LOAD FORECASTING APPLICATIONS for THE ENERGY SECTOR

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A) Short-term load forecasting at industrial plant Ravne:

- Load forecasting using linear regression,
- Short-term forecasting with seasonal ARIMA,
- Load forecasting when data mining.

B) Long-term load forecasting at transmission network of seasonal models.

Introduction
We would like to predict complete daily load at the industrial plant.
Daily production plan at a arc furnace moved to night hours.

Seasonal week (7,5) in observed data at July 2008 (arc furnace is off).

Additive loads form arc furnace and other production facility
Planed and observed number of loads at arc furnace are different.

Our regressor, predictor was observed number of loads at arc furnace.

Descriptive for a days at industry plant
Correlation between PLANED number of loads at electric arc furnace and load at plant.

Correlation between OBSERVED number of loads at Arc Furnace (AF) and el. load at plant. Observed – that mean identified number of loads by day, calculated with SQL from observed energy at 15 minute intervals.
Linear regression - planned loads

- Independent variable explain 60% of variance in load, which is highly significant, that F-test say we can trust $\beta_0$ and $\beta_1 > 99,9 \%$.

- An examination of the t-test indicates that planned number of loads at arc furnace contribute to electric load, we can trust $\beta_0 > 99,9 \%$ and $\beta_1 > 99,9 \%$.

$$[\text{Load Forecasting}] = 266.470 + 28.823[\text{Planed Number of Loads at AF}] + \epsilon$$
Independent variable explain 89% of variance in load, which is highly significant, that F-test say we can trust $\beta_0$ and $\beta_1 > 99.9\%$.

An examination of the t-test indicates that observed number of loads at arc furnace contribute to electric load, we can trust $\beta_0 > 99.9\%$ and $\beta_1 > 99.9\%$.

[Load Forecasting] = 212.241 + 40.732[Observed Number of Loads at AF] $+\varepsilon$

Linear regression—observed loads
Load forecasting using linear regression - observed loads at AF

Prediction period one year

<table>
<thead>
<tr>
<th>Prediction</th>
<th>R^2</th>
<th>Number of predictions</th>
<th>AVG observed</th>
<th>STDEV observed</th>
<th>AVG prediction</th>
<th>STDEV prediction</th>
<th>MAE</th>
<th>MAPE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 days</td>
<td>0.89</td>
<td>366</td>
<td>447006</td>
<td>159481</td>
<td>451180</td>
<td>153007</td>
<td>43390</td>
<td>18.3%</td>
<td>53324</td>
</tr>
</tbody>
</table>

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ARIMA\((1,0,0)(1,0,1)\), where 1 is the order of autoregression, 0 is the order of differencing (or integration), and 0 is the order of moving-average, and \((1,0,1)\) are their seasonal counterparts.

Learning with 100 past days in sliding mode.

Load forecasting at traditional ARIMA-model
First day forecast and observed time series. Prediction period 190 days.

Forecasting at traditional ARIMA + predictor observed loads at AF

First day
### Load forecasting statistic at ARIMA + predictor

#### The second day
- **Prediction for a Day**: + 5
- **$R^2$**: 0.91
- **Number of predictions**: 190
- **AVG observed**: 456302
- **STDEV observed**: 146232
- **AVG prediction**: 456858
- **STDEV prediction**: 131294
- **MAE**: 34954
- **MAPE**: 13.1%
- **RMSE**: 44835

#### The third day
- **Prediction for a Day**: + 4
- **$R^2$**: 0.91
- **Number of predictions**: 190
- **AVG observed**: 455955
- **STDEV observed**: 146192
- **AVG prediction**: 456471
- **STDEV prediction**: 132049
- **MAE**: 35002
- **MAPE**: 13.0%
- **RMSE**: 45031

#### The fourth day
- **Prediction for a Day**: + 3
- **$R^2$**: 0.9
- **Number of predictions**: 190
- **AVG observed**: 456573
- **STDEV observed**: 146107
- **AVG prediction**: 459212
- **STDEV prediction**: 133240
- **MAE**: 35685
- **MAPE**: 13.5%
- **RMSE**: 46705

#### The fifth day
- **Prediction for a Day**: + 2
- **$R^2$**: 0.9
- **Number of predictions**: 190
- **AVG observed**: 455875
- **STDEV observed**: 146269
- **AVG prediction**: 459094
- **STDEV prediction**: 135112
- **MAE**: 34248
- **MAPE**: 12.9%
- **RMSE**: 45642

- **Prediction for a Day**: + 1
- **$R^2$**: 0.92
- **Number of predictions**: 190
- **AVG observed**: 456516
- **STDEV observed**: 146594
- **AVG prediction**: 457422
- **STDEV prediction**: 140678
- **MAE**: 31212
- **MAPE**: 10.9%
- **RMSE**: 41001

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Load forecasting when Data Mining (DM)

Seeking patterns of data through the use of artificial intelligence, machine learning, and statistics and data warehouse.
This nonlinear model was realised according to the methodology of ART (Autoregressive Tree Models), ARMA and sessional ARMA.

### Short-term load forecasting when data mining

<table>
<thead>
<tr>
<th>Prediction for a Day</th>
<th>$R^2$</th>
<th>AVG measurements</th>
<th>STDEV measurements</th>
<th>AVG prediction</th>
<th>STDEV prediction</th>
<th>MAE</th>
<th>MAPE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>+5</td>
<td>0.36</td>
<td>441.054</td>
<td>141.209</td>
<td>431.911</td>
<td>111.789</td>
<td>92.377</td>
<td>27.5%</td>
<td>113.107</td>
</tr>
<tr>
<td>+4</td>
<td>0.28</td>
<td>440.322</td>
<td>142.076</td>
<td>432.756</td>
<td>109.034</td>
<td>97.250</td>
<td>29.6%</td>
<td>120.284</td>
</tr>
<tr>
<td>+3</td>
<td>0.37</td>
<td>440.265</td>
<td>143.129</td>
<td>433.972</td>
<td>109.567</td>
<td>90.999</td>
<td>27.9%</td>
<td>113.231</td>
</tr>
<tr>
<td>+2</td>
<td>0.43</td>
<td>439.630</td>
<td>143.994</td>
<td>439.262</td>
<td>113.404</td>
<td>85.064</td>
<td>27.1%</td>
<td>108.680</td>
</tr>
<tr>
<td>+1</td>
<td>0.72</td>
<td>438.210</td>
<td>144.951</td>
<td>437.343</td>
<td>123.829</td>
<td>59.186</td>
<td>17.6%</td>
<td>77.032</td>
</tr>
</tbody>
</table>
• Difference between forecasting with DM and traditional seasonal ARMA is, that DM predict two time series: number of loads at arc furnace (predictor) and load. Traditional ARIMA predict only el. load, for predictor we get values from time table predictor.

• Traditional ARIMA forecasting working numeric stable, DM ARTx get some times numeric unstable.

• At this moment, we prefer for daily work traditional ARIMA with one predictor or simple linear regression.
Long-term load forecasting at transmission network of seasonal models – node 1
Long-term load forecasting at transmission network of seasonal models – node 2
Result are good. Reason is that input time series are good prepared and observed data are statistic relevant. We have only 50 samples to learn a model.

### Long-term load forecasting of seasonal models

<table>
<thead>
<tr>
<th>Prediction value description</th>
<th>Model type</th>
<th>MAPE</th>
<th>Forecasting period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum month value of P at node 1</td>
<td>Winters Additive</td>
<td>5.4 %</td>
<td>12 months</td>
</tr>
<tr>
<td>Monthly hour extreme values of P at node 1</td>
<td>Simple Seasonal</td>
<td>7.1 %</td>
<td>12 months</td>
</tr>
<tr>
<td>Average month value of P at node 2</td>
<td>Simple Seasonal</td>
<td>6.2 %</td>
<td>12 months</td>
</tr>
<tr>
<td>Monthly hour extreme value of P at node 2</td>
<td>Simple Seasonal</td>
<td>6 %</td>
<td>12 months</td>
</tr>
</tbody>
</table>
• Linear regression predicted at MAPE 18 % and R square 0,89 - for one year prediction. Change to observed loads at AF was good decision.

• Traditional ARMA forecasting is theory that we know over 30 years, that we suggest for daily work. MAPE 11 % and R square 0,92 - for halves year prediction.

• Data mining put at more applications satisfaction result, but our sample with arc furnace was average (MAPE 17%, R square 0,72). It is necessary to find way how integrate observed loads at AF into DM engine.

• Long term prediction is possible, our experiment show MAPE from 5,1 % to 7,1 %, we suggest more test at different transmission networks.
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