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Implementation of a load prediction program system for the Norwegian power pool

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Keywords: *power system control; load prediction; parameter estimation; Kalman filters; prediction.*

A model for short-term load prediction (24 hours) has been developed. It is implemented as a part of an interactive program system for load prediction within the different areas of the Norwegian Power Pool. The model consists of two parts, describing the slow, seasonal variations (normal conditions), and short-term deviations from normal conditions, respectively. Kalman filtering techniques are used for updating the states of the models, and the parameters are estimated with a maximum likelihood method. The model has been tested with load data from various areas in Norway, and the system has been in on-line use at the Norwegian Power Pool since October 1979. Better control of the power system has been obtained through improved prediction and production planning.

1. Introduction

Good prediction of future load demand is necessary when making an optimal production plan for the power system. The best way to estimate this load is probably through use of modern control theory methods.

In 1978 the Royal Norwegian Council for Scientific and Industrial Research (NTNF), EFI and the NPP agreed to finance a project for development of a load prediction model, to be implemented on a minicomputer for use in the Norwegian electricity supply control centers. The goal was to make 24 hours predictions with time resolution of one hour. The project period has been two years and the cost about \$120 000.

2. Model description

The predicted load within each supply area is derived from a model consisting of two major parts:

—submodel M_N describing long-term or seasonal variations of load and temperature, with typical time constants of one week or more. This submodel estimates the optimal linearization point for the other submodel, M_Δ,

—submodel M_Δ describing the functional relationship between deviations in load and temperature, involving time constants of less than one week. This is a linear multiple input single output model (Åstrøm and Bohlin, 1966).

The model structure is shown in Fig. 1.

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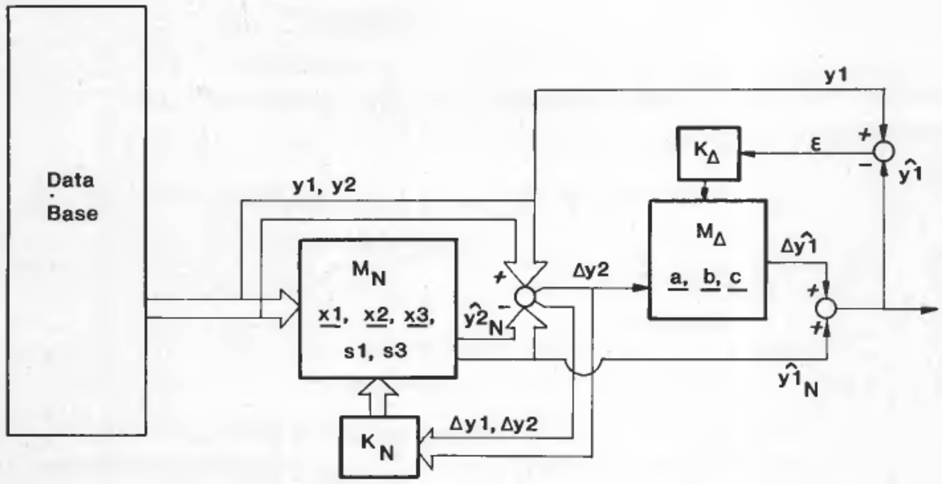

Figure 1. Model structure.

Seasonal variations

The seasonal variations are defined by a discrete set of process equations with two independent vectors ***x1*** and ***x2*** concerning load, and a vector ***x3*** describing the long-term behaviour of the temperature, as follows:

State model

$$x1_i(k_1+1)=x1_i(k_1)+s1(k_1)+v_1(k_1) \tag{1}$$

$$x2_j(k_2+1)=x2_j(k_2)+v_2(k_2) \tag{2}$$

$$x3_i(k_1+1)=x3_i(k_1)+s3(k_1)+v_3(k_1) \tag{3}$$

where

$i=1, 2, \ldots, 24$; vector component number of vectors ***x1*** and ***x3***,

$j=1, 2, \ldots, 168$; vector component number of vector ***x2***,

k_1 = time parameter for seasonal variations for ***x1*** and ***x3***, incremented by one every 24 hours,

k_2 = time parameter for ***x2***, incremented by one every week (168 hours),

$x1_i(k_1)$ = average weekly load (MWh/h) for the *i*th hour of the day, under normal temperature conditions,

$x2_j(k_2)$ = deviation from average weekly load (MWh/h) for the *j*th hour of the week, under normal temperature conditions,

$x3_i(k_1)$ = normal temperature for the *i*th hour of the day,

$\left.\begin{matrix} s1(k_1) \\ s3(k_1) \end{matrix}\right\}$ = seasonal deviations from annual average of load and temperature respectively,

v_1, v_2, v_3 = process noise.

The seasonal deviations $s1$ and $s3$ are assumed to be sine-wave functions of time:

$$s1(k_1)=\omega_1 A_1 \cos(\omega_1 k_1+\beta_1) \tag{4}$$

$$s3(k_1)=\omega_3 A_3 \cos(\omega_3 k_1+\beta_1) \tag{5}$$

where

ω = seasonal angular frequency,

A = amplitude of seasonal deviation from annual average,

β = initial phase angle.

Observation model

$$y1_j(k_2) = x1_i(k_1) + x2_j(k_2) + w_1 \tag{6}$$

$$y2_i(k_1) = x3_i(k_1) + w_2 \tag{7}$$

where

$j = 1, 2, \ldots, 168,$

$$i = \begin{cases} 24 \text{ when } j = 24, 48, \ldots, 168 \\ j(\text{modulo } 24) \text{ otherwise,} \end{cases}$$

$y1_j(k_2)$ = measured load,

$y2_i(k_1)$ = measured temperature,

w_1, w_2 = measured noise.

A number of independent Kalman filters (24, 168, 24) are used to update the state vectors ***x1***, ***x2***, and ***x3*** over the year (Eykhoff, 1974). The feedback is low in order to reproduce only the slow seasonal variations and trends. A simplified filter for the submodel M_N is designed as follows:

The gain is constant through the year with the same value for all components of the state vectors ***x1***, ***x2*** and ***x3***. The gain is estimated in such a way that the sum of squared 24 hours prediction errors is minimized. For each step of the search procedure the parameters of the submodel M_Δ are estimated with a maximum likelihood method (Åstrøm and Bohlin 1966). We have estimated the gain for several load areas in Norway and the values all seem to be practically the same, 0·15. The sensitivity in the prediction error with respect to reasonable variations (0·1–0·2) in the gain, is small. As a general rule we may use the value 0·15 for other areas. With this feedback the time constant for the components of the vectors ***x1*** and ***x3*** will be six days, and six weeks for the components of the vector ***x2***.

In fact only the sum of the respective components of the vectors ***x1*** and ***x2*** is observable. Therefore, a bias with opposite sign can occur in the mean value of the vector components of ***x1*** and ***x2***. From the physical interpretation of the vector ***x2*** as the week day variation, we know that the mean value of the components should be zero. Therefore we have a restriction to avoid the development of such a bias.

Short-term deviation from normal conditions

To estimate and predict the load fluctuations caused by short-term deviations from normal weather conditions, an ARMA model is used (Åstrøm and Bohlin, 1966). We define the short-term deviations as

$$\Delta y1 = y1 - \hat{y}1_N \tag{8}$$

$$\Delta y2 = y2 - \hat{y}2_N \tag{9}$$

where

$\hat{y}1_N$ = normal load estimated by the model M_N,

$\hat{y}2_N$ = normal temperature estimated by the model M_N.

This model runs with a time increment of one hour. The ARMA model describes the relation between load and temperature variations as follows:

$$\Delta y1(k)+\sum_{m=1}^{n} a_m \Delta y1(k-m)=\sum_{m=1}^{n}\{b_m \Delta y2(k-m)+c_m \epsilon(k-m)\}+\epsilon(k) \qquad (10)$$

where

$$a_m, b_m, c_m = \text{model parameters},$$
$$n = \text{model order},$$
$$\epsilon(k) = \text{innovation}.$$

A Kalman filter is used to update and predict values for $\Delta y1$. Estimates of the parameters ***a***, ***b*** and ***c*** are updated every week, based on data from the previous three weeks. A maximum likelihood method including Newton–Raphson iteration as described by Åstrøm and Bohlin (1966), is used for this estimation. It is well known that these parameters also give the optimal feedback in the submodel M_Δ.

The actual load estimates, $\hat{y}1$, is then found by adding the estimates from the two models M_N and M_Δ

$$\hat{y}1(k)=\hat{y}1_N(k)+\Delta\hat{y}1(k) \qquad (11)$$

A typical time constant for the model M_Δ is about 12 hours. This is therefore well separated from the model M_N having a time constant of six days (***x1***).

Variations in the signal $\Delta y1$ with time constants ranging from hours to six days which cannot be explained through temperature variations, will be modeled by the terms $c_m\epsilon(k-m)$ in eqn. 10. For a first order ARMA model, the environment will be a simple time constant model. This is the best way to model an unknown environment when the expected value of the environmental noise is zero.

If the dynamics of the environment are known, a more detailed model should be used, for example by adding one more input signal to the ARMA model, or by separating well known load variations from the load measurements.

Treatment of anomalous load patterns

In some periods of the year the model M_N fails to describe the normal load. Such anomalous load patterns occur during: holidays, Christmas and Easter, and other special periods.

For holidays the index j of the model M_N is temporarily changed to give the ordinary load pattern of a Sunday. Load prediction during all other special periods are taken care of by adding one more state variable, $x4$, to the combined model. The predicted load is then given by the following model:

$$\hat{y}1(k)=\hat{y}1_N(k)+\Delta\hat{y}1(k)+x4 \qquad (12)$$

This new state variable, $x4$, is not actually observable unless the vectors ***x1*** and ***x2*** of M_N and $\Delta y1$ of M_Δ follow a ballistic trajectory throughout the particular period. To predict $\Delta y1$, however, a parallel model with the same feedback as usual is used.

During Christmas and Easter, ***a priori*** estimates of $x4$ are given by observations from earlier years. The values of $x4$ are calculated relative to ***x1*** in order to take into consideration the trend in the load, and also the variable dates of Easter from one year to another.

During periods when the expected load variations is unknown, $x4$ is modeled as a pure integrator with initial value zero.

Model discussion

An advantage of this model is that the seasonal variations are described by using only one unknown parameter, the common feedback to state vectors ***x1***, ***x2*** and ***x3***.

The parameters of the ARMA model, M_Δ, are estimated in an adaptive way, to fit the slow variation in weather sensitivity over the year. From the maximum likelihood method for estimation of these parameters, we also get the optimal feedback of the ARMA model. In this way there is no need to cut and try to determine the noise covariance.

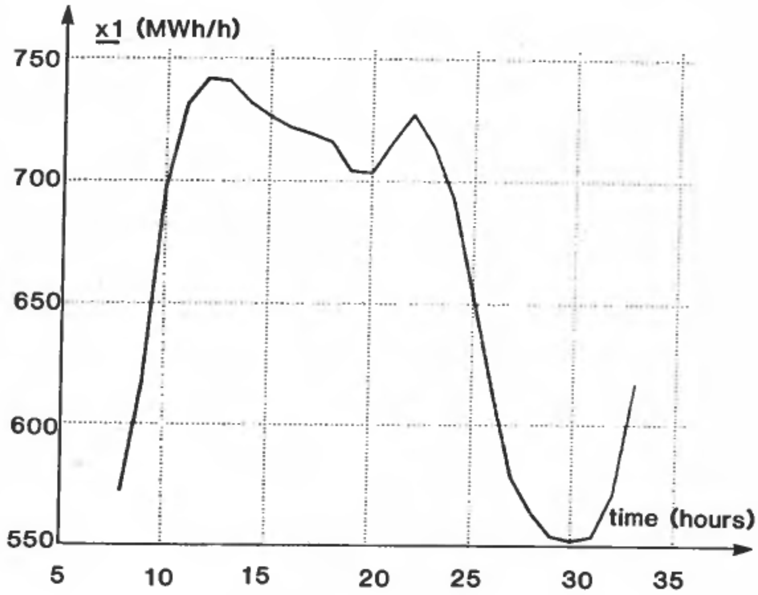

Figure 2. The vector $x1_i$, $i=1, 2, \ldots, 24$, at a given day.

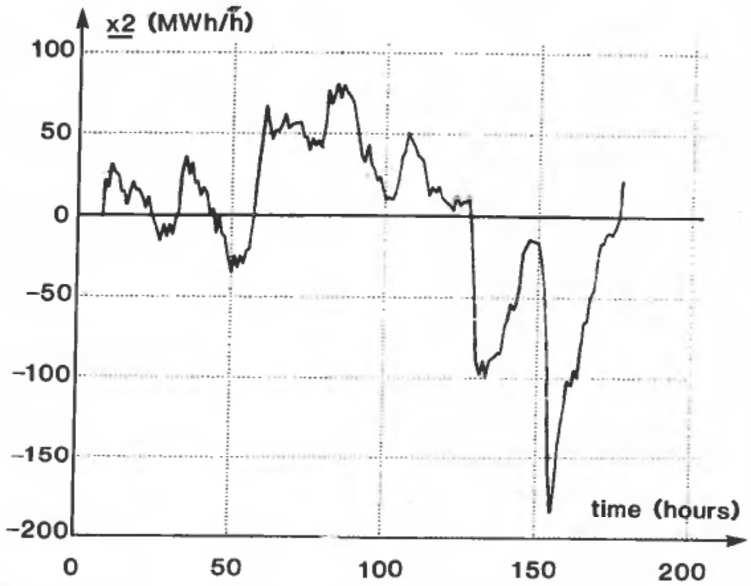

Figure 3. The vector $x2_j$, $j=1, 2, \ldots, 168$, at a given week.

The model is capable of incorporating more than one weather variable as input such as radiation and wind velocity. In this project we have only used temperature.

It is possible to initiate the model with only three weeks of data. After this the model will tune itself in a couple of weeks. The model is also capable of running automatically with updating and prediction every hour.

A disadvantage of the ARMA model is that it is a linearization of a non-linear process, e.g. under extremely low temperature conditions during the winter certain saturation effects will occur. As described by the model in eqn. 10, deviations in temperature and load should be a stationary time series. This is not quite true due to the simple structure of the submodel M_N. A more physically based model would probably be better, but will certainly require a large number of measurements.

3. Results from laboratory tests

The model was tested on data from three different load areas in Norway. Here we will show some typical results from a test period of about 6 weeks (1000 hours) for the load in Oslo. The period starts at 1975-01-21. Almost all the load is weather sensitive. Only 3·9% is used by power intensive industry. 50·3% is household usage and the rest is used by schools, offices etc.

In Figs. 2 and 3 the components of the vectors ***x1*** and ***x2*** are plotted at a given time of the year. We can regard ***x1*** as the mean value of the normal load over a week, for each hour of the day. The components of ***x2*** are the deviations in the normal load from this mean value (***x1***) for each hour of the week.

Figure 4 shows how the updating of the vector component $x1_4$ works for a period of one year. It is plotted together with the measured load, which has a drop each weekend. The variation over the year of the state vectors ***x2*** and ***x3*** are estimated in a similar way.

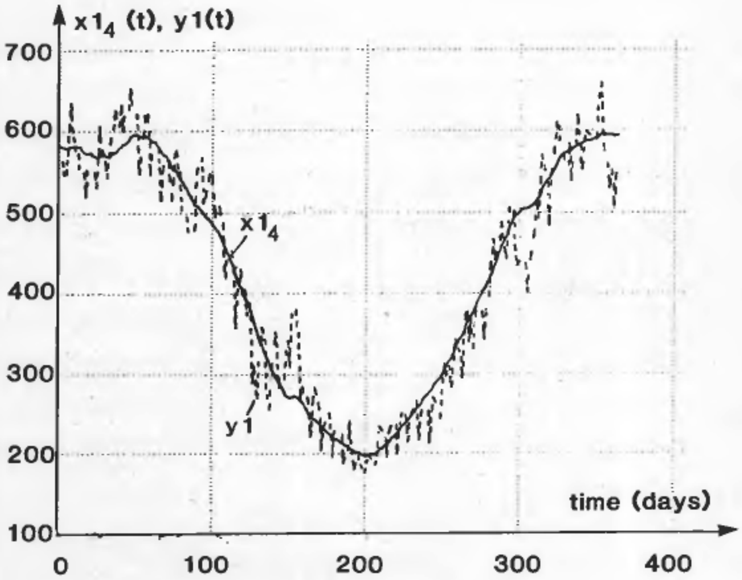

Figure 4. The vector component, $x1_4$, estimated over a period of one year. Measured load, $y1$, is dotted.

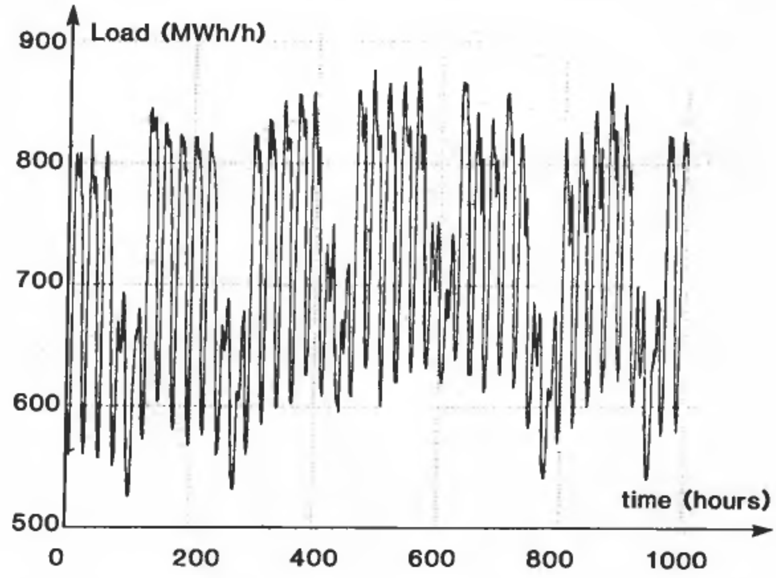

Figure 5. Measured load, $y1$, for a period of 6 weeks from the date 1975–01–21.

In Fig. 5 the measured load is plotted for the test period of 1000 hours. The mean value of the load is 714 MWh/h.

Figure 6 shows the estimated deviations from normal conditions in the load and temperature for the same period. The excitation of the system is sometimes rather high. Once the deviation in temperature varies from -6 to $+8°C$ in about 45 hours. As expected the two deviations seem to be almost symmetric around the zero line. The period for the slow variations corresponds to the passage of the high and low pressure weather zones.

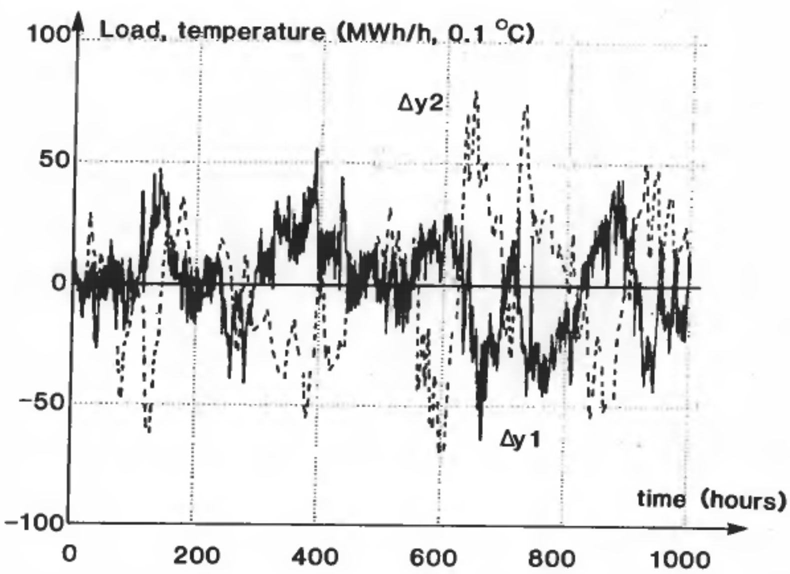

Figure 6. Deviation from the estimated normal conditions of the load ($\Delta y1$) and temperature ($\Delta y2$).

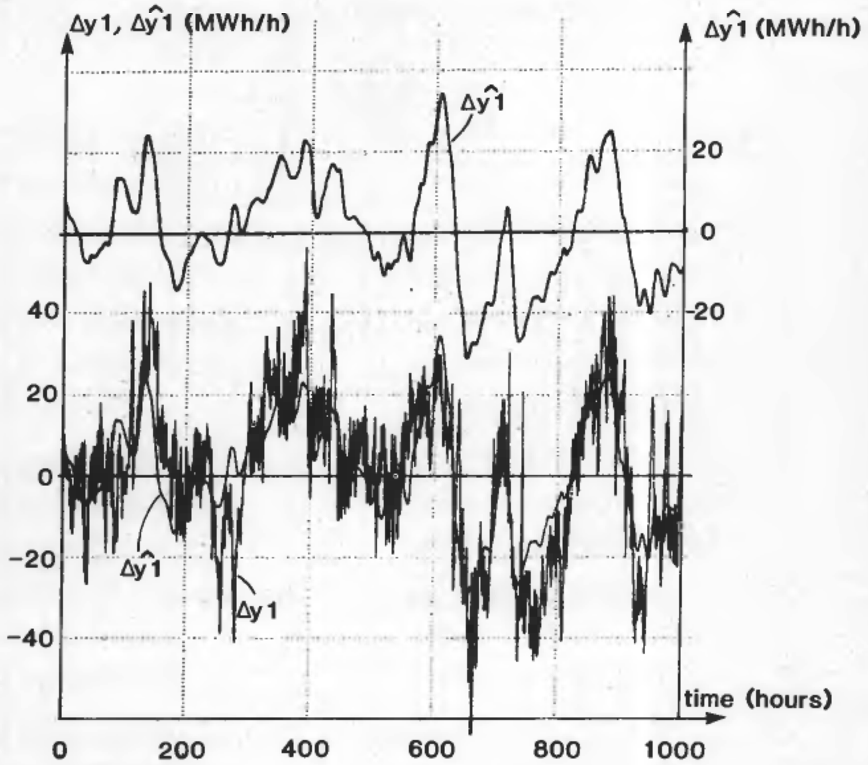

Figure 7. Comparison between deviation in the load and a ballistic simulation with a 1st order ARMA-model.

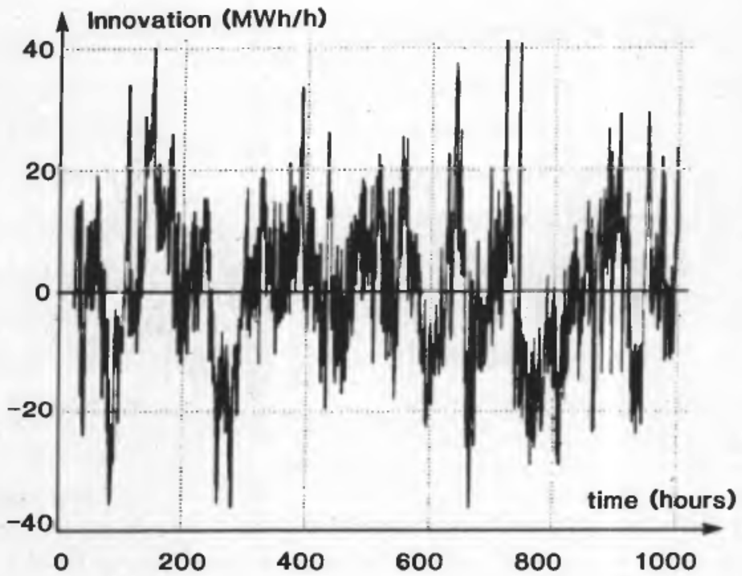

Figure 8. The 24 hours prediction error when observed temperature is used.

To investigate the dynamics of the ARMA model we have carried out a ballistic simulation. As seen in Fig. 7, the model fits the short term variations in the load very well.

Figure 8 shows the 24 hours prediction error when observed temperature is used as input to the prediction model. The standard deviation of the prediction error is 12·5 MWh/h or 1·75%. The worst case is an error of 5·9% for this period. (One should note that this might be an observation error instead of a model error). The standard deviation of the signal in Fig. 8 is almost as great as the one obtained with a ballistic simulation. This gives an idea of the noise involved in estimating the environmental state $x4$ during Christmas, Easter and other special periods.

In Fig. 9 the autocorrelation function for the one hour prediction error for a 2nd order ARMA model is plotted with delays from 0 up to 30 hours. We can see that the innovation is almost a white noise process, although there might be a very small daily correlation in the prediction error. The reason is probably that the deviations in the load and temperature are not quite stationary time series.

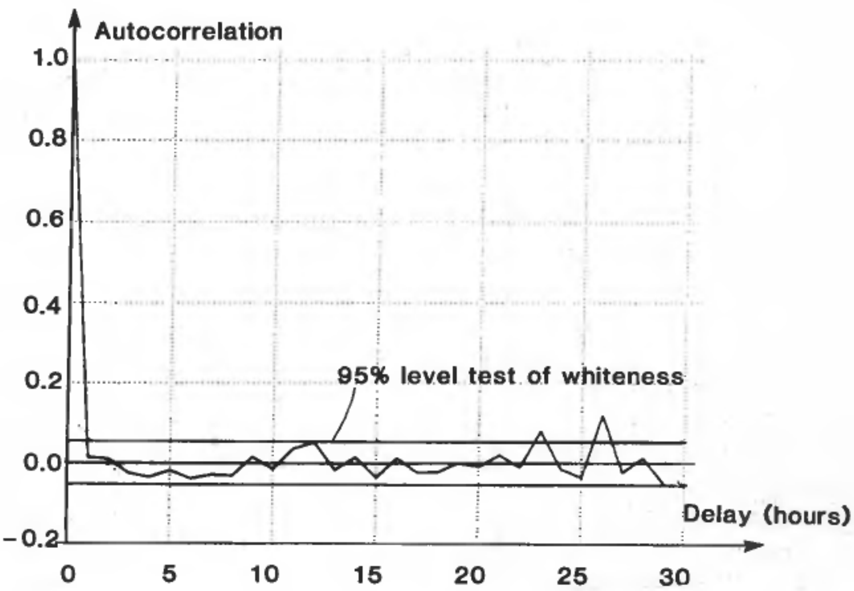

Figure 9. Autocorrelation function of the one hour prediction error, with a 2nd order ARMA-model.

Figure 10 shows the standard deviation in the prediction error as a function of the prediction horizon when three different models are used. In the first case an ARMA model with observed temperature is used for prediction. In the second case we have used an ARMA model with no input. In the third case we have tried to make a 'manual' model, where in principle the load deviation during the next 24 hours is assumed to be equal to its initial value. The equation for this prediction is as follows:

$$\hat{y}(k+24)=y(k-168+24)\cdot y(k)/y(k-168) \tag{13}$$

This equation also takes care of the weekly load pattern.

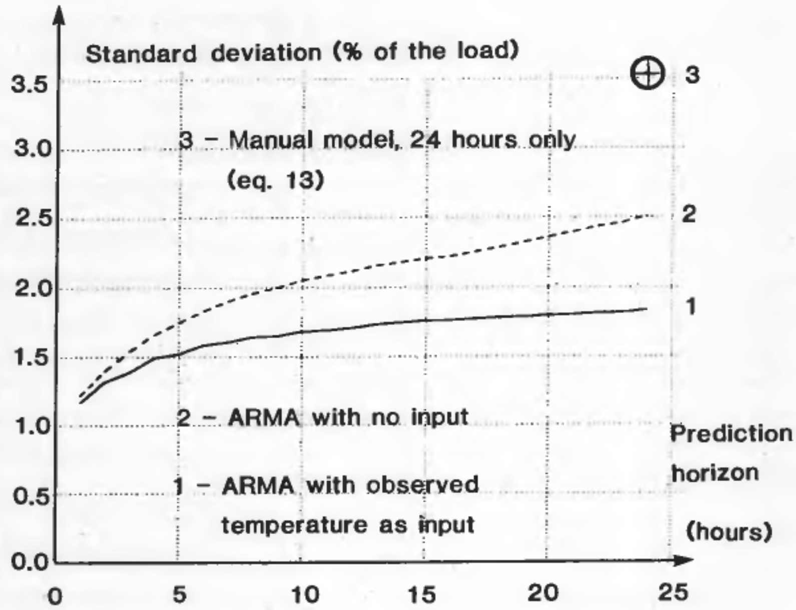

Figure 10. Standard deviation in the prediction error as a function of the prediction horizon for three different models.

It would be natural to compare the first two cases with this one, because eqn. 13 is so simple that it is almost like having no model at all.

When used for real prediction the first model will not be as good as suggested by Fig. 10 because of error in temperature prediction. The result will depend on the quality of this prediction. If it is bad, the results may become even worse than in the second case, where no temperature is used.

When the model is used, we can sum up that the standard deviation in the 24 hours prediction error is reduced from 3·5% to about 2–2·5%, depending on the quality of the weather forecast.

It was found that a first order ARMA model was almost sufficient, although there still was a small two hours correlation in the noise (0·1).

The table shows the least-squares and maximum likelihood estimates of the parameters and their relative standard deviations for first and second order models.

We can see that the standard deviation of the parameter estimates increases considerably with the model order.

The temperature sensitivity of the load can be expressed by the parameters of the ARMA model in the following way:

$$-\Delta y1/\Delta y2 = \sum_{i=1}^{n} b_i \Big/ \left(1 + \sum_{i=1}^{n} a_i\right) \tag{14}$$

For the first order model this gives the value 0·56 and 0·48 MWh/h, 0·1°C or 0·78 and 0·67%/°C for the M–L and L–S methods respectively. For the second order model the values are 0·84 and 0·74%/°C. The L–S method somewhat underestimates the weather sensitivity. It is typical that the sensitivity is slightly higher in the spring and autumn and almost zero in the summer.

ARMA Model Parameters for the Test Period. $b = \text{MWh}/0{\cdot}1°\text{C}$

		Least-Squares (L–S)		Maximum-Likelihood (M–L)	
		Value	Standard Deviation (%)	Value	Standard Deviation (%)
	a_1	$-0{\cdot}76$	3·8	$-0{\cdot}915$	1·4
1. order	b_1	$-0{\cdot}12$	14	$-0{\cdot}048$	16
	c_1	—	—	$-0{\cdot}44$	7
	a_1	$-0{\cdot}46$	41	$-0{\cdot}13$	76
	a_2	$-0{\cdot}40$	42	$-0{\cdot}76$	13
2. order	b_1	$-0{\cdot}43$	18	$-0{\cdot}53$	14
	b_2	0·35	21	0·46	16
	c_1	—	—	0·26	41
	c_2	—	—	$-0{\cdot}34$	22

The parameter $a_1 = -0{\cdot}915$ for the first order model gives a time constant of 11 hours. This agrees well with the general experience of the control centre operators. The delay can be interpreted as a physical property of thermal insulation in buildings. Also, the ballistic simulation of the ARMA model (Fig. 7) confirms that the model has a good response.

The value of the parameter a_1 is close to $-1{\cdot}0$. There may be two reasons for this: the feedback in the model M_N is too small, or the sampling interval is too short. We have optimized the feedback K_N as explained earlier, so that the reason is probably that the sampling interval is only 1/11 of the time constant. This interval (MWh/h) is used by the utility companies in their measurement and forecasting routines and was therefore a natural basis for estimation of the parameters $\boldsymbol{a}$, $\boldsymbol{b}$ and $\boldsymbol{c}$. An optimal interval is expected to be somewhat greater (3–4 hours). The sensitivity of the parameter estimates and their covariance with respect to the sampling interval was therefore tested. The stationary response was found to be the same with sampling interval of 1, 2, 3 and 4 hours.

4. Load prediction for the Norwegian Power Pool

The NPP Control System

The power producing utilities in Norway are organized in a countrywide power pool, The Norwegian Power Pool (NPP), which coordinates network operation, optimal power production and exchange of surplus power. The main characteristics of the Norwegian power system are (1979): installed hydro power generating capacity 18 179 MW, power consumption 84 TWh, public consumption 65%, power intensive industry 33%, others 2%. The load variation is mainly a two peak curve, with a night/day ratio about 0·84 and a summer/winter peak ratio of 0·47. Maximum load is about 14 000 MW.

The NPP control system consists of three regional control centres and one combined regional/national control centre. During the autumn 1980 the first step of a computer-based control system was installed. Some of the functions implemented in this control system are: network surveillance, generation control, generation co-ordination, maintenance co-ordination, and load prediction.

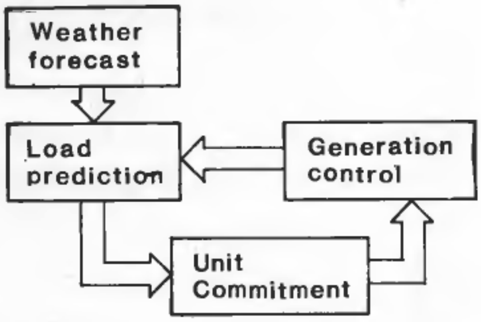

Figure 11. The production control system.

Figure 11 shows that the load prediction program is only a part of a total system for production planning and control. The production plans for each utility are collected and entered into the program system for unit commitment. From these plans and the load forecasts, the planned power exchange between the different control areas are computed for the next 30 hours with time resolution 1 hour. The exchange plan for each control area is fed into the generation control system, which runs on-line on the foreground computer. Here, the control error (planned—measured exchange) is computed as a generation control signal. This control is a manual change of the set-points of the units in the system.

Program design

Specifications made by NPP when the load prediction program SAFO was designed, were as follows: input of data should be simple, with data presentation and data correction facilities, load prediction should be made for n independent areas (n parallel models, $n_{max} = 35$ at present). The load prediction program should take into account abnormal load conditions, such as holidays, industry shutdowns and load variations due to network disturbances.

Much emphasis has been put on good man-machine communication. The main functions of the program system as experienced by the operator, are shown below:

MAIN PROGRAM:
- STANDARD SESSION = SIMULATION + PREDICTION
- SIMULATION
- PREDICTION FOR THE NEXT 24 HOURS
- PREDICTION FOR THE NEXT TWO WEEKS
- SUM LOAD FOR DIFFERENT GROUPS OF REGIONS
- PARAMETER ESTIMATION
- GO BACK UP TO SIX DAYS
- GO FORWARD *N* DAYS
- PRESENT TIME
- INITIALIZATION
- CHANGE REGION
- GENERATE A NEW REGION
- HELP
- STOP

(STANDARD SESSION through PARAMETER ESTIMATION):
- PLOT RESULTS
- WRITE RESULTS
- EDIT RESULTS

Program operation

The operation of the load prediction program SAFO is done by the control centre engineer. SAFO predicts the hourly load for each NPP area for the next 30 hours. Real-time load measurements are transmitted from the foreground computer to the background computer on which SAFO is implemented. This is done automatically every hour. The temperature is measured and predicted with intervals of six hours by the national weather service. This information, and information about abnormal load variation are given manually by the operators while running the program. This is done at least once a day, or more frequently, if the prediction error is unacceptable.

The results from the prediction are presented to the operators as plots and tables. Corrections of the prediction can easily be done by the operator. It takes about five minutes to make a load prediction. A load prediction for the whole country is made automatically by adding the results from each sub-area.

The program system SAFO is almost self-explanatory, and the need for education and training of the operators has been very little. We do, however, need a special supervisor, to take care of parameter inspections, parameter estimation, program maintenance and program corrections.

SAFO is a necessary part of the NPP control system. An isolated evaluation of SAFO is therefore difficult. The control system is still in its installation phase, and the measurement noise is not yet at an acceptable level. Therefore the prediction error in on-line operation is greater than in the laboratory tests. Sometimes the model is influenced too much by bad data which are not discovered by the operator. In order to overcome this problem we plan to use the prediction error covariance to detect bad data automatically. In spite of these problems with the measurement noise, the feed-back control during the real-time operation is significantly reduced due to improved prediction and planning.

5. Conclusions

State and parameter estimation techniques have been successfully implemented for load prediction in the Norwegian Power Pool. For the load in the Oslo region the project has shown that it is possible to reduce the standard deviation in the 24 hours load prediction error from 3·5% to about 2–2·5% by using a dynamic model and estimation techniques. A lower bound for the error is 1·8% since this is obtained with observed temperature as input to the prediction model. Non-predictable process noise and measurement noise contribute 1·2% of the error in the one hour prediction. The difference between 1·8 and 1·2% is the maximum improvement by taking into account weather variables other than the temperature, when the same type of ARMA model is used. However, the prediction error varies from one power system to another because of different composition of the type of consumers (Handshin and Lutke-Daldrup 1980).

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