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Forward Temperatures and Production Planning in District Heating Systems

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Abstract

The paper deals with short-term planning in district heating systems. The major goal is to minimize the operation cost, subject to the condition of fulfilling the heat demand. Focus is on how to handle the forward temperature. Two alternative approaches are suggested. The first applies transformation of data before an ordinary load prediction algorithm is applied. The second models the district heating system as a network. Numerical tests show that the predictions are improved using the transformation method. Using the network approach, also restrictions in distribution capacity are considered.

1 Introduction

District heating is used to supply cities with heat from a common heating system. The heat is produced in units of different types. In Combined Heat and Power (CHP) plants, both heat and power are produced from biomass or fossil fuels. Heat only boilers produce heat from biomass or fossil fuels, and heat pumps and electric heaters produce heat from electricity. The heat is distributed to the consumers through a pipe system in which the distribution water circulates continuously.

Due to relatively high operation costs, it is necessary for the energy companies to optimize the production. Planning for the next few days is called short-term planning. Typically the planning is performed by first predicting the heat load, and then committing the units to produce the required demand. In Section 2, the heat load and its components are discussed. The load prediction is constructed by combining a weather forecast with historical load and weather. The planning horizon is often divided into one-hour intervals, and the heat load prediction is normally based on delivered energy from the plants. An observation is that such load curve reflects energy, while district heating is in fact hot water with a certain temperature and flow. It is of course impossible to model the network dynamics using only one single load curve for the whole network.

Different approaches modeling the network can be found in the literature, e.g. [2], [8]. However, many references focus on network simulation rather than on production planning. This paper discuss how to consider the distribution in the planning, with focus on how to handle the forward temperature. Two different methodologies are suggested. In Section 3, a transformation method is applied in combination with an ordinary load forecasting algorithm, and in Section 4, the district heating system is modelled as a network with nodes and arcs. Section 5 gives some numerical results.

2 Heat load and forward temperature

The heat demand in a district heating system consists of three components: heat for warming buildings, heat for warming tapwater, and losses in the distribution network. Their respectively contribution are about 70% for warming buildings, 25% for warming tapwater and 5% is losses. The outdoor temperature, together with the behavior of the consumers, referred to as the social component, have the greatest influence on the demand. Weather conditions like wind, global radiation (sunshine) and precipitation have less effect.

The heat needed for warming buildings is depending on the difference between the indoor and outdoor temperatures. This load is mainly driven by the outdoor temperature, but also other weather conditions, such as wind and sunshine, influence. The heat needed for warming tapwater is a consequence of the social component, which may consist of both yearly, weekly and daily patterns. The losses in the network decreases with the water flow, and increases with the difference between the water temperature and the temperature in the surrounding ground. During the winter, the flow and the difference between the temperatures are both high. During the summer, the opposite is true. This implies that the losses in absolute value is almost the same during the year.

The heat, q_i, delivered from a production plant during hour i is

$$q_i = c_p m_i \left(t_i^f - t_i^r \right), \tag{1}$$

where c_p is the specific heat capacity of water, m_i is the water flow, t_i^f is the forward temperature and t_i^r is the return temperature. The forward temperature is chosen in the range from 70 to 120 degrees Celsius, which implies that the return temperature becomes 40 to 60 degrees. In this paper we simplify the problem and assume that the return temperature is constant. This means that we only need to use the forward temperature when modelling the influence of the temperatures.

The forward temperature is controlled by the system operator. However, often it is just chosen from a predefined function of the outdoor temperature, the so called steering curve. It is of course possible to choose another temperature, which implies that the distribution network is either charged or discharged. A low forward temperature normally implies a lower return temperature, which increases the alpha-values in the CHP plants (the ratio between produced power and heat is called alpha-value). The losses decline with a low forward temperature. On the other hand, restrictions in distribution capacity may imply that it is favorable to increase the forward temperature. Thus, the choice of forward temperature is an optimization problem that has to be solved by the system operator.

3 Algorithms for load forecasting

Several methods for load prediction have been suggested and implemented, including e.g. time series models [1] and Artificial Neural Networks [5]. Some applications consider prediction of electrical power loads rather than heat loads, but similarities between the two problem types indicate that the same type of algorithms may be used. In this paper, time series models of SARMAX type and regression models are applied. The theories behind the methodologies are well-know and will not be described in detail. Roughly speaking, both methods find an expression that describes the heat load as a function of weather and consumption patterns. For a detailed description of the models applied, see Liljedahl [6].

In the above mentioned methods, it is possible to also consider the forward temperature as an explaining variable. This was suggested by Wiklund [9] in purpose to model the network dynamics. However, the drawback with the approach is that the forward temperature still needs to be predicted, or more correctly, be optimized. In that sense the load forecasting problem and the planning problem are linked. Thus, to find the global optimum, the two problems must be solved simultaneously. A possibility to overcome this is to base the load forecast on data from the consumers rather than on data from the production plants. However, such data are often not available. An alternative is then to transform the plant data to the consumers and make the forecast on these transformed data. This can be done as follows.

Assume the district heating network consists of only one production plant and one large consumer. The distance between the plant (supply node) and the consumer (demand node) is defined as the energy weighted average distance between the real plants and demands. On this simple network model, it is easy to compute how a change in forward temperature moves from the supply node to the demand node. Used here is the knowledge that a change in water flow results in an immediate change in flow in the whole network. A change in water temperature, on the other hand, moves with the speed of the water. Measured flow and temperature at the supply node is transformed to the demand node. Then a load forecasting algorithm is applied to the transformed data. This results in a prediction of the demand (including losses in the distribution network). The predicted load serve as base for planning the forward temperature. Then, given the future forward temperature, the consumer load is transformed back to the supply node, which results in a prediction of the heat that shall be produced.

4 A network model

Applying the transformation method described in the previous section is an attempt to handle the influence of the forward temperature. However, it is of course a simplification that may not be suitable, especially not for district heating systems with restrictions in distribution capacity. For these systems it is necessary to use an approach that models the network. The current section presents such model.

Mixed Integer Programming (MIP) [10] is a powerful modeling methodology often applied in short-term planning of district heating systems [3], [4], [7], [11]. The model developed here is adopted to fit the MIP framework and can thus be implemented in any MIP based planning tool. The principal formulation of a MIP is

$$\begin{aligned} &\min_x \left[c^T x\right] \\ &\quad s.t. \quad Ax = b, \end{aligned} \tag{2}$$

where the vector c is modeling the production costs and the constraints $Ax = b$ the process. The vector x contains the decision variables, which are here interpreted as the production plan, i.e. produced heat and power, forward temperature, etc. The vector x may include integer variables, e.g. binary variables modeling if a production unit is running or not.

The distribution system is modeled as a network with nodes and arcs. Production and consumers are located in the nodes, referred to as supply nodes and demand nodes, respectively. The arcs are interpreted as pipes. Depending on the current system, the modeling may be more or less intricate. District heating networks with production in several plants and networks with loops are more difficult to model. However, many systems have a simple structure with most production in one base load plant and a network formed as a tree. Here we assume such system.

Define the following parameters and variables. Let I be the number of one-hour intervals in the planning horizon and let N be the number of nodes in the network. The heat demand in time interval i at node n is $q^n_{i,D}$. Let the variable $e_i^{(m,n)}$ be the energy distributed from node m to node n during time interval i, and let the variable $q^n_{i,P}$ represent the produced heat at node n during i.

For each node n in the network an energy balance equation must hold,

$$\sum_{m=1}^{N} e_i^{(m,n)} + q^n_{i,P} = \sum_{m=1}^{N} e_i^{(n,m)} + q^n_{i,D}. \tag{3}$$

We assume the forward temperature t_i^f is controlled from the base load plant. The steering curve, $t^f = s(t^o)$, which gives the forward temperature as a function of the outdoor temperature t^o, is used to define the bounds on the forward temperature,

$$s(t_i^o) \leq t_i^f \leq \bar{t}_i^f. \tag{4}$$

Restrictions in distribution capacity is a consequence of the dimensions of the pipes, which thus can only let a certain water flow pass. If the forward temperature is increased, it is possible to distribute more energy. This implies the following bounds on $e_i^{(m,n)}$,

$$0 \leq e_i^{(m,n)} \leq \bar{e}_1^{(m,n)} + \bar{e}_2^{(m,n)} t_i^f. \tag{5}$$

Increasing the forward temperature thus have the positive implication that more heat can be distributed with the same flow. However, higher losses, decreasing alpha-values in CHP plants, and the application of flow fee give incitement to keep the forward temperature low.

Increased losses is modeled by adding

$$q^n_{i,L} = \sigma^n \left(t_i^f - s(t_i^o)\right), \tag{6}$$

$\sigma^n > 0$, to the right hand side in the energy balance equation (3).

Decreasing alpha-values in CHP plants are modeled as follows. First, simplify the description by assuming that the alpha-value, $\alpha(t_i^f)$, depends on the forward temperature, but not on the produced heat, q_i, and power, p_i. The model can be generalized to also consider the production. The relation $p_i = \alpha(t_i^f)q_i$ is obviously non-linear and must be linearized. This is done by assuming constant alpha, $\alpha_{i,j}$, on different segments j of the forward temperature, defined by $\tau_0 < \tau_1 < ... < \tau_J$, where J is the number of segments. On each segment, also a binary variable $w_{i,j}$ and continuous variables $q_{i,j}$ and $t_{i,j}^f$, are defined. Assuming the plant is in operation, the constraints

$$\sum_{j=1}^{J} w_{i,j} = 1, \tag{7}$$

$$\tau_{j-1} w_{i,j} \leq t_{i,j}^f \leq \tau_j w_{i,j},$$

and

$$\underline{q}_i w_{i,j} \leq q_{i,j} \leq \overline{q}_i w_{i,j}, \tag{8}$$

assure that the plant operates at only one segment. The parameters $\underline{q}_i$ and $\overline{q}_i$ are the lower and upper bounds, respectively, of the heat production. The forward temperature, heat and power produced at the plant are given by

$$t_i^f = \sum_{j=1}^{J} t_{i,j}^f, \tag{9}$$

$$q_i = \sum_{j=1}^{J} q_{i,j}, \tag{10}$$

and

$$p_i = \sum_{j=1}^{J} \alpha_{i,j} q_{i,j}. \tag{11}$$

The influence of the flow fee is modeled by adding

$$c^{flowfee} = \rho \left(t_i^f - s(t_i^o) \right), \tag{12}$$

to the objective function in (2). Here $\rho > 0$ reflects lost income due to the flow fee.

The equations (3) - (12) do not model the time delays in the distribution network. Thus, it is here assumed that the heat is consumed at the same moment it is produced. The ideas may be extended to also consider the network dynamics, which is also the main task in an on-going project.

5 Numerical results

The SARMAX and regression algorithms discussed in Section 3 are applied to a district heating system in Stockholm, Sweden. The system has a total water volume of 32200 m^3 and a total pipe length of 326 km. A typical winter load is 500 MW. Different versions of the models are implemented and analyzed. What differs between them are e.g. what weather parameters that are considered, the period from which the historical data are taken, and if the forward temperature are chosen as an explaining variable or not. The models are applied to data for one year. Table 1 illustrates some of the results. The table presents the absolute and relative prediction errors for twenty-four hours. In the calculations, measured weather data is used, i.e. the figures do not include possible errors in weather forecasts. Also measured forward temperature is used. Details of the models and results are found in Liljedahl [6].

The main conclusions from the analysis are the following. During spring, winter and autumn, linear regression models preform better or at least as well as more complicated models. In these linear regression models, data shall be adopted to historical data from the previous year. Time series models give better results during the summer period. The average error is about 20 MW, or $3 - 10\%$ depending on season. The network dynamics can partly be modelled using the forward temperature. Conclusions regarding the

Model	F temp	AE Autumn	AE Winter	AE Spring	AE Summer	RE Autumn	RE Winter	RE Spring	RE Summer
SARMAX	yes	18	21	19	6.9	6.3	3.9	6.1	9.5
SARMAX	no	19	24	22	7.0	6.8	4.6	6.9	9.6
lin reg	yes	15	16	18	12	6.4	3.2	6.2	17
lin reg	no	16	18	20	13	6.7	3.6	6.7	18
lin reg	yes	22	15	26	15	9.1	3.0	9.3	21
lin reg	no	23	19	27	15	9.4	3.7	9.6	22
non-lin reg	no	20	20	24	13	8.5	3.9	7.9	18
pw lin reg	no	21	26	27	10	8.4	5.5	9.2	14

Table 1: Absolute error (AE) and relative error (RE) for different models and seasons. The absolute error is given in MW and the relative error in percent. The column 'F temp' shows if the forward temperature is chosen as an explaining variable, 'lin reg' means linear regression, 'non-lin reg' means non-linear regression, and 'pw lin reg' means piecewise linear regression.

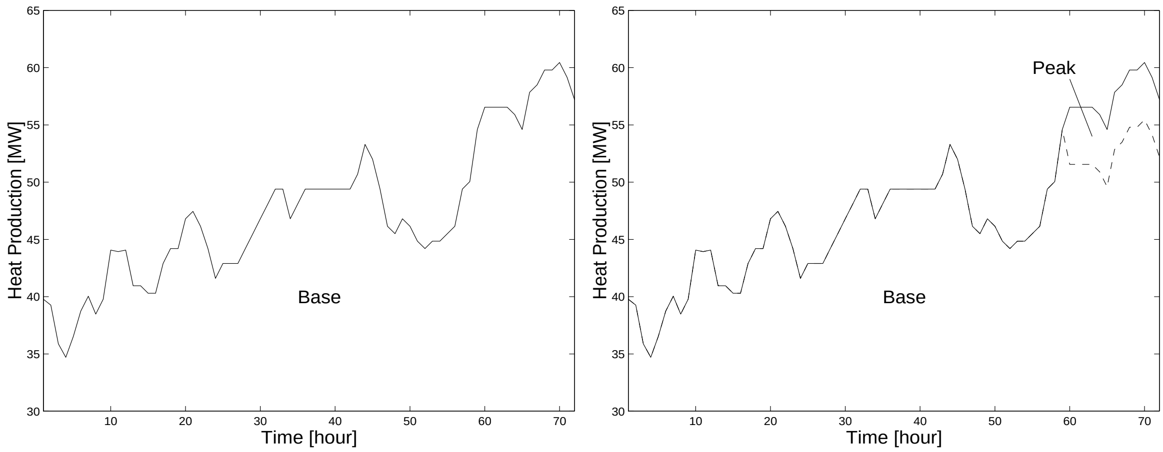

Figure 1: Production plans considering (left) and not considering (right) the forward temperature. Peak means production in peak units and Base means production in base load plants.

regression models are the following. The outdoor temperature is the most important parameter. Modeling the dynamics in buildings improves the relative error with 0.5. To consider the forward temperature improves the relative error with 0.5, and to consider the wind improves the error with about one. To consider the global radiation gives almost no improvement. The main conclusion for time series models is that they perform poorly during periods with big changes in the load.

The transformation method described in Section 3 is applied. A regression analysis is performed on both original and transformed data. The analysis shows that the standard deviation decreases from 26.99 to 24.12 using transformed data, i.e. the adaptation is better. When load predictions are calculated on transformed data, the absolute and relative errors decrease with 2.5 MW and 0.5, respectively, compared to calculations on original data.

The network model developed in Section 4 is implemented in the planning software ZEBRA [3], which models a district heating systems in Stockholm. As an illustrating example, Figure 1 depicts two production plans: one that considers and one that not considers the forward temperature. As we see, it is not necessary to start the peak unit in the case considering the forward temperature. The reason is that more heat can be distributed from the base load plant by increasing the temperature.

6 Conclusions

Short-term planning in district heating systems was considered. The focus was on how to handle the forward temperature. Two different approaches were suggested. The first applies a transformation of data before an ordinary load prediction algorithm is applied. Numerical tests show that the error in the load prediction using original data is about 20 MW. Applying the transformation improves the result with in average 2.5 MW. The second approach models the district heating system as a network. Using the model, also restrictions in distribution capacity are considered.

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