INDIRECT REGULATION OF MANY DER UNITS THROUGH BROADCASTED DYNAMIC PRICE SIGNAL

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ABSTRACT

Broadcasted dynamic power price is used as a cost efficient way to indirectly regulate the power flow from many DER units. The control concept is experimentally tested with a limited number of DER units at the SYSLAB facility Examples from space heating are demonstrated.

INTRODUCTION

In future power systems, a growing part of the power generation is expected to come from small-scale, distributed power generating units. As a consequence, the number of large-scale power plants in the system will decrease. Most of the power system services (PSS) required for maintaining a proper operation of the power system is traditionally provided by the large-scale power plants, and other components in the power system must take over.

Several Distributed Energy Resources (DERs) may, with minor modifications and little additional cost, become able to provide various power system services, including regulation of the active and the reactive power on requests. DER units are (by definition) controllable, small-scale units, connected to the distribution system and can be any combination of generation, consuming, storage and conversion. Except for the storage units, the main purposes for the DER units are to provide other services – their primary energy services.

The contribution from the individual units may be modest, but the aggregated contribution from many units can be significant. As the volume of the power system services from the individual DER units is limited, the value of the PSS from the individual DER unit is correspondingly low, and the additional cost of the associated control for the individual DER unit must be kept low as well. This implies that

- the number of active DER units must be high;
- the additional investment costs and control costs for the individual DER unit must be low.

This can only be achieved through simplified communication and fully automatically provision of the power system services. The main challenge is how to control these many units in a simple, cheap, efficient and reliable way. The existing power systems and power markets are typically not design for this.

Control principles

Most control principles for DER power systems can be divided into the three overall classes:

- **direct**, centralised control of each unit involving direct two way communication to each unit – applied in most ‘virtual power plant’ (VPP) applications;
- **policy** based, distributed control, requires autonomous, distributed control and advanced communication with a central controller;
- **indirect**, centralised control of many units with broadcasted request, volunteer responses and the aggregated response as the control feedback.

The central controller in the direct control principle controls each unit directly, which requires on-line overview of the status of each unit.

The policy based control principle requires distributed controllers that can operate autonomous and that can change control strategy on request from the central supervisory controller.

The indirect control principle requires many independent active units and the expected response must be based on experience and will never be known exactly.

The broadcasted control signal for the indirect control can be a request for positive or negative regulation of the active or reactive power, it can be automatic responses to the local frequency or voltage, or it can be a dynamic power price.

This paper presents an example of an indirect control principle based on dynamic power price and distributed intelligence. Forecasts of the power price and of the energy service needs are important for the optimisation of the control of the individual units.

The FlexPower project

investigates the perspectives of using dynamic power prices for indirect control of power regulation provided from DER units on volunteer basis. As a first step, the dynamic power price will be a global 5 minutes add-on price to the NordPool Spot price on hourly basis. But more advanced concepts are also investigated, including dynamic nodal pricing, taking into account the local congestions in the grid. The control algorithms developed in the FlexPower project for the individual DER units are implemented and tested experimentally at Risøs experimental facility SYSLAB and in a dedicated simulation tool, developed as part of the project.

The experimental power system, SYSLAB, consists of real power components, including wind power, solar power, electrical heated office building (FlexHouse), electrical vehicles and electrical storage units – see Figure 1. Control algorithms designed for dynamic power prices are developed for the space heating, for the electrical vehicles and for the storage units. Each of the power units are treated as independent costumers and are supposed to have their own individual controllers with individual control strategies. They may all shift their loads few hours in time with minor impact on the energy services. They all try to obtain an acceptable energy service at lowest cost. The storage units simple try to optimise the earnings.

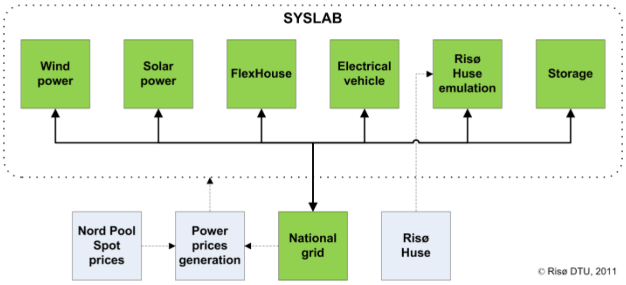

Figure 1: Diagram of the Risø SYSLAB experimental power system facility.

The controllers constantly update their status and actions based on the information available. In general, except for the storage units, they all try to minimise the sum

$$\sum(c_1E^2 + c_2C^2) \quad (1)$$

for the next period (24 hours), where E express the deviation from the desired energy service (e.g. the deviation in temperature), C is the cost of electricity, and c_1 and c_2 are weighting factors.

One aim of the project is to evaluate the value of the availability of different information. The control algorithms are therefore tested and compared, based only on historical data and based on advanced forecasts of both power prices and power needs for the next 24 hours period – including weather forecasts.

FORECASTING

Forecasting plays a central role in the concept. Forecasts of the 5 minute electricity price and consumption are used to derive the optimal control actions.

Electricity price forecasting

Electricity spot price forecasting are considered Jónsson, Pinson & Madsen (2010) showing that the forecasted wind power penetration influence the expected spot price. In FlexPower the actual 5 minute price for a specific time interval is broadcasted just before the beginning of the time interval. Consequently, the price is known for the time interval for which control actions should be effectuated. However, in order to incorporate the future development, forecasts of the price for the following time intervals must be available to the controllers. The control is based on minimization of the conditional expected cost of the electricity used over a rolling horizon. The first price is known, and it may be argued that it is sufficient to know the conditional expectation of the subsequent 5 minute prices.

The 5 minute prices in the proposed system does not exist and hence forecast methods cannot be investigated based on actual data and the dependence on external (predictable) signals cannot been investigated. However, following the arguments above it is reasonable to track the expected value as it varies over time. Furthermore, it is very plausible that the price signal will contain some autocorrelation. An adaptively estimated AR(1) model with a free mean is the most simple model fulfilling the above. If p(t) denotes the price at time t this model may be written:

$$p(t) = a + bp(t-1) + e(t) \qquad (2)$$

where e(t) is white noise error and a and b are coefficients which must be tracked over time. If t denotes the current 5 minute time interval the price for the following interval p(t+1) will be know at the before initiation of the interval and hence forecasts of the prices p(t+2), p(t+3),… must be produced given p(t+1) and other information available at time t. Given the model above the forecasts can be derived. E.g. the forecast of p(t+2) is a + b p(t+1) and the forecast of p(t+3) is a + b (a + b p(t+1)).

As mentioned the model considered above is a very simple and in reality it must be expected that such 5 minute prices contain some of the same behaviour as the spot prices do today. Therefore, it must be expected that the 5 minute prices are also affected by the wind power penetration.

Consumption forecasting

As an example, heat load forecasting is considered. Assuming that the actual indoor temperature is close to the desired temperature, well defined consumption forecasts are available. The control actions will be the deviation of the actual heat input from the heat input required in order to maintain the indoor temperature at the desired level.

Nielsen and Madsen (2006) describe models of the relation between the heat consumption, climate variables and the time of day, week, and year. It is evident that measurements of the indoor temperature are available to the forecasting system. The outdoor temperature must be available either as a direct measurement or as a meteorological forecast. The paper mentioned above forms the basis of the PRESS-Prognosis heat load forecasting system, which is recognised as a very accurate system.

A system such as PRESS-Prognosis requires observations from the house (total heat consumption and indoor temperature) and meteorological forecasts in order to produce heat load forecasts. Forecasts are based on time intervals substantially longer that the 5 minutes intervals at which the controller operates. The reason is that the precise timing of the behavioural pattern of the inhabitants is probably unpredictable. Preliminary results indicate that 2-4 hours are appropriate time intervals.

Technical setup

Figure 2 shows the technical setup of the FlexPower system for a single household. The use of a central forecasting service allows state-of-the-art forecasts to be delivered to the controller. If a price forecast model as simple as described above is used it should be possible to include it in the local controller. For the consumption forecasts there is no benefit in including it in the local controller unless the use of meteorological forecasts is avoided.

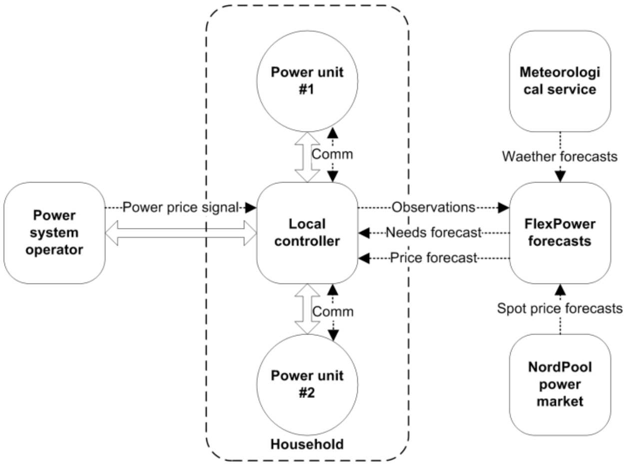

Figure 2: The technical set-up of the FlexPower forecasts.

CONTROL ALGORITHMS

As an example, the management of the domestic electric heating is presented. The considerations are based on the response of a linear dynamic thermal model of FlexHouse [3], an independent, 100 m^2 office building, equipped with 10 kW electric heating. The thermal model describes the variation of the internal temperature as a function of the heat flux provided by the heaters, solar irradiation and external temperature.

The general discrete objective is to minimize:

$$J = \frac{1}{2}(T_N - T^o)^2 F + \sum_{i=0}^{N} \frac{1}{2}((T_i - T^o)^2\, Q + u_i^2 R_i) \quad (3)$$

where the scalar values T_i is the indoor temperature, T^o the comfort temperature for the house, u_i the controllable heating power, R_i the price of energy and F and Q two weighting coefficient; N defines the length of the optimization horizon.

Classical LQ (Linear model, Quadratic cost) theory provides a closed form solutions for this problem; the control has the form of a feedback and most of the calculations can be performed offline, stored and used to get the feedback control only by multiplications. However, it doesn't take into account the constraints and disturbance (solar irradiation) on the control. Therefore we've used the algorithms of the gradient [4] applied to the Euler-Lagrange equations.

Algorithm Overview

The constrains on the control have been transferred into the penalty function, as shown in equation 4, with the barrier function R(u). This function has got a linear grow in the middle and assumes an infinite value when the control u approaches its limits so the optimal solution can't lie in those point.

$$L(\underline{x}(t), u(t), t) = \frac{1}{2}\underline{x}^T(t)\ \frac{Q}{c_1}\ \underline{x}(t) + R(u(t))\,\frac{p(t)}{c_2 * 0.5} \quad (4)$$

$$\phi(\underline{x}(t), t) = \frac{1}{2}\underline{x}^T(t)\ \frac{F}{c_2}\ \underline{x}(t) \quad (5)$$

$$J(\underline{x}(t), u(t), t, N) = \phi(\underline{x}(t), t_T) + \int_0^N L(\underline{x}(t), u(t), t)\, dt \quad (6)$$

$$R(u(t)) = -\frac{1}{u(t) - P_{max}} + \frac{1}{u(t)} + u(t) \quad (7)$$

Subject to:

$$\begin{cases} \underline{\dot{x}}(t) = A\underline{x}(t) + \underline{B}u(t) + B_d\, \underline{u}_d(t) \\ T(t) = [1\ 0\ \cdots]\ \underline{x} \end{cases} \quad (8)$$

In order to obtain a suitable form to penalize the optimal temperature deviation from the expression of the cost (equation 3) a new state – without dynamic but just with an initial condition equals to the optimal temperature– has been added to the dynamic system and the cost matrixes F and Q have been modified in this way:

$$F = Q = \begin{bmatrix} 1 & -1 & 0 & \dots & 0 \\ -1 & 1 & 0 & & \\ 0 & 0 & 0 & & \vdots \\ \vdots & & & \ddots & \\ 0 & \cdots & \cdots & \cdots & 0 \end{bmatrix} \quad (9)$$

Choosing the coefficient for the weighting matrixes is important for obtaining a satisfactory result from an optimization algorithm. The two coefficients c_1 and c_2 have been introduced in equation 4 in order to introduce a per unit representation. c_2 is defined as the average price of the forecasted price signal multiplied by the nominal heating power (10 kW). Assuming $c_1 = 1$, it means that the final user having a deviation of 1°C from the optimal temperature. Acting on c_1 (a 'pay more/less' trimmer) it is possible to determine how to vary the temperature comfort as a function of price variation.

Euler-Lagrange equations are the result of the calculations of the variations applied to a penalty function where the states are subject to a dynamic system; if they're all satisfied the control trajectory is optimal for the defined penalty function. Introducing the Hamiltonian function:

$$H(\underline{\lambda}(t), \underline{x}(t), u(t), t) = L(\underline{x}(t), u(t), t) + \underline{\lambda}^T(t)\underline{\dot{x}}(t) \quad (10)$$

The Euler-Lagrange equations are [4]:

$$\underline{\dot{\lambda}}^T(t) = -\frac{dH(\underline{\lambda}(t), \underline{x}(t), u(t), t)}{d\underline{x}} \quad (11)$$

$$\underline{\lambda}^T(N) = \frac{d\phi(\underline{x}(t), t)}{d\underline{x}} \quad (12)$$

$$\left[\frac{dH(\underline{\lambda}(t), \underline{x}(t), u(t), t)}{du}\right]^T = \underline{0} \quad (13)$$

The gradient descent method defines a nominal control history; in this case the heating power necessary to maintain the optimal temperature at steady state assuming zero disturbs. The values of dynamic system can then be derived taking into account the disturb control (solar irradiation). This allows to compute the dynamic of the adjoin vector lambda integrating backward from the terminal condition (equation 11 and 12). With these values it is possible to compute equation 13. The control is perturbed and the algorithm is iterated until some satisfaction criterions are met. At each step the control values are modified according to this expression:

$$u_{j+1}(t) = u_j(t) - k\,\frac{dH(-)}{du} (14)$$

Each new control is obtained subtracting from the

previous one a quantity proportional to the derivate of H with respect to control: the derivate value gives the direction on how to move the control in order to reduce the penalty. Coefficient k is important because it affects the speed of the convergence of the algorithm.
The algorithm produces a control history for the coming future; however only the first control is applied. As soon as new electricity prices are available, the algorithm produces another control history – known as receding horizon control.

Result

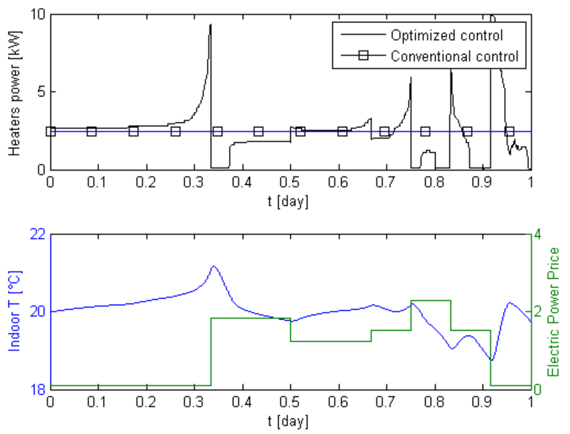

Figure 3: The result of the optimization process and the effects on the temperature as response to the dynamic energy price.

Figure 3 (top) shows the optimal control, compared to the power necessary to maintain a steady temperature (20°C); and the behaviour of the indoor temperature when the optimal control is applied (bottom). The green curve is the price of the energy.
As expected, electric power is consumed more when it is cheap and it's used to store thermal energy if the price forecast indicates an increase. c_2=2 has been used. The dimensionless representation has proved to be an effective way to decouple the effect of the absolute value of energy price from the temperature in the penalty function.
Figure 4 shows a simulation of the receding horizon problem. At each step of the optimization process only the first slice of the computed control is used. The forecast for the price is obtained using a form of the equation 2 and so it suffers from uncertainty. At the next instant of time a new real price for energy is released, a new forecast is produced, just the first slice of the control is applied and so on. Figure 4 (top) shows the effects of uncertainty on the temperature and it compares the real behaviour with the one that comes from an exact forecast of price. The (dimensionless) price that the user should pay for the whole period for the exact forecast (blue line) is: 5.95, for the real case: 6.17, while he should pay 10.36 for maintaining an optimal indoor temperature. So both price and temperature show an acceptable performance, even when the price forecast is not exact.

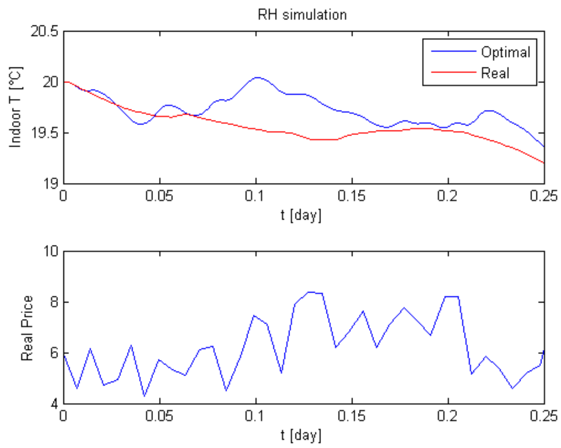

Figure 4: A Receding Horizon simulation with a zero mean random noise on the forecast of price.

Limitations and considerations

There are a couple of issues before trying to apply this optimization method to the FlexHouse. The signal for power heating is continuous while the power of the heaters is discrete (on or off). This problem can be solved applying a duty cycle to the on/off signal inside each time slice. The main problems come from the thermal model of the house and the factors that afflict the real life which aren't taken into account. Thermal models usually have different states, but only one is normally accessible for the measure (the indoor temperature). This creates a problem because the initial conditions for all the states except one are uncertain. Finally, the aggregated response comes from many different houses with different characteristics. Creating a specific model for each building is not realistic, but the modelling can be improved by adding some adaptive capabilities.
After considering these limitations that can afflict the optimality of the control we should evaluate also the use of some simpler algorithms that produce a control only on the bases of the certain available variable.

REFERENCES

[1] Jónsson, T.; Pinson, P. & Madsen H. ,2010, *On the market impact of wind energy forecasts*, Energy Economics, 32, 313-320.
[2] Nielsen, H.Aa. & Madsen, H., 2006, *Modelling the heat consumption in district heating systems using a grey-box approach. Energy and Buildings*, 28, 63-71.
[3] P. Bacher, A. Thavlov, H. Madsen, 2010, *Models for Energy Performance Analysis*, IMM-Technical Report, DTU, 35.
[4] R.F. Stengel, 1986, *Optimal Control and Estimation*, Dover Publication, NY, USA, 259, 205.