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THE DAILY LOAD FORECASTING AT THE INDUSTRIAL COMPLEX

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Introduction

The aim of the forecast is to predict the load profile as accurately as possible, which means minimizing the cost of electricity at the industrial complex. There are load forecasting applications at an industrial plant with an electric arc furnace in the City of Ravne, Slovenia.

Methodology

In this paper we discuss the daily hourly load forecasting of load for the industrial complex using ARIMA methodology [4] with one predictor [1]. For the daily forecasting of Min, Max (EnInov 2016), we made predictions of +5 steps from the moment of zero. For predicting the daily walk, we need to make a forecast of +24 steps from the moment of zero, in the case of the 15 minutes interval and the announcement 24 hours forward, we should perform +96 steps of the predictions.

The basis for predicting is the time series of energy consumption data, which is a time series from a 15 min values. Preparation of the time series for learning the forecasting models was carried out with a different SQL aggregate functions. Energy consumption at the industrial plant had a seasonal week, hours feature (7/24) and one dominant predictor – a big arc furnace.

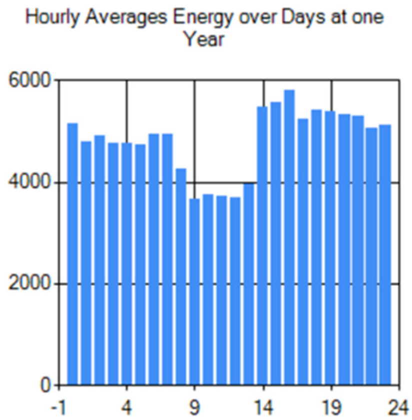

Figure 1: Daily load curves

The presented load forecasting system needs at the learning phase two input historic time series: energy consumption and real production data. We get production data from the Production Planning Department and understand that 75 % of the annual energy consumption is directly dependent on the number of loads at the electric arc furnace. We wanted to use a simple and robust predictor, so the predictor has a value of 1 when the furnace is running and 0 when the furnace is not in operation.

The time resolution of the predictor is 1 hour. The issue is the production time; real production will be moved to the past afternoon, next to the evening (cheap electricity), over midnight, up to 9:00 AM the next day (Figure 1).

Results

Production time at the arc furnace is dependent upon the types of input material etc. To learn and to improve a forecasting model (Table 1) we need exact production data. How do we get it? The answer is hidden in the industrial plant energy consumption time series and in discussion with the Production Planning Department. So, we research and develop an advanced algorithm, like the forecasting pre-processor, which captures best predictor data.

The tariff policy of electricity has the potential to improve forecasts, for example, by introducing new predictors. Another option to perform prediction is with non-linear prediction models, as described in [2] [5] and [6]. The purpose of load flow forecasting is to enhance the performance of the electricity trading, so it would make sense to continue to work towards the integration of forecasting with the tariff policy and the system trading of electricity.

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Prediction for a Hour	MAPE	MAE	RMSE	R square	Number of predictions	AVG observed	STDEV observed	AVG prediction	STDEV prediction
+ 23	13.35 %	2537,87	3385,74	0,84	80	19424,1	8414,2	19322,5	6859,6
+ 22	12.87 %	2449,85	3322,91	0,85	80	19280,4	8473,2	19118,3	6793,2
+ 21	13.07 %	2406,33	3199,62	0,85	80	18925,5	8301,8	18902,7	6731
+ 20	12.76 %	2341,5	3148,12	0,86	80	18853	8308,4	18738,3	6646,6
+ 19	13.07 %	2376,44	3248,57	0,85	80	18651	8281	18568,3	6571,4
+ 18	13.19 %	2401,27	3299,28	0,84	80	18502,7	8291,2	18396,8	6490,1
+ 17	13.53 %	2418,79	3335,39	0,84	80	18364,2	8347	18216	6399
+ 16	13.87 %	2436,3	3286,32	0,84	80	18109,8	8183	18065,5	6310,6
+ 15	14.29 %	2494,19	3341,5	0,83	80	17894,7	8142,7	17886,7	6236
+ 14	14.6 %	2559,37	3440,3	0,82	80	17726,3	8089,9	17722,2	6204,5
+ 13	14.82 %	2580,3	3446,63	0,81	80	17555,2	7979	17562,3	6188,4
+ 12	15.49 %	2669,45	3536,92	0,8	80	17377,5	7855,8	17404,4	6201,1
+ 11	15.73 %	2599,4	3383,8	0,8	80	17096	7588,6	17206,4	6277,4
+ 10	15.8 %	2634,04	3430,33	0,79	80	16949,6	7487,7	17029,2	6323,4
+ 9	16.06 %	2654,45	3411,6	0,79	80	16772,4	7390,7	16836,5	6397,1
+ 8	15.81 %	2600,55	3393,01	0,78	80	16658,5	7266,1	16707,5	6407,1
+ 7	15.41 %	2490,88	3262,55	0,78	80	16377,2	6908,8	16528,1	6394,8
+ 6	15.35 %	2426,79	3206,3	0,78	80	16247,8	6793,7	16512,8	6455,5
+ 5	15.21 %	2502,01	3418,03	0,76	80	16393,6	7024,9	16538,2	6535,3
+ 4	14.73 %	2417,13	3308,55	0,78	80	16413,1	7034,3	16556,1	6536,5
+ 3	14.12 %	2385,65	3344,71	0,79	80	16677	7318,3	16717,8	6603
+ 2	13.57 %	2309,76	3303,4	0,8	80	16787,1	7396,8	16881,1	6696,5
+ 1	11.02 %	1951,3	2860,87	0,85	80	16924,8	7507,2	17026,4	6948,1
+ 0	11.28 %	2011,82	2903,37	0,86	80	17149,4	7653,9	17211,4	7002,3

Table 1: Observed, model assessment and prediction

References

[1] Janez Bratina, Elektroobločna peč, Ravne na Koroškem, 1994.

[2] Jamie MacLennan, Zhao Hui Tang, Bogdan Crivat. Data mining with Microsoft SQL Server 2008, Wiley.

[3] Douglas C. Montgomery, George C. Runger, Applied Statistic and Probability for Engineers, Wiley, 2003.

[4] George E. P. Box Gwilym M. Jenkins Gregory C. Reinsel. Time Series Analysis Forecasting and Control, 2014, Wiley.

[5] C. Meek, D.M. Chickering, D. Heckerman, Autoregresive Tree Models for Time-Series Analysis, Microsoft Research.

[6] Bo Thiesson, David Maxwell Chickering, David Heckerman, Christopher Meek, ARMA Time-Series Modeling with Graphical Models, Microsoft Research.