

ANALYSIS OF OPTIMAL DYNAMIC PRICE CONTROL OF HEAT PUMP HOUSES WITH SOLAR POWER

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ABSTRACT

Time of use tariffs are in large scale use in Finland, but the electricity market prices do not any more follow such regular time pattern. Dynamic demand response is increasingly needed and dynamic retail tariffs are available. Heat pumps and solar panels affect electricity consumption of houses. This paper analyses and demonstrates the benefits of forecasting and optimisation in dynamic price control of such houses.

INTRODUCTION

The subject addressed is dynamic optimal price control of residential houses that have heat pumps and solar power generation. The control signal may be the sum of the day-ahead price and the distribution tariff, or it may be a price determined by the electricity retailer or aggregator in a way agreed with the consumer to take into account other markets, balancing, and distribution network issues. The responses to the price signal must be automated, because only timely, reliable and predictable responses are useful for the electricity markets, emission mitigation and power distribution.

The benefit potential from optimal control for heat pump houses with solar power is studied. Also the suitability of a classical nonlinear constrained optimal control method to optimal price control of such houses is analysed and demonstrated. An own Matlab implementation of the generalised reduced gradient optimisation and the principle of Pontryagin. The nonlinear optimal control enables appropriate formulation of the optimisation criterion. It can also take into account the partial dimensioning of the heat pump and the nonlinear coefficient of performance.

Two test houses had been modelled using measurements. A non-linear heat pump model was added to these models of the thermal dynamics of the houses. A ground source heat pump was installed in one of the houses and measurements from it were used to tune and verify the model parameters. Full 2 week periods in four different seasons are studied. The price signal was the sum of static ToU distribution tariff and the dynamic area day-ahead spot market price. Feed-in to the network was allowed with the spot market price and taking into account the small maximum allowed distribution tariff for feed in to the network. A penalty term was applied to mitigate rapid load variations typically occurring around the change of the hour in the optimal solutions. With the method such penalty terms and hard constraints or additional price terms can easily be used for taking into account possible network constraints etc.

METHODS

Forecasting the solar power production

Finnish Meteorological Institute (FMI) open weather forecast data [1] are utilized in the photovoltaic production forecasting algorithm. Implementation is presented in [2]. Sun position angles are modelled according to [3] and used to calculate the solar radiation on a tilted surface. It comprises direct, diffuse and reflected radiation. The radiation on tilted panel surface is calculated with the HDKR model (the Hay, Davies, Klucher, Reindl model). The total radiation on tilted panel surface is [4]:

$$I_T = (I_b - I_d A_i) R_b + I_d (1 - A_i) \left(\frac{1 + \cos\beta}{2}\right) \left[1 + \sin^3\left(\frac{\beta}{2}\right)\right] + I_{\rho_g} \left(\frac{1 - \cos\beta}{2}\right).$$
(1)

Where I_T is the total radiation on the tilted surface, I_b the beam radiation, I_d the diffuse radiation, $I_{\rho g}$ the ground reflectance (also called the albedo), R_b the ratio of beam radiation on the tilted surface to beam radiation on the horizontal surface, A_i is the anisotropy index, β the tilt angle and f the final factor. The anisotropy index determines a portion of the horizontal diffuse and according to [4] it is:

$$A_i = \frac{I_b}{I_a} \quad . \tag{2}$$

Where I_0 is the extra-terrestrial horizontal radiation. The final factor is related to the cloudiness of the location and it is given by [4] as:

$$f = \sqrt{\frac{I_b}{I}}.$$
 (3)

Where *I* is the global horizontal radiation on the earth's surface. Total radiation on the tilted panel surface is utilized in photovoltaic (PV) panel temperature calculations [5]:

$$T_{module} = T_a + \frac{NOCT - 20}{80} I_T \quad . \tag{4}$$

Where T_{module} is panel temperature, T_a the ambient temperature, and *NOCT* the nominal operating temperature of the cell. The PV system production estimate is:

$$P_{module} = P_n f_D \frac{I_T}{I_{T,STC}} (1 + k_T (T_{module} - T_n)).$$
(5)

Where, P_{module} is the power production estimate, P_n the nominal power under standard test conditions, $I_{T,STC}$ nominal radiation at standard test conditions, f_D derating



factor, T_n panel temperature in standard test conditions, and k_T a temperature dependent performance factor. Location specific derating factor that models the efficiency of the rest of the system is verified from measurements.

Dynamic thermal balance models

Models for the dynamic heat balances of the buildings were developed based on preliminary information on the buildings and measurements made during 2004-2015. MATLAB System Identification Toolbox was used. The models are linear except for constraints and the heat pump coefficient of performance. Also ventilation rate affects nonlinearly in the model, but now it was kept constant.

Ground source heat pump with water circulation and a photovoltaic panel were added to the model used in [6]. One of the two houses was already included in that study.

The state variables are the following lumped temperatures:

- temperature of the indoor air
- temperature of internal walls
- temperature of the outside walls
- temperature of the heat storing floors
- temperature of the heat storing fireplace
- temperature of the sauna
- temperature of the hot water storage
- temperature of the circulating heating water.

The main uncontrollable input variables are outdoor air temperature, solar radiation and occupancy. Occupancy affected via the usage of appliances and hot domestic water. The controllable inputs were electrical powers to 1) the heat pump, 2) direct electrical heating via the heating element of the heat pump system and 3) the storing floor heating. The heat pump system takes only the sum of 1) and 2) as input and internally always prioritises the using of the heat pump. The losses of the circulation pump are modelled as a minimum limit for the direct heating power. Domestic hot water is heated by the heat pump system.

Non-linear constrained optimisation of dynamic control

Determining the best response of the house to price variations is an optimisation task, where the objective is to minimise power purchase costs while maintaining comfortable indoor conditions. A nonlinear constrained optimization method was previously developed for the purpose and implemented in MATLAB. The method is based on the generalized reduced gradient method with the gradient calculated from the adjoint state using the principle of Pontryagin. The approach is explained in detail in [7].

Time step dt = 10 minutes was used in the optimisations. In the simulations an optimisation period of two weeks was used without excessive computation times. For online spot price control optimisation a period that covers two days is usually sufficient and the additional benefit from longer periods is rather small.

With minor simplifications the optimisation problem formulation is

$$\begin{aligned} x(t+dt) &= f_{1}(x(t), u(t), w(t)), \quad x(t_{0}) = x_{0}, \\ y(t) &= Dx(t), \\ u_{min}(t) \leq u(t) \leq u_{max}(t), \\ p_{house}(t) &= sum(u(t)) + Ew(t) + p_{module}(t), \\ J &= \sum (f_{2}(p_{house}(t)) + (x(t) - x_{des}(t))^{T}Q(x(t) - x_{des}(t))). \end{aligned}$$
(6)

Where x is for each time point $t \in [t_0..t_{max}]$ the state vector comprising temperatures, u the controlled heating powers, u_{min} and u_{max} the control constraints, w the noncontrollable inputs, f_I the thermal balance function, y the measurement vector, D the measurement matrix, Ewthe non-controlled power consumption, p_{module} the solar power production, p_{house} the power of the house, Q the matrix weighting state deviation from the desired state x_{des} , f_2 the electricity cost, and J the optimisation criterion summed over the time period of optimisation.

When using the method occasional failures to converge were observed. This was completely solved by generating five different initial guesses with other methods and taking the best solution reached. The methods for producing the initial guesses included noprice control base case, two differently tuned heuristic price control approaches, and two Time of Use methods.

The main advantage of the nonlinear optimisation method is that it allows formulating nonlinear criteria. With linear optimisation such modelling that uses the storage both before and after the price peak is difficult and sensitive to model changes. With heating and cooling loads a quadratic criterion describes the problem better than a linear one and gives solutions with more benefit. Also nonlinearities due to heat pump coefficient of performance and dimensioning are easy to model. As such the method is not yet able to handle clumped start-up and shutdown cost. Integrating to a mixed integer approach or detailed modelling of startups and shut-downs are obvious potential solutions.

Adjusting the forecast based solution by feedback from the current state

The optimisation was based on early morning forecasts. Thus the forecasting errors affect the solution and the indoor temperatures may fluctuate outside the acceptable region. Thus simple feedback from the state of the building was applied to adjust the indoor temperatures towards those that the forecast based



solution would have given, if the actual would have been according to the forecasts. In addition feedforward was included to add self-consumption to heating in case of actual solar power production exceeded the forecasted one. These adjustments are still under development. Improving the forecast accuracy or the feedback structure and tuning will move the results towards the optimisation with perfect forecast case that is also calculated as an estimate of maximum potential benefit.

SIMULATION TEST CASES

Electricity prices

The variable electricity costs for the consumers were as in Helsinki in 2015 with Nord pool spot market dayahead prices. Time of use distribution tariff was applied and all the taxes included, see Fig. 1. The distribution tariff for feed-in was assumed to be the maximum allowed. The electricity retailer was assumed to buy back the feed-in with the spot price. Only the retailer margins were ignored.



Fig. 1. Electricity price to the customer 5-19 October 2015.

Solar power generation and forecast

The forecasted and measured solar power productions are shown in Fig. 2. The forecast is from the equations (1)-(5).



Fig. 2. Forecasted and measured solar power production 5-19 October 2015 for a PV system with nominal power 10 kW.

Outdoor temperature and its forecast

The forecasted and measured ambient temperatures are in Fig. 3. They are open data by FMI.



Fig 3. Forecasted and measured outdoor temperature 5-19 October 2015.

Simulated houses

Two typical detached houses in Helsinki were measured, modelled and simulated. The internal volume of one house is 500 m^3 and the other is 640 m^3 . The heat demands of the houses are very similar. The bigger house is older and it now has a ground source heat pump. In the simulations both houses use the same model of the heat pump system. The dependence of the heat pump coefficient of performance on the water temperature is simulated according to the technical data given by the manufacturer. The heat storage capacities of the structures were found to be similar but only the smaller house has storing floor heating installed. The models were verified with measurements.

RESULTS

As the ground source heat pumps are not dimensioned to meet the full peak demand, the benefit from the optimal control remained the same although the variable electricity costs were reduced very much by adding the heat pump. Optimal control also increases the selfconsumption of the locally produced power.

Examples of optimised responses

The following figures show simulation responses 5-19 October 2015 with a 5 kW solar panel. Negative balance means that solar power production exceeds own consumption. In Fig. 4 the heating is controlled by feedback from the house temperatures only. The electricity prices and the solar power production are not in any way used to control the powers. Only the weather, occupancy, appliances and domestic hot water usage cause temperature variations that via feedback control vary the power. The losses of the heat pump are included in the item heating element of heat pump.

In Fig. 5 the optimisation has been applied to the forecasts and then feedback and feedforward controls have adjusted the heating powers to better fit to the actual situation. The benefit in the electricity costs of the two week period was





Fig. 4. Heating powers and total house power in the base case where no price control is applied and there is a 5kW solar panel.

3.86 €. Storing floor heating is applied only when the price is lowest before the high prices. Heat pump load is shifted to lower price and excess solar power periods. Minor exceeding of the heat pump maximum power, meaning usage of the heating element, can be seen.



Fig. 5. Powers in the solution optimised based on forecasts and adjusted by feedback.

Perfect forecast based optimisation is shown in Fig. 6 for comparison. There the benefit in the electricity costs of the two week period was $4.74 \notin$, so there is some benefit potential by improving the forecasts. Neither the heating element nor storage heating is used in this case. During higher price volatility and colder weather all the optimal solutions use also storage heating and the heating element to take advantage of low prices.



Figure 6. Powers in the optimisation based on perfect forecasts.

Simulated benefits of automatic price response

Fig. 7 shows summed variable electricity costs for four 2 week periods. The "optimised based on the forecasts" case often includes too much loss of comfort. Adding feedback leads to acceptable comfort but also somewhat higher costs. Perfect forecasts are never available in practise. Optimisation with them for the 8 weeks and



Fig.7. Benefits from optimisation in the variable electricity costs of 8 weeks.

SUMMARY

The simulations demonstrate the following. 1) Forecasting of solar power generation enables automatic optimisation of the price control responses. 2) Improving the forecast accuracy can further improve the benefits to some extent. 3) For the price control of storage type electrical loads the nonlinear constrained optimisation applied with the principle of Pontryagin is a good approach for both operational on-line optimisation of price control responses and for off line studies for dimensioning and analysis.

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REFERENCES

- [1] Finnish Meterological institute, 2013, *Open Data Manual*. http://en.ilmatieteenlaitos.fi/open-datamanual.
- [2] A. Löf, R. Pasonen, H. Murtaza, 2015, Energy storage optimisation tool with photovoltaic power estimation. VTT series VTT-R-05736-14, 23 p.
- [3] C. Bratu, 2008, "Evaluation of solar irradiance to a flat surface arbitrary oriented". Ann. Univ. Craiova, Electrical Engineering series, No.32, 2008, pp. 310-314.
- [4] J.A.Duffie, W.A.Beckman, 2013. Solar Engineering of Thermal Processes, 4th edition. Wiley, 936 p.
- [5] C. Honsberg, S. Bowden, 2013, *Photovoltaic Education Network*. <u>http://pveducation.org/</u>
- [6] P. Koponen, S. Kärkkäinen, 2007, "Experiences from spot-market based price response of residential customers", *CIRED 2007*, Vienna, Paper 0508, 4 p.
- [7] L. Hassdorf, 1976, Gradient Optimization and Nonlinear Control, John Wiley & Sons, 264 p.