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THE INTERACTION OF THE UTILITY AND ITS CUSTOMERS IN LOAD CONTROL

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ABSTRACT

Load control consists of the interaction of two optimization problems with different objectives. One minimizes the purchase costs of the needed power and the other maximizes the comfort or the profit of the customer. In this paper the load control and the interaction of the two optimization tasks are studied by simulations of three cases.

Keywords: optimization of load control, dynamic tariffs, advanced EMS

1. INTRODUCTION

The energy management system of a power distribution utility minimizes the production and purchase costs of the required power. At the same time the optimization of the end use maximizes the comfort or the profit of the customer. The interaction of these two optimization tasks can substantially reduce the power purchase costs by adjusting the timing of the end use and by giving more reliable predictions. Sormunen [1] has studied the value of load control to the power company.

The effective use of dynamic tariffs requires, that the customer has an automated control system. This applies also for space heating, ventilation and air conditioning [2]. Manual real time response is too expensive and too unreliable. Modern building control systems and process management systems have capabilities to integrate also the optimization of energy consumption.

Energy utilities could benefit from the load predictions given by the customers. Those are based on the production plans and known or sudden shutdowns of the customer factory or on the measured state and planned usage of buildings. However, the predictions may be confidential and there may be temptations to manipulate predictions or prices. An interface that gives mutual benefits and trust must be agreed. Also the interaction of the two optimization tasks should be co-ordinated to prevent convergence problems.

In [3] a group of base metal plants has been studied from the point of view of electric energy management, load control and time variable or dynamic tariffs. It included both continuous and batch processes and a power plant. The group has a centralised energy management that co-ordinates the local energy and process management systems and gets load predictions from them. It participates in the energy trade much like a power utility.

This paper presents simulation examples of the interaction between the utility and its customer. Three cases of load control and dynamic tariffs are studied also from the point of view of the customers of the utility.

2. SPACE HEATING AND VENTILATION

2.1 Model and cost function

Heating and ventilation loads in a building are considered in the first example. The timing of heating and ventilation is optimized using a criterion that takes into account both the needs and comfort of the house and the heating costs. The use and occupancy of the room define a time dependent quadratic cost and hard constraints. In the optimization criterion this rather imaginary cost is added to the linear heating costs. Tuning between the costs and comfort can be easily done by adjusting the weights of this cost function.

A simple model of heat capacities and heat conductivity of the walls and the interior is used. Outside temperature is taken into account as a time variable non-controllable input to the system. Also the effect of ventilation on the quality and temperature of the air and on the power consumption is included in the model. The system model is linear except the state and control constraints and two non-linear terms due to ventilation.

The system equations are

$$\begin{aligned} C_1\dot{x}_1 &= -k_1x_1 + k_1x_2 + k_{h1}u_1 \\ &\quad - k_{v1}(x_1 - T_{out})u_2 \\ C_2\dot{x}_2 &= k_1x_1 - (k_1 + k_2)x_2 \\ &\quad + k_2T_{out} + k_{h2}u_1 \\ V\dot{x}_3 &= -k_f x_3 u_2 + k_{Occ}O + k_0 \end{aligned} \tag{1}$$

where

$x_1(t)$	temperature in the building
$x_2(t)$	wall temperature
$x_3(t)$	air contamination (e.g. CO_2 percentage) in the building
C_1, C_2	heat capacities
V	internal volume of the building
$u_1(t)$	electric power for heating
$u_2(t)$	electric power for ventilation
k_1, k_2, k_{h1}, k_{h2}, k_{v1}	constants related to heat transfer
k_f, k_{Occ}, k_0	constants related to air contamination
$T_{out}(t)$	outside temperature
O(t)	occupancy of the building (e.g. number of persons)
t,t0,tf	time, start time, end time.

The objective is to find u(t) that minimizes

$$\begin{aligned} J &= [x(tf) - x_s(tf)]^T F[x(tf) - x_s(tf)] \\ &\quad + \int_{t0}^{tf} [(x - x_s)^T Q(x - x_s) + P(u_1 + u_2) \\ &\quad + (u - u_s)^T R(u - u_s)]dt \end{aligned} \tag{2}$$

where

$x = x(t) = (x_1,x_2,x_3)^T$	state vector
$u=u(t) = (u_1,u_2)^T$	control vector
F	positive definite diagonal 3x3 matrix for end state weights
Q(t)	time variable positive definite 3x3 diagonal matrix for state weights
R	positive definite diagonal 2x2 matrix for soft bounds on control
P(t)	price of the electricity at time t
$x_s(t)$	reference values for the state variables at time t
u_s	reference or stationary value of the control vector

The weights in the criterion are tuning variables that are chosen to balance comfort and the power cost. Two terms in state weight Q(t) are important. They weight the inside temperature and the air quality. Other terms in Q and R are used so that they have only small effects on the result. R is used to prefer small control actions more than large ones and also to improve convergence. The end weight F is necessary in order to move the optimization horizon further in time. It is chosen proportional to the state weights Q.

The occupancy of the building is taken into account in two ways to reduce heating and ventilation costs. In the model (1) the occupancy of the building increases the air contamination. The state weights Q(t) in the criterion (2) are smaller during the non-occupied periods in order to let the temperature and the air quality vary more then.

A temperature controller is added in the model (1) and the optimization gives its set-point. Real systems may have higher dimension and use alternative fuels. However the character of the model is similar.

The model (1 and 2) is kept simple. The reactive power and the varying power factor of ventilation and heating are not considered. Although there are non-linear terms in the model it is not intended to be realistic on a very wide temperature range. The temperature exchange with the ground and with adjacent rooms is not included.

2.2 Methods

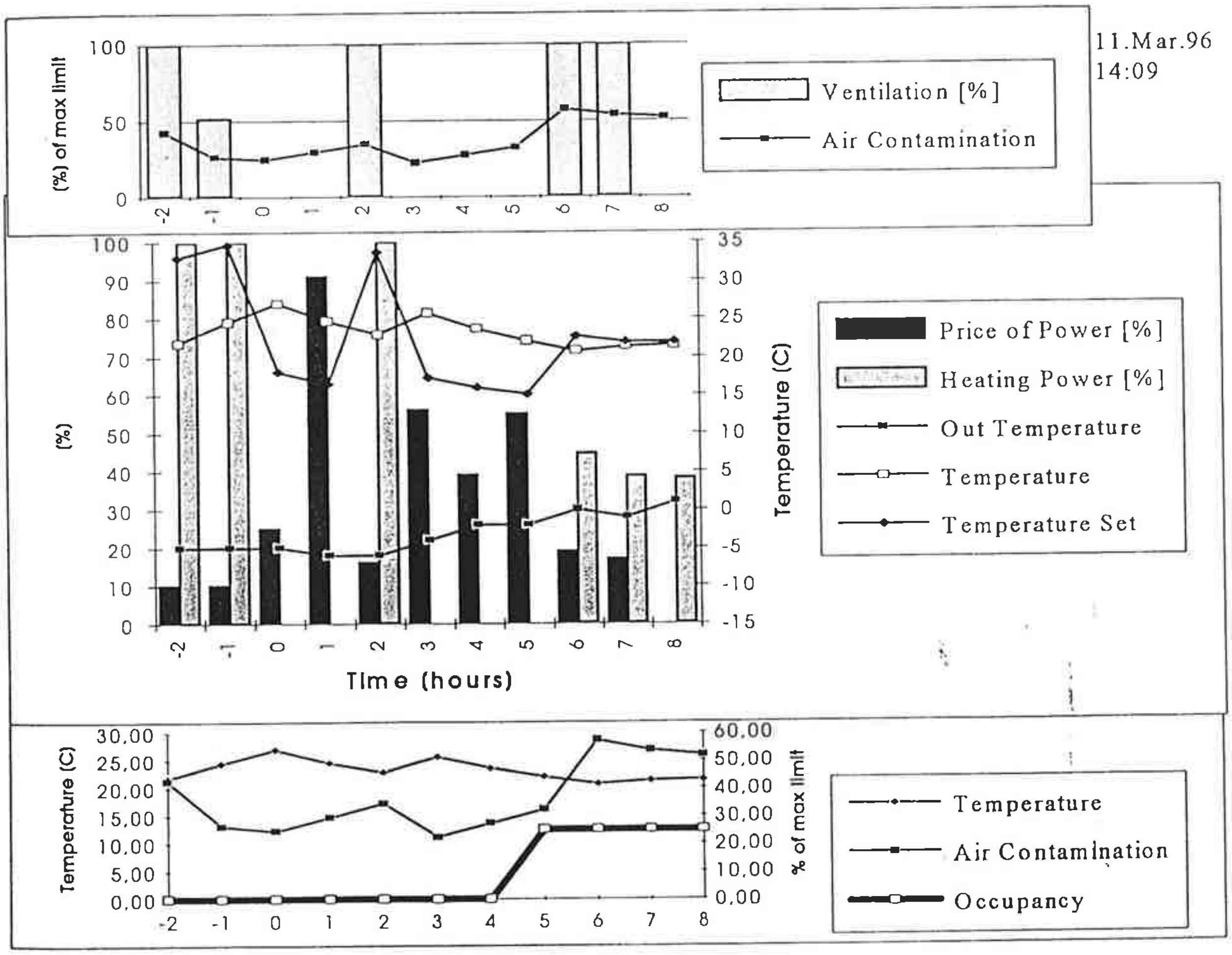
The model is discretized with 16 time steps into a constrained non-linear programming problem. Optimization program, that is based on the generalised reduced gradient method GRG2 of Lasdon and Warren, is used to solve the optimization. Two methods are compared. In the first a piecewise constant control as a function of time is directly optimized; the fact, that the model is a dynamic system with causality, has not been utilised in any way to improve the optimization speed. Figure 1 shows a solved case in a possible user interface. The other method is known to be more accurate but less reliable [4]. It uses the Pontryagin's maximum principle and solves the resulting two point boundary value problem by searching the initial values of the adjoint system using the non-linear optimization method. The methods were implemented in a spreadsheet program in a personal computer (486-33).

The non-linear optimization of the control functions can be made faster. With the direct method sparse matrix techniques give a great benefit [4] because the gradient matrix is very sparse. Another way is to calculate the gradient of the optimization criterion via the solution of the adjoint system [5]. With larger models the speed of the method is crucial.

2.3 Experience

1) With the method that solves the two point boundary value problem failures to converge occurred often. Direct optimization of the control functions was more reliable and less sensitive to the starting guess. Initial guesses for both methods were generated by gradually increasing the number of time steps.

2) Different starting points gave often different solutions because of local minima and poor convergence. Solutions depending on



	Power Costs	Comfort	End State	Total Criterion
Weights	1	80	240	
Costs	3627	836	190	4653

Figure 1. An example of heating and ventilation load optimization

the starting point have sometimes been removed when an implicit hard constraint hidden in the model has been explicitly given to the optimization method.

3) With the optimization the customer can much better take advantage of dynamic tariffs.

4) Advance information on the changes in the prices is important for the customer. It almost doubles the potential to reduce the costs.

5) With hourly prices the optimization time step of half an hour gives smaller costs than an hour.

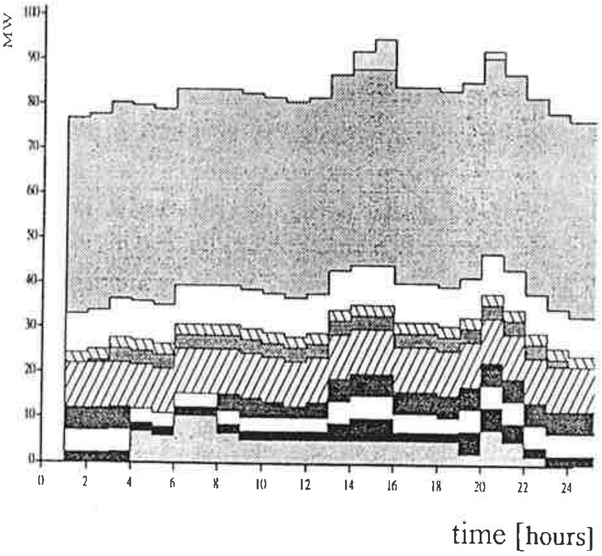
6) The planned power consumption of the house could be given to the utility in order to get more accurate short term load predictions. If the tariff gives credit of accurate predictions, this will be in the customers' interest too.

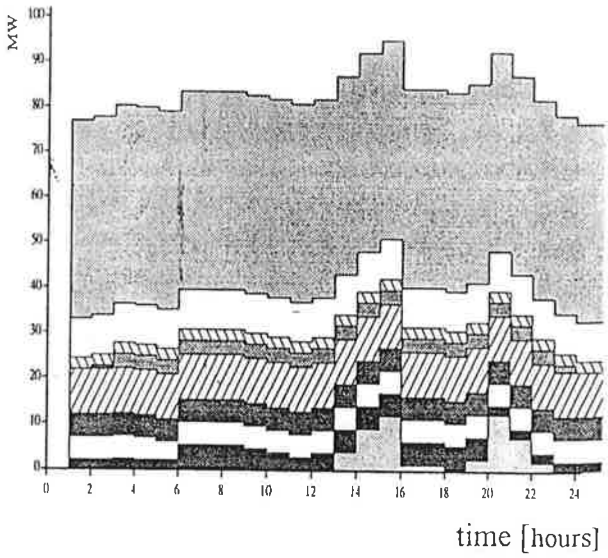
3. OTHER CONTINUOUS PROCESSES

In many continuous energy intensive processes like electrolysis, the power limitations of medium size mean only loss of production proportional to the limited energy. Only large limitations create start-up and shutdown costs and degrade the quality of the production. The integration of process phases and decreasing of buffers between them cause dependencies that cannot be ignored in load control. Based on the market value of the products and raw materials the energy price that leads to limiting production can be calculated. Here it may be better for the utility to know the price that leads to restrictions than to get from the customer the predicted power based on the dynamic price variations.

Loads that do not have complicated dynamics and scheduling problems can be integrated to the optimization of power purchase of the utility. That has been done in the second simulation example where the load model is static. The optimization method is described in [6] and [7]. Figure 2 shows the solution with and without load control. The method already optimizes heat and water storage using a linear model of their dynamics. Also load dynamics could be included the same way. This may even improve solution convergence. For example the model of the first example, (1) and (2), can be piecewise linearised at its normal operating point and included this way.

All continuous processes are not easily suitable for load control. Many are run based on static optimization and electricity costs may be small compared to other costs. For example, the integrated system in [8] would make it easy





Legend: Top: Load Control; Bottom: Controllable Hydro Power; Between: Other Sources

Figure 2. Optimized power dispatch with load control (left) and without (right)

to implement load control but it is not mentioned.

The distinction between continuous and batch processes is not clear. The optimization of a continuous process may include changing states and scheduling operations because of costs of start-ups, shutdowns of motors or subprocesses in addition to energy costs. The control of drinking water supply system with pumps in [9] shows among other things a way ~~The distinction between continuous and batch rocesses is not clear. The optimization of a continuous process may include changing tates and scheduling operations because of~~ to take time variable or even dynamic tariffs into account in such an optimization. Solutions are, however, tailored to processes, because there is not any general method that effectively can solve all dynamic optimization problems. The solution provides the planned power consumption, that could be given to the utility.

4. BATCH PROCESSES

An example of short term energy management of batch processes is the scheduling of a steel plant. Here a prototype is described, that automates the heuristics of scheduling experts and shows the connections to energy management. The method can also be applied to other steel plants that have different flow of production. For example in [10] various scheduling methods and case studies, including steelmaking in pp. 607-654, are described.

The production consists of different batch operations following each other. The capacity, availability and timing of the operations are important constraints. The due times of orders must be met. Waiting times between process operations should be minimized because they increase consumption of energy and refractory materials. Long delays cause also quality problems and the result may be a cheaper steel grade than desired or even waste or reprocessed production. Reprocessing wastes production capacity and energy for example in remelting. The energy price makes a remarkable share of the production costs. However, restrictions in power consumption increase costs if the requirements of the production process are ignored.

The scheduling problem as such leads to the explosion of the number of alternative actions. The specialists of the steel plant have developed heuristics that reduce the dimension of the problem and solve it in two phases that proceed backwards in time. This has been necessary in order to create the production schedule and to adjust executing schedules to disturbances and unexpected events. In this example the dynamic price of the electricity and natural gas have been included in the input information. The user will see the energy prices and costs of his plan on the display. He can tune the schedule and replace some electricity usage with natural gas or the opposite. Figure3 is a display of this prototype system. It shows how the timing of individual process operations contributes to the total power.

The planned energy consumption is known for several hours ahead and could be given to the utility. If there are disturbances they delay the steel production and thus reduce the power consumption in the near future. Sudden unpredictable increases in load would be expensive to purchase, but there are none. On the long run the disturbances in the production increase the energy consumption and reduce the steel output of the plant. Executing schedules can be adjusted as a response to unexpected changes in power prices also.

5. PEAK CONTROL SYSTEMS

Systems that restrict the consumption peak by controlling the loads usually hide the dynamics from the optimization of the power purchase. They minimize the power exceeding a given level or curve. They may also give the predicted power consumption both with and without the load control actions. Typically these systems cannot directly use dynamic tariffs as input, because they take into account only the amount of the overshoot but not its price.

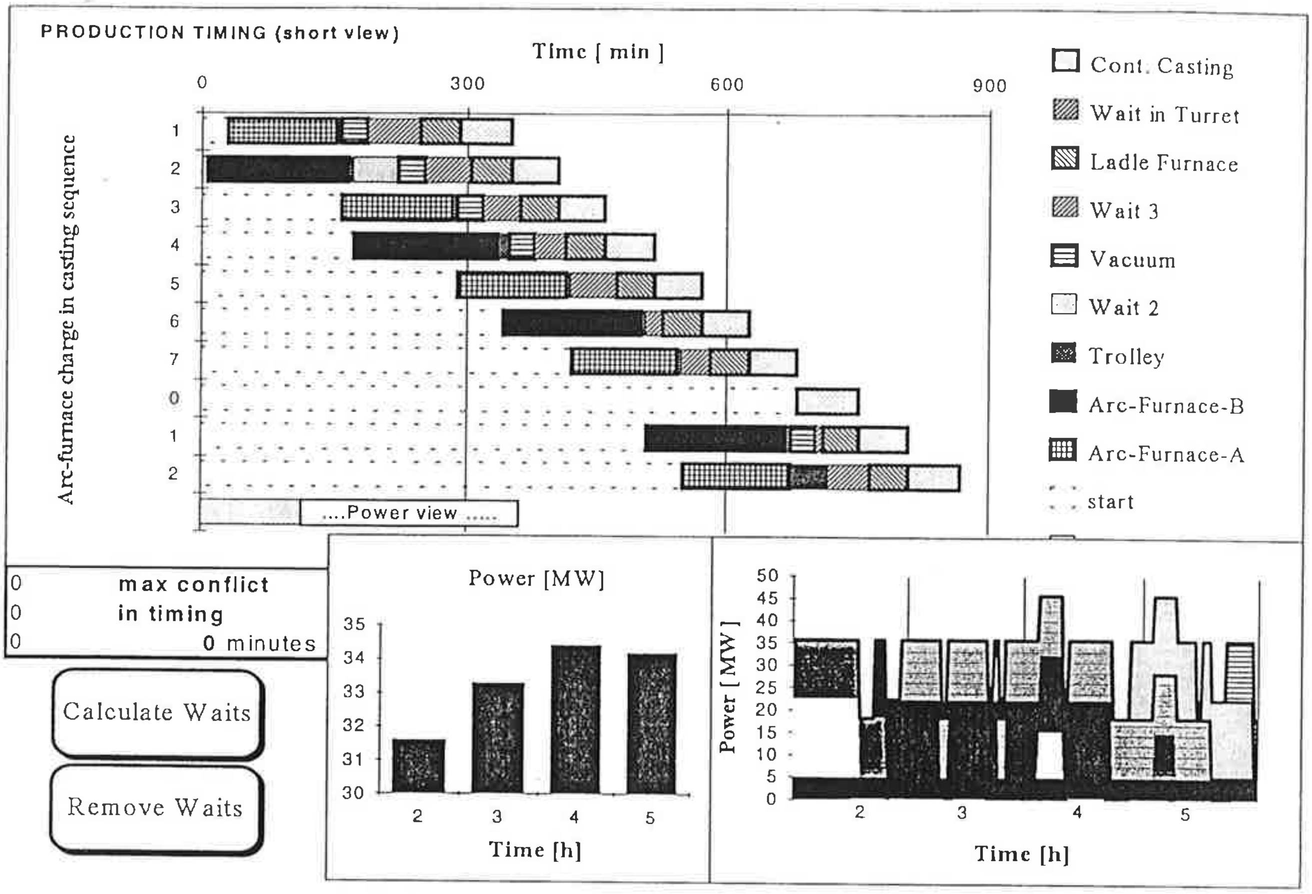


Figure 3. A display of a steel plant scheduling prototype with short term energy management

6. DISCUSSION

The first and third example show how customers could get advantage of the dynamic tariffs and give the predicted consumption to the power utility also. The utility can then use these predictions in its power purchase optimization, like the one in the second example. In this approach the main problems seem to be:

- The customer may not have an automatic control or process management system where the short term energy management could be situated.
- There are some problems in getting or using the predictions: They may contain confidential information. It may also be possible to cheat the other party by manipulating the predictions or dynamic prices. If there is not enough mutual trust, binding offers may be exchanged instead of predictions although the interaction is then slower.
- The control is sensitive to prediction accuracy.
- The plans and predictions include different types of uncertainty and the actual distributions of error probabilities of individual targets are far from normal. The sum of very many relatively small demands can usually reasonably well be calculated by assuming normally distributed errors but large units must be individually dealt with. Their predicted maximum demand can be easier to determine than the most probable demand. The maximum can be more useful also because it may be very expensive to purchase power for unforeseen demand peaks. Further research is needed on how a utility can aggregate the planned power consumptions to get the total demand.
- How the optimization of the power purchase in the utility interacts with the customer's system The interaction may cause convergence problems between the two optimizations. The prices and predictions may start to oscillate, if the interaction is too strong

and too slow. There may be a need to use dynamic load response models and similar techniques as with the decomposition and co-ordinating of optimization problems, see for example the books[11, 12].

The second example does not have such interaction problems and does not set requirements on the automation system of the customer because the whole problem is treated by one optimization system. However, the dimension of the power purchase optimization problem and so the computation task may increase.

All changes of plans and control actions include also such costs and risks that are not included in the optimization criterion in the examples. For example transfer of information may have a certain cost. Thus the solutions tend to include too frequent load control actions compared to real benefits and costs. There is a need to solve this problem efficiently.

The time span of interest is here about 24 hours. That is because it is one of the dominating periods in the power prices and most loads. The power prices are assumed to change in one hour intervals. Then shorter time step gives clear benefits in the load optimization, because it enables the use of short buffering capacity to move loads between consecutive hours. In the steel plant scheduling example the time step is one minute. In the heating and ventilation example a time step of half an hour could be a good choice if the data processing capacity is adequate.

Load control is often needed to cope with sudden loss of power production or transfer capacity. Then it is used instead of more expensive production than in prescheduled power dispatch. Only loads that can be controlled at short notice can be reserved for this purpose.

7. CONCLUSIONS

The cases described have different interfaces between the utility and its customer. Alternative principles of interaction are needed depending on the characteristics of the loads and control systems of the customers.

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