_e = \dot{m}_r[h_{oe}(P_e) - h_{oc}(P_c)] \qquad (7)$$

$$\dot{m}_r = N_c \alpha \rho_r(P_e), \qquad (8)$$

where m_{cs}, c_{cs} and T_{cs} is the mass, specific heat capacity and temperature of the refrigerated goods, respectively. UA_{cs} is the overall heat transfer coefficient from cold storage to surroundings, $\dot{m}_r$ is the mass flow of the refrigerant through the compressor, N_c is the speed of the compressor in Hz, α is a compressor dependent constant, ρ_r is the density of the refrigerant and h_{oe} and h_{oc} are the evaporator- and condenser outlet enthalpies.

To model power consumption of the system only the compressor is considered as it is by far the main consumer. The static equation for the compressor work is given by

$$\dot{W}_c = \beta N_c \alpha \rho_r(P_e) \left[h_{ic}(P_c) - h_{oe}(P_e) \right], \qquad (9)$$

where β is a constant describing losses from electrical energy to actual work done on the refrigerant (*e.g.* heat loss, loss in conversion from electrical- to mechanical energy etc.), h_{ic} is the condenser inlet enthalpy.

The above equations can be combined to form a state space model of the system, where the state variable is temperature in the cold storage T_{cs}, the input variable is compressor speed N_c and the disturbance is ambient temperature T_a. If the mass m_{cs} and specific heat capacity c_{cs} of the cold storage is kept constant, the state equation becomes

$$\frac{dT_{cs}}{dt} = -\frac{\mathrm{UA}_{cs}}{m_{cs}c_{cs}}T_{cs} - \frac{C_c(P_e,P_c)}{m_{cs}c_{cs}}N_c + \frac{\mathrm{UA}_{cs}}{m_{cs}c_{cs}}T_a, \quad (10)$$

with

$$C_c(P_e, P_c) = \beta \alpha \rho_r(P_e)(h_{oe}(P_e) - h_{oc}(P_c)). \qquad (11)$$

This results in the following system matrices

$$\mathbf{A} = -\frac{\mathrm{UA}_{cs}}{m_{cs}c_{cs}}, \quad \mathbf{B} = -\frac{C_c(P_e, P_c)}{m_{cs}c_{cs}} \qquad (12)$$

$$\mathbf{C} = 1, \quad \mathbf{D} = 0, \quad \mathbf{E} = \frac{\mathrm{UA}_{cs}}{m_{cs}c_{cs}} \qquad (13)$$

C. Fitting Cold Storage to Grid-Node Model

The cold storage can now be fitted to the generic grid node model.

a) Stored Energy: In order to account for the minimum power needed to run the system, the upper ($\overline{E}$) and lower ($\underline{E}$) bounds on energy are functions of both ambient temperature as well as maximum and minimum display case temperatures, thereby describing the total energy stored, instead of only excess. The equations are as follows:

$$\underline{E} = m_{cs}c_{cs}\left(T_a - T_{cs,max}\right) \qquad (14)$$

$$\overline{E} = m_{cs}c_{cs}\left(T_a - T_{cs,min}\right) \qquad (15)$$

$$E = m_{cs}c_{cs}\left(T_a - T_{cs}\right). \qquad (16)$$

b) Power Limits: Given the compressor power consumption stated in Eq. (9) it can be seen that this is directly dependent on compressor speed, N_c, and therefore the constraints on it. It also depends on the evaporation- and condensation pressure, thus the constraints may change over time. The equations can be stated as:

$$\underline{P} = \dot{W}_c(N_{c,min}, P_e, P_c) \qquad (17)$$

$$\overline{P} = \dot{W}_c(N_{c,max}, P_e, P_c). \qquad (18)$$

c) Drain & Fill Rates: As stated previously the storage rate, b, can be identified as the refrigeration systems COP. The drain rate times the stored energy, aE, can be identified as $\dot{Q}_{load}$, thus the drain rate is dependent on the cold storage heat transfer coefficient, the mass and specific heat capacity of the refrigerated goods. The two equations are given as

$$b = \frac{\dot{Q}_e}{\dot{W}_c} \qquad (19)$$

$$aE = \dot{Q}_{load} \Rightarrow a = \frac{\mathrm{UA}_{cs}}{m_{cs}c_{cs}}. \qquad (20)$$

III. CONTROLLER SYNTHESIS

The algorithms developed for the two different MPCs described in the following rely on methods described in [10] and [11] which has been adapted for use with the CVX Toolbox [12].

A. Grid-Node Controller

The purpose of the grid-node controller is to track the given power reference with the only exception being when constraints cannot simultaneously be met. Thus inside the feasible region it is simply a matter of solving one equation in one unknown for each sample over the horizon, while a more

complex minimization problem arises when considering the inequality constraints, as in Eq. (21).

$$\begin{aligned}
\text{minimize} \quad & \|P_n(u(k)) - P_{\text{ref}}(k)\|_1 \quad (21)\\
\text{subject to} \quad & T_{\text{cs}}(k+1) = \mathbf{A}T_{\text{cs}}(k) + \mathbf{B}u(k) + \mathbf{E}T_a\\
& T_{\text{cs,min}} \leq T_{\text{cs}}(k) \leq T_{\text{cs,max}}\\
& u_{\text{min}} \leq u(k) \leq u_{\text{max}},
\end{aligned}$$

where k is the set of samples over the horizon $[1, N]$, P_n is in this case equivalent to $\dot{W}_c$ from the modeling section, the matrices $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{E}$ constitute the local model of the refrigeration system and $u(k)$ the choice of controllable input.

The choice of cost function is based on the fact that the model is inherently inaccurate and repeatedly updated over time. Using the 1-norm will result in many samples reaching the reference over the horizon and predicted infeasibility is not preemptively handled to the same extent as higher norms. This allows the controller to avoid reducing tracking performance and allow for the updated flexibility model to cause the power reference received from the smart grid controller to become feasible again. Had the 2-norm been used instead, the system would disregard the reference prior to reaching the infeasible region, through the use of the prediction in the minimization, and thereby attempt to reduce the larger predicted errors. In the extreme end using the ∞-norm to minimize the largest predicted error. Again with emphasis on predicted as these larger norms risk reducing the tracking capabilities in cases of reduced prediction accuracy.

B. Virtual Power Plant

The objective of the VPP is kept simple as the focus is on the flexibility of refrigeration systems. Figure 4 presents an overview of the inputs available and outputs required for the overall system. As seen, the VPP must provide a power reference for each of the nodes along with one for the power plant(s) and a measure of the overproduction. To calculate these, the flexibility models of each node are provided in addition to knowledge of available (present and predicted) renewable energy.
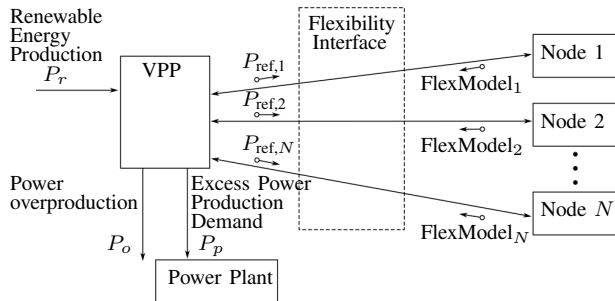

Fig. 4. Illustration of the VPP's inputs, outputs and connection with nodes. All signals contain a vector of current and predicted values.

The power plant is assumed governed simply by:

$$P_p = P_n - P_r + P_o, \quad (22)$$

where P_p is the controlled power production, P_n the sum of power consumed by nodes, P_r the available power from renewable sources and P_o as a description of excess power not consumed in the local grid.

Using this as one constraint on the VPP the remaining optimization problem is constructed by use of the models provided from each node as additional sets of constraints and minimizing the amount of power required from the power plant as seen in Eq. (23). Additionally, the power gradient is minimized to avoid unnecessary fluctuations of the references when there is an excess amount of renewable energy, as it otherwise would have been possible to run with a cost of zero for a whole range of different consumptions.

$$\begin{aligned}
\text{minimize} \quad & W_1\|P_p(k)\|_2 + W_2\|P_\Delta(k)\|_1 \quad (23)\\
\text{subject to} & \\
\end{aligned}$$

$$\text{Production} \begin{cases} P_p(k) = P_n(k) - P_r(k) + P_o(k)\\ P_p(k) \geq 0\\ P_o(k) \geq 0 \end{cases}$$

$$\text{Node} \begin{cases} E_n(k+1) = a_n^d E_n(k) + b_n^d P_n(k)\\ \underline{E}_n \leq E_n(k) \leq \overline{E}_n\\ \underline{P}_n \leq P_n(k) \leq \overline{P}_n \end{cases}$$

$$\text{Power gradient} \begin{cases} P_\Delta(k) = P_n(k-1) - P_n(k), \end{cases}$$

where a_n^d and b_n^d constitutes the provided discrete bucket model, $P_\Delta(k)$ is the gradient of the power reference for the node and $P_n(k-1)$ is the previously applied reference, thus not a variable over the MPC horizon.

The choice of norm has been made based on several simulations of the VPP, showing that the 2-norm was a compromise between minimizing the energy production or the peak power production. This setup can be further expanded to facilitate multiple nodes by adding a corresponding set of constraints for each.

IV. EXPERIMENT SETUP

The test facility used to obtain the data discussed later is a 4 kW vapor-compression refrigeration system, using refrigerant R134a and with a 60 liter water tank simulating a cold storage. To control the load a water heater is installed and the transfer of energy in the evaporator is done from refrigerant to water [9]. The refrigeration system has two distributed controllers for maintaining condensation pressure and superheat, respectively, each of them kept at a constant reference. The control is handled by a PC connected through Matlab Simulink and xPC Target which is also used to implement the grid-node MPC in combination with the optimization toolbox CVX. All refrigerant enthalpies and the density are found using the refrigerant properties toolbox: REFEQN [13]. The parameters obtained for the model are:

$\alpha = 35.5 \cdot 10^{-6}$ [-], $\beta = 1.02$ [-], $m_{cs} = 63.0$ [kg], $c_{cs} = 3730$ [J/(kg·K)] and $UA_{cs} = 120.0$ [-].

During the experiment the condensation pressure is kept at a controlled constant reference of 9 [bar] and a water heater is used to simulate a fixed load. Thereby, the water tank temperature is only controlled by altering the compressor speed, which affects the evaporation pressure. Given that there are a relationship between compressor speed and power consumption, the system is able to follow a power reference set by the virtual power plant. The compressor speed is restricted to be in the interval 35-60 Hz, thus it is not possible to stop power consumption only lower it, i.e. $\underline{P} > 0$.

The VPP governs the real system alongside three similar virtual nodes, based on a simulated prediction of future wind power production. The experiment is run for approximately 7 hours with a sampling time of 30 sec. and the horizon for the VPP MPC is 6 hours, enabling it to see a full period of the simulated wind power production signal.

When the real node is running at its constraints and at times violating them, because of the nondeterministic behavior of it, the refrigeration system controller will do what ever is in its power to bring the system back in the constraint region. If *e.g.* the system has violated the upper temperature (lower bucket) bound, it will increase its consumption up to $\overline{P}$. By doing so the flexibility of the system is suddenly changed, giving fluctuations in power plant production, which is of course undesirable when the objective is to stabilize the grid. One way to account for it could be to have a boundary area before the constraints, slowly increasing the cost, as the system approaches the constraints. Solving this problem is a subject for further research. Because of this, the test has been conducted so the real system does not violate the constraints on temperature.

V. EXPERIMENTAL RESULTS

Fig. 5 and 7 show the results of implementing the proposed method. It is clear that when ever wind power production is high the VPP stores energy in the four nodes by raising power consumption references. By doing so the VPP can utilize the stored energy, when wind power production lowers, to minimize the need for power plant production. In contrast to a system without flexibility, shown in Fig. 6. Fig. 7 shows how well the estimated bucket of the real system fits with the simulated nodes.

In the experiment setup all nodes have relatively fast dynamics (energy drains fast) which in combination with the nondeterministic behavior of the real node results in a very little decrease in power plant peak production (approximately 1%) and an increase in overall production (approximately 1%). This indicates that for a consumer to offer energy storage capabilities the drain rate should be improved compared to the real refrigeration system used for the test. A suggestion could be to use thermal storage units as in *e.g.* [7] or a larger cold storage room (only 60 liter tank for the test setup) containing frozen foodstuff, as these have a wider temperature band.

The main difference in production, between the system with flexible nodes and the system without, is the overproduction. Without flexibility there is a large overproduction when wind energy production is high. This overproduction needs to be handled elsewhere in the grid. With the flexible nodes this overproduction is lowered significantly (approximately 75%), indicating that the system used for the experiment could be used as an overproduction "blowoff valve", thereby offering some flexibility services to the grid.
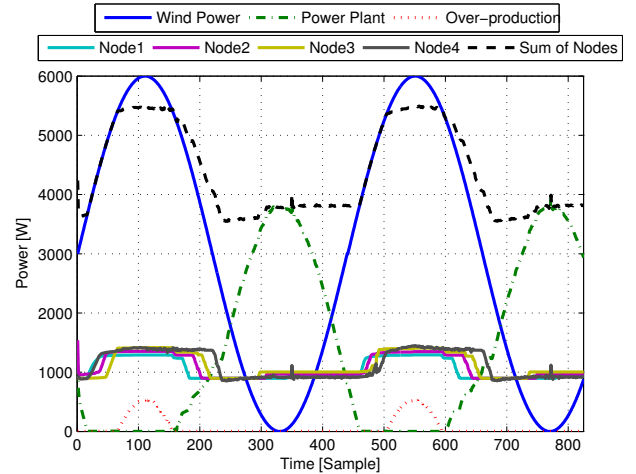

Fig. 5. Test run for approximately 7 hours, with a sampling time of 30 sec. Where (blue) is simulated wind power production, (red) is power overproduction, (green) is power plant production, (yellow, cyan, magenta) are power consumption references for the virtual nodes, (black, solid) is power consumption reference for the real node and (black, dashed) is the overall consumption. Each bucket is filled/emptied to utilize as much as the wind energy as possible, thereby trying to minimizing the power plant production.

VI. DISCUSSION

In the presented work a strictly static method for modeling the refrigeration system governing the cold storage was taken. This resulted in a pure deterministic linear model of what in fact is a highly nondeterministic and nonlinear system. This simplified model is expected to be the main reason why the system can not run closer to constraints without violating them. A natural step for future work would be to derive a more describing model.

A natural expansion would be to look into more sophisticated MPC algorithms, such as stochastic model predictive control (SMPC) as presented in *e.g.* [14] and [15], which takes into account nondeterministic disturbances in the model and a mean of handling constraint violation.

Another issue is the simplified grid stabilization example, which does not bare resemblance to the real power grid. There are made rough assumptions such as no power plant startup time, no capacity limits on distribution networks (see *e.g.* [3]) and all nodes are always available. This leads to the need for future research, incorporating more detail into the grid setup.

However, it has been shown that it is possible to modify the bucket model to a cold storage unit and use it as a
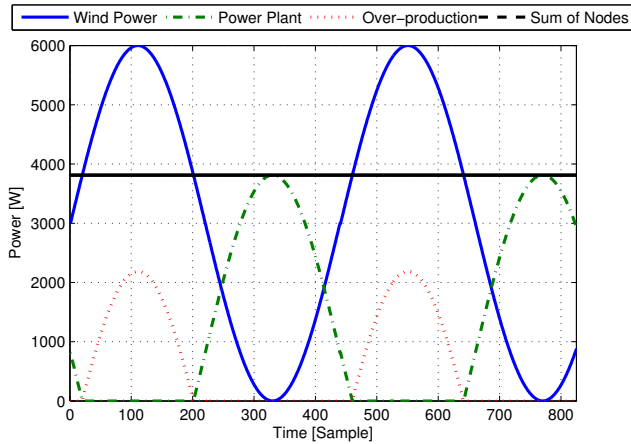
Fig. 6. Simulation of the same run seen in Figure 5, but without flexible nodes, meaning that the nodes always will run at there minimum power consumption (bucket is always empty). The minimum power consumption of the real node is estimated to a constant by taking the mean value of samples from 360 to 450 in Figure 5. The consumption references for the nodes are not plotted as they are constant.
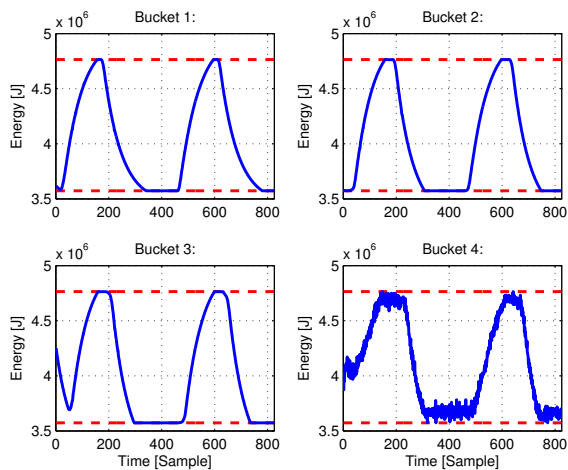

Fig. 7. Bucket levels of the three virtual nodes and the real node. Where (red, dashed) is the constraints on bucket limits and (blue, solid) is the bucket level. The buckets are filled/emptied according to Figure 5.

flexibility model. Cold storages can indeed be used for grid down-regulation, thereby lowering power overproduction. Provided a cold storage with larger capacity and lower drain rate it would be possible to decrease overall power plant production as well as peak production.

VII. CONCLUSION

In this paper, an approach for implementing a refrigeration system into a directly controlled smart grid, using a predictive control strategy was investigated. The MPC framework is well suited for this task as estimations of the system states can be used for communicating its flexibility, adhering to constraints. This gives the VPP an opportunity to intelligently stabilize the grid based on the nodes ability to offer flexibility

and estimations of future renewable power production. To implement the system as a flexible consumer it is shown how a refrigeration system can be fitted to a generic bucket model.

The presented experiment showed that the simplified VPP tried to minimize power plant production by utilizing the flexibility of the connected nodes to shift consumption, by storing energy in them. Due to the examined refrigeration system dynamics only slight decrease in power plant peak production was achieved, while an increase in overall production was seen, compared to a setup with no consumption flexibility. However, this is caused by the systems low storage capabilities and high drain rate and is therefore easily improved. The main difference between the two setups was in the power overproduction, which was significantly decreased with flexible consumers, indicating that the investigated system could be used for down-regulation, thereby offering a balancing service to the grid.

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