LOAD FORECASTING APPLICATIONS for THE ENERGY SECTOR

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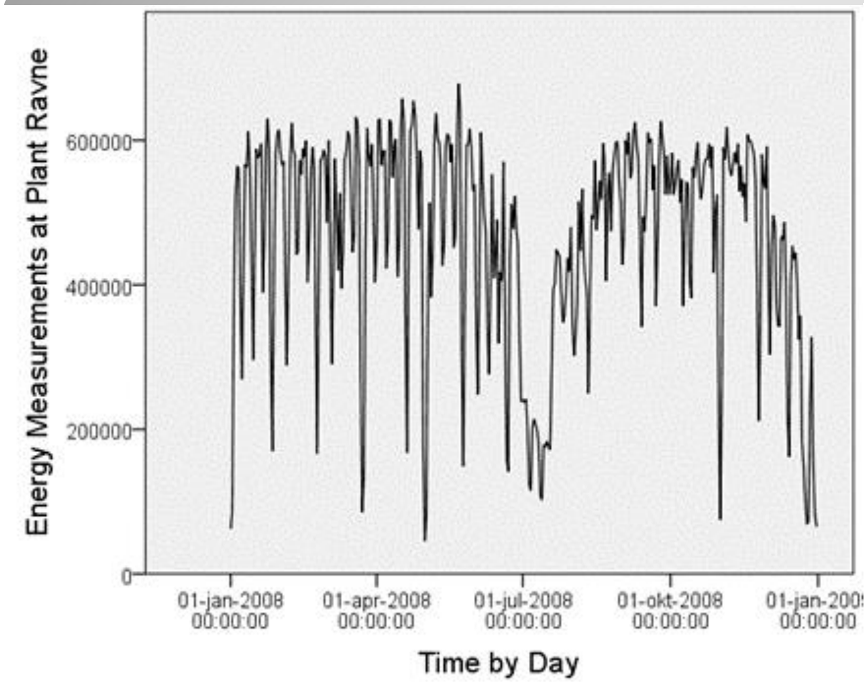
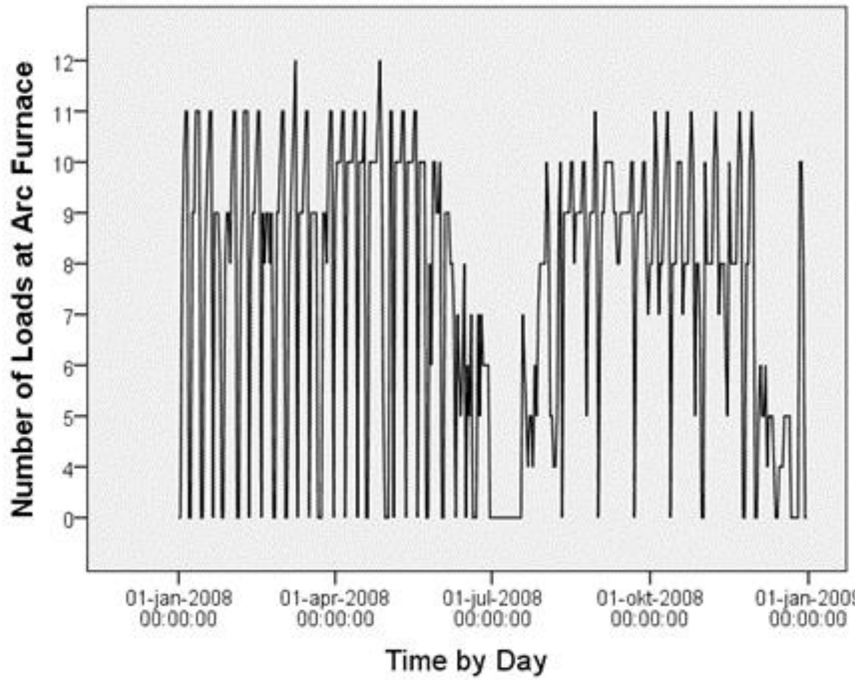
A) Short-term load forecasting at industrial plant Ravne:

- 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

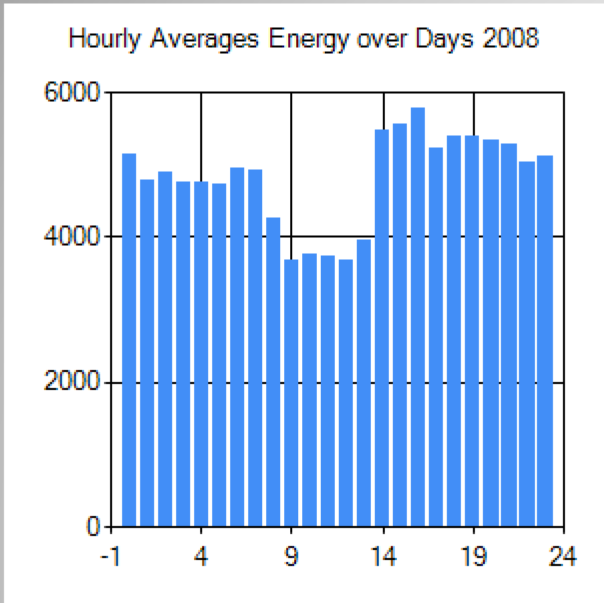


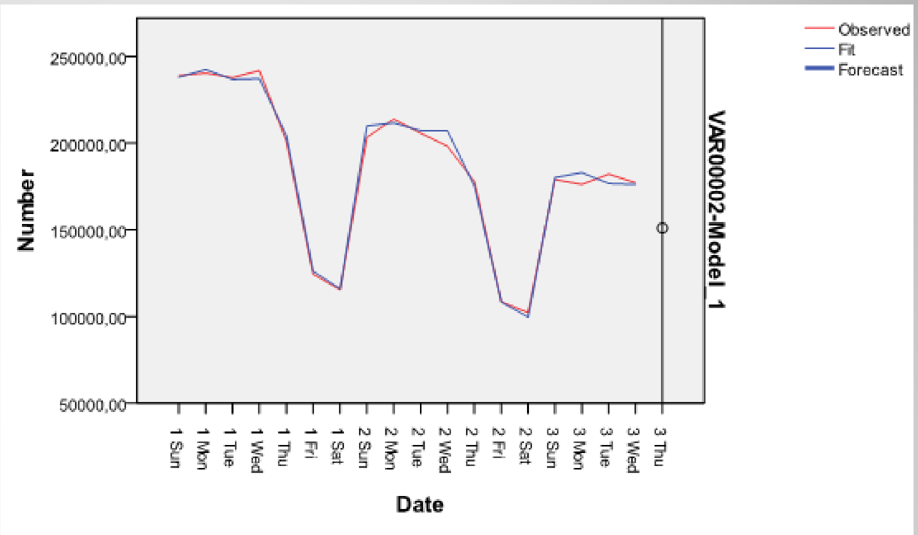


Load curves at plant Ravne for one year.

Number of loads at electric arc furnace.

We would like to predict complete daily load at the industrial plant





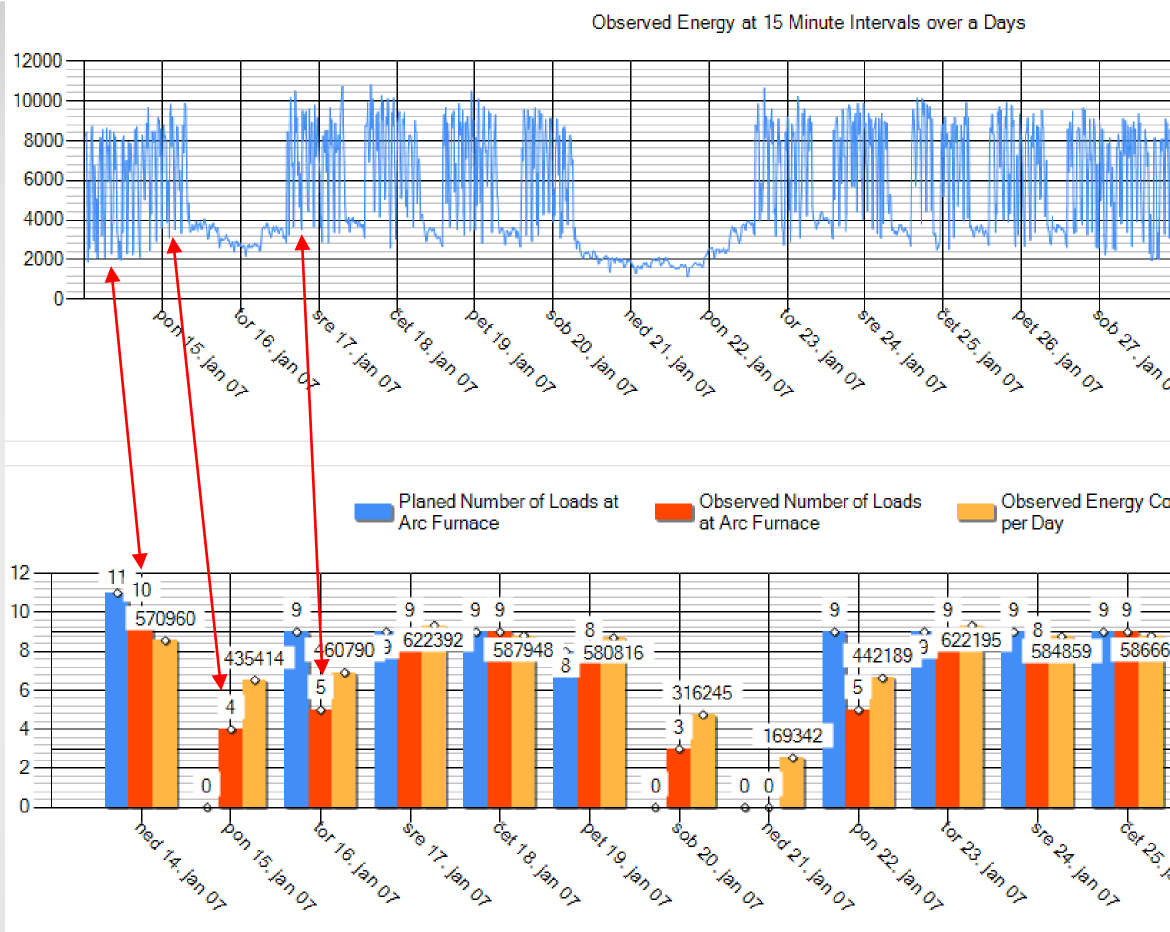
Daily production plan at a arc furnace moved to night hours.

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

Additive loads form arc furnace and other production facility

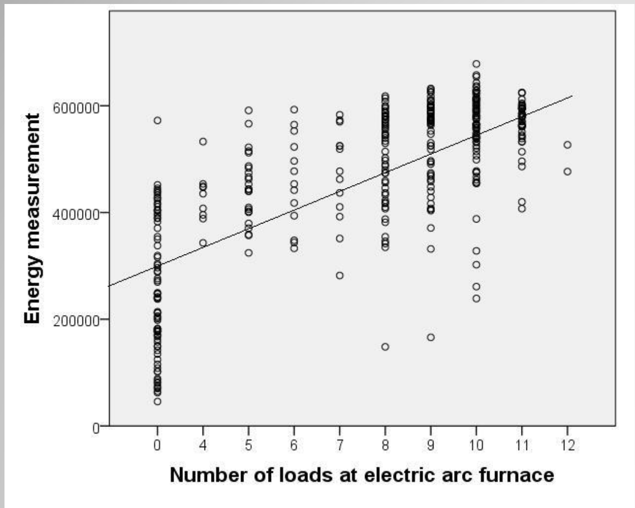
Planed and observed number of loads at arc furnace are different.

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

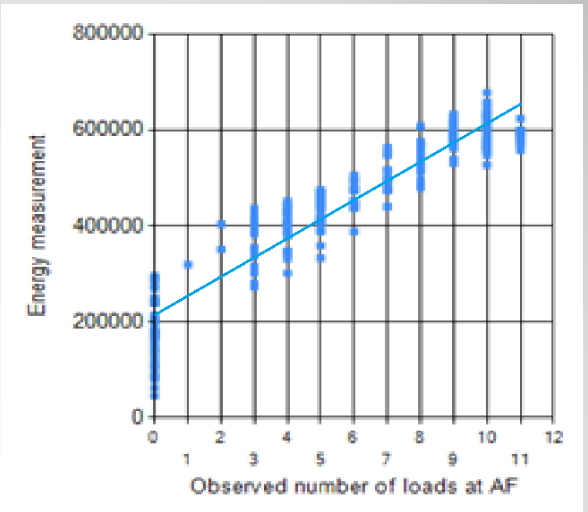


Descriptive for a days at industry plant

Input data for linear regression

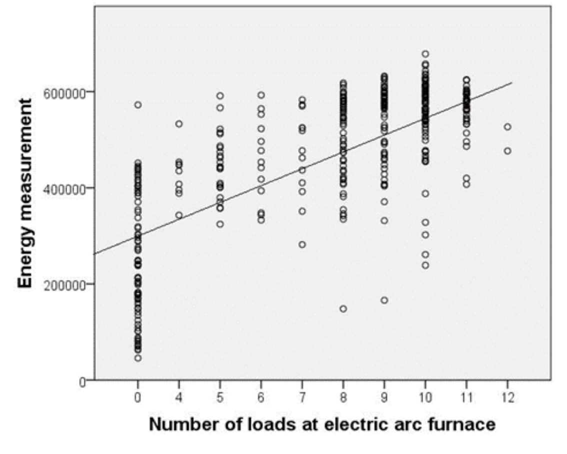


Correlation between PLANED number of loads at electric arc furnace and load at plant.



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.

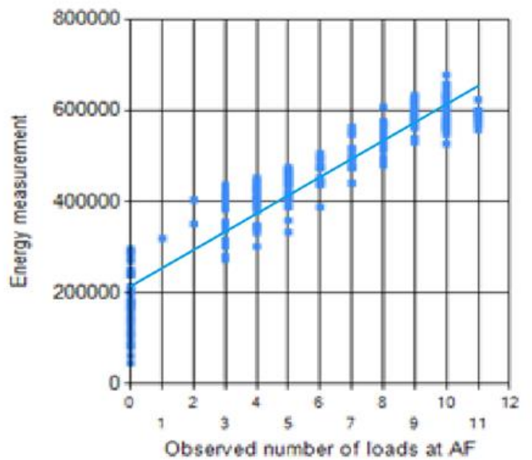
Linear regression-planed loads



- Independent variable explain 60% of variance in load, which is highly significant, that F-test say we can trust β_0 and β_1 > 99,9 %.

- An examination of the t-test indicates that planed number of loads at arc furnace contribute to electric load, we can trust β_0 > 99,9 % and β_1 > 99,9 %.

[Load Forecasting] = 266.470 + 28.823[Planed Number of Loads at AF] $+\varepsilon$

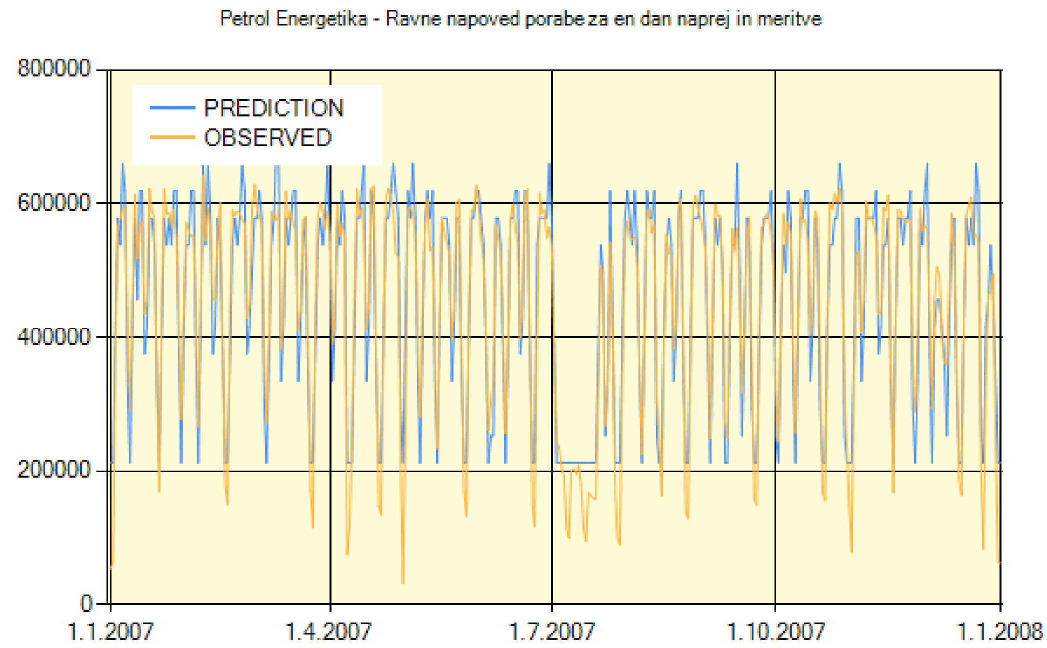


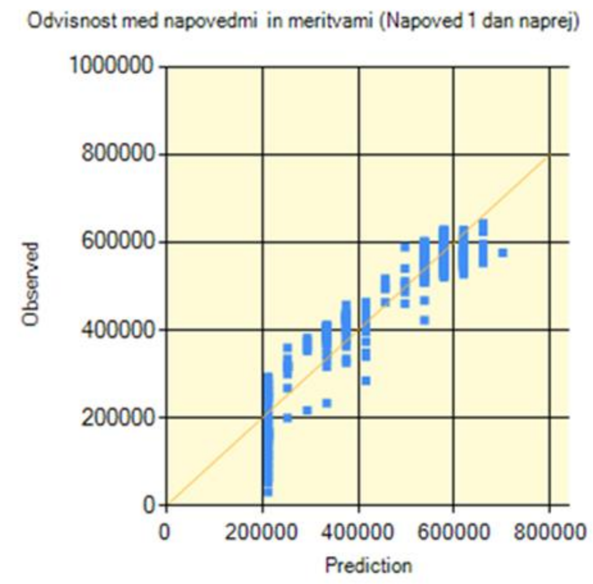
- Independent variable explain 89% of variance in load, which is highly significant, that F-test say we can trust β_0 and β_1 > 99,9 %.

- An examination of the t-test indicates that observed number of loads at arc urnace contribute to electric load, we can trust β_0 > 99,9 % and β_1 > 99,9 %.

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

Linear regression-observed loads





Prediction period one year

Prediction	R^2	Number of predictions	AVG observed	STDEV observed	AVG prediction	STDEV prediction	MAE	MAPE	RMSE
5 days	0,89	366	447006	159481	451180	153007	43390	18,3 %	53324

Load forecasting using linear regression- -observed loads at AF

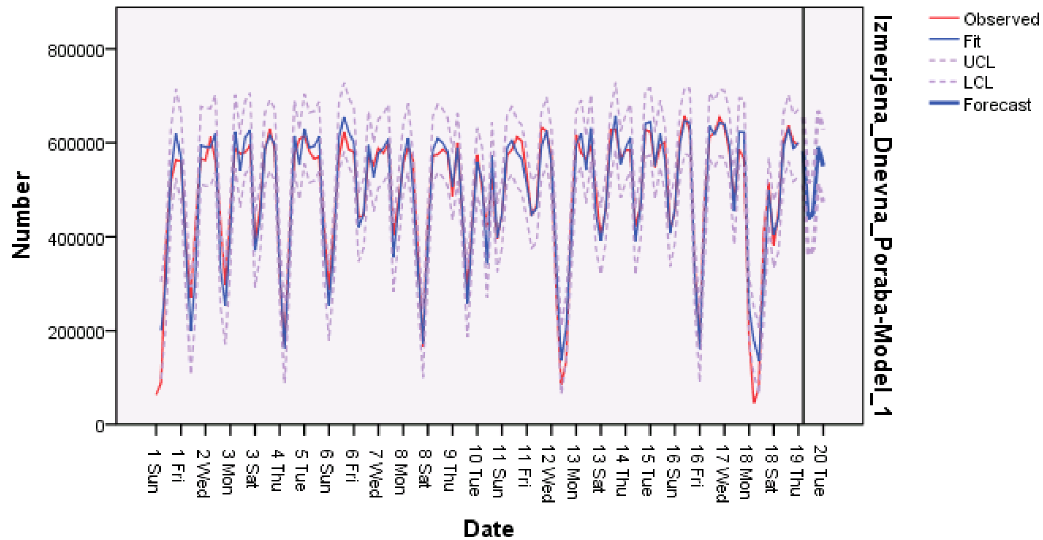
Load forecasting at traditional ARIMA-model

Model Description

			Model Type
Model ID	Izmerjena_Dnevna_Poraba	Model_1	ARIMA(1,0,0)(1,0,1)

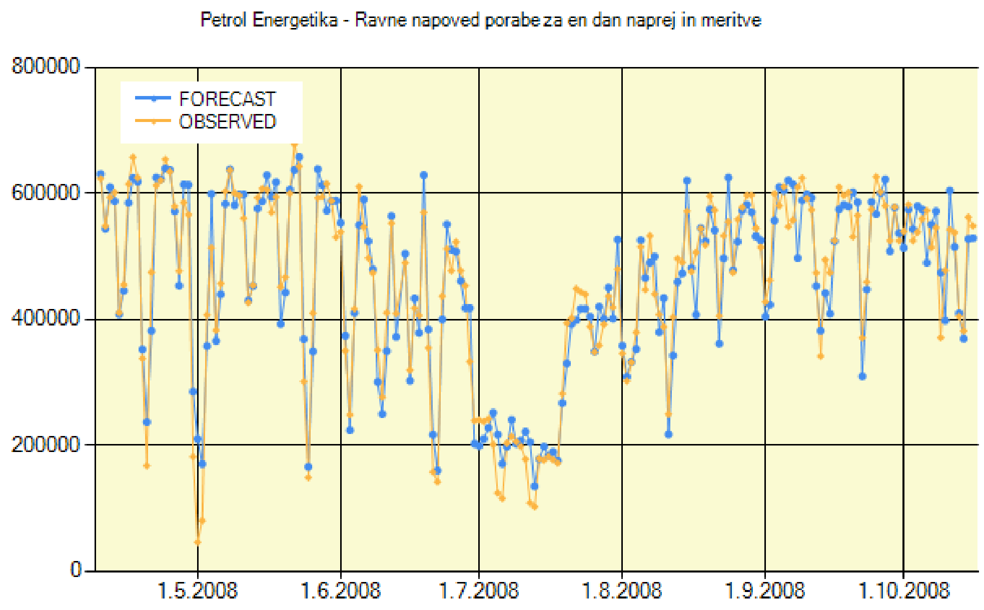
Model Statistics

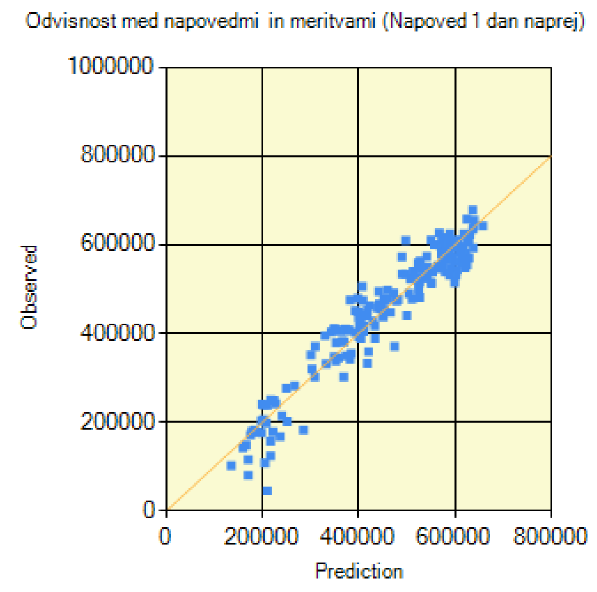
Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
Izmerjena_Dnevna_Poraba-Model_1	1	,924	9,272	15	,863	0



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.

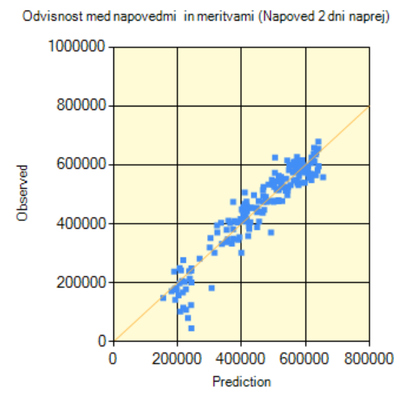


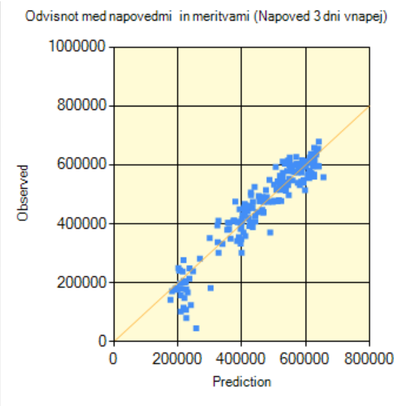


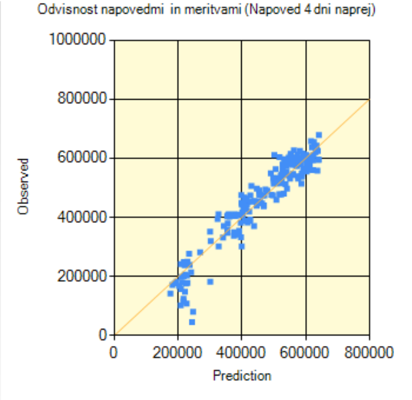
First day

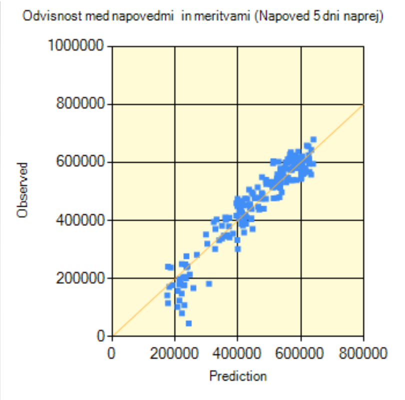
First day forecast and observed time series. Prediction period 190 days.

Forecasting at traditional ARIMA + predictor observed loads at AF







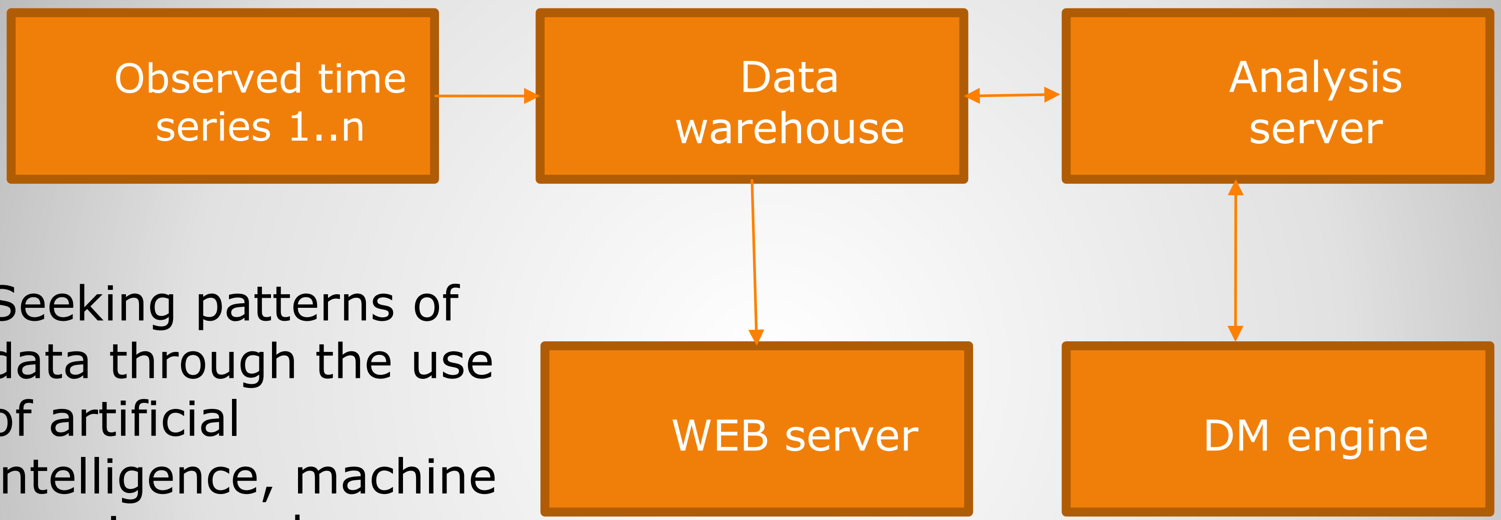


The second day | The third day | The fourth day | The fifth day

Prediction for a Day	R^2	Number of predictions	AVG observed	STDEV observed	AVG prediction	STDEV prediction	MAE	MAPE	RMSE
+ 5	0,91	190	456302	146232	456858	131294	34954	13,1 %	44835
+ 4	0,91	190	455955	146192	456471	132049	35002	13.0 %	45031
+ 3	0,9	190	456573	146107	459212	133240	35685	13.5 %	46705
+ 2	0,9	190	455875	146269	459094	135112	34248	12.9 %	45642
+ 1	0,92	190	456516	146594	457422	140678	31212	10.9 %	41001

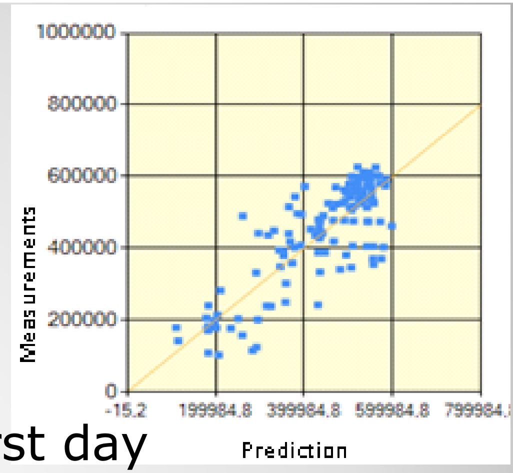
Load forecasting statistic at ARIMA + predictor

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.



First day

Prediction for a Day	R^2	AVG measurements	STDEV measurements	AVG prediction	STDEV prediction	MAE	MAPE	RMSE
+5	0,36	441.054	141.209	431.911	111.789	92.377	27,5 %	113.107
+4	0,28	440.322	142.076	432.756	109.034	97.250	29,6 %	120.284
+3	0,37	440.265	143.129	433.972	109.567	90.999	27,9 %	113.231
+2	0,43	439.630	143,994	439.262	113.404	85.064	27,1 %	108.680
+1	0,72	438.210	144.951	437.343	123.829	59.186	17,6 %	77.032

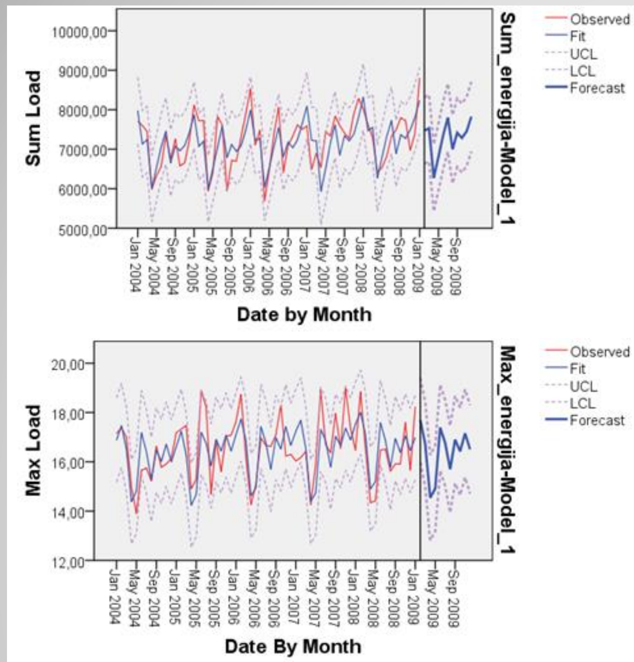
Short-term load forecasting when data mining

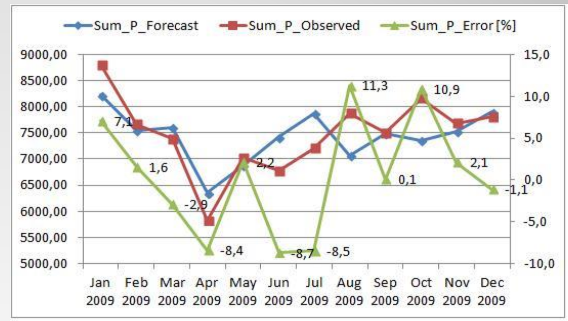
- Difference between forecasting with DM and traditional seasonal ARMA is, that DM predict two time series: number of loads at arc furnace (predictor) and load. Traditional ARIMA predict only el. load, for predictor we get values from time table predictor.

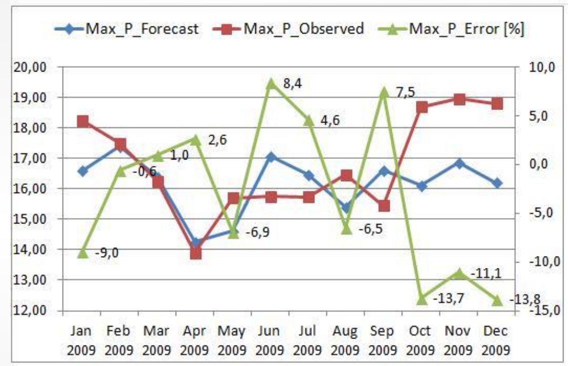
- Traditional ARIMA forecasting working numeric stable, DM ARTx get some times numeric unstable.

- At this moment, we prefer for daily work traditional ARIMA with one predictor or simple linear regression.

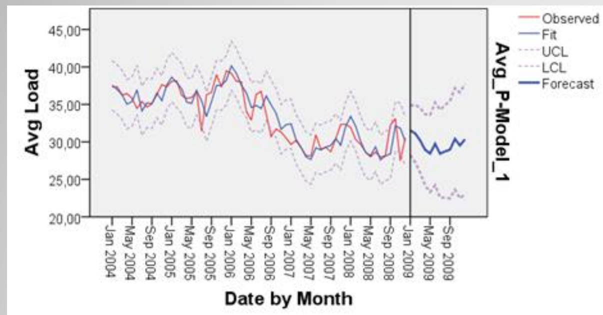
Data mining, ARIMA, linear regression

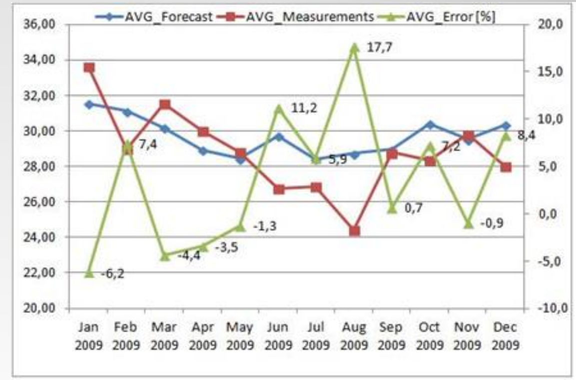


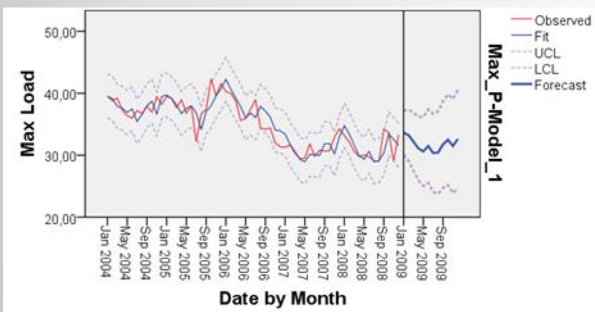


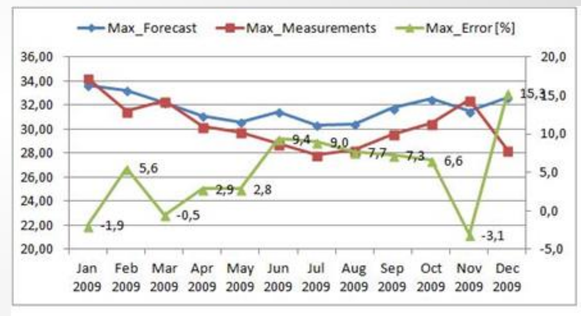


Long-term load forecasting at transmission network of seasonal models –node 1









Long-term load forecasting at transmission network of seasonal models – node 2

Prediction value description	Model type	MAPE	Forecasting period
Sum month value of P at node 1	Winters Additive	5,4 %	12 months
Monthly hour extreme values of P at node 1	Simple Seasonal	7,1 %	12 months
Average month value of P at node 2	Simple Seasonal	6,2 %	12 months
Monthly hour extreme value of P at node 2	Simple Seasonal	6 %	12 months

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

Conclusion

- 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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