POWER CONSUMPTION PREDICTION METHODS IN METALLURGICAL COMPANIES

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Abstract

Power consumption is a key component in all technical branches, not only in metallurgical companies. The reason is quite simple. Consumed energy is often the last area, where can be realized economical saving. If the company want to save some energy fees, it has to reduce penalty fees, which arise from wrong power consumption estimation over the time. This paper is dedicated to prediction methods, based on historical energy data, which can be used to proper power consumption estimation.

Keywords: Prediction, estimation, energy consumption, historical data, optimal, penalty fees

1. INTRODUCTION

The power consumption is a key component especially in metallurgical companies, because there is necessity to heat up almost all inputs, to be better workable, or liquid. It does not matter if the energy medium is gas or electricity. There are many regulations which has to be obeyed. Among most significant limitations belongs maximum power supply and quarter-hour maximum power. If any of these limitations are violated, a penalty occurs. The example can be heavy machinery startup process when shift start. If company is limited in maximum power from the grid, drawn in quarter of hour, it is unwise to start all machines at a time. By doing that, a massive peak occurs and penalty is generated. If the machine's start is well-considered and spread into longer time, everything is all right and no penalty generated. Another example can be presented, in case of massive overload is in place. If there are running arc furnace and several lower consumption processes, it is again unwise to run another high demand process. The power grid can withstand it with any harm, but the absolute maximum power draw is exceeded and penalty generated. It could be short time process, tens of minutes, but the regulation is violated.

To avoid these conditions, the prediction model is necessary. Aim of the article is to present a prediction model based on averaging current and passed energy consumption. This approach can be applied on those factories or workshops, which has stable withdraw of energy. If the seasonal variations are in place, the other methods have to be used. The goal of the prediction model is to tell us, how much energy will be consumed in the end of specific time. If the final number is in limits, no actions are required. But if the final consumed energy value, predicted by model, will be over the limit, some action has to take place to avoid unwanted penalty. Further presented averaging methods should clearly defined theirs proper usage.

These conditions can be predicted and startup of high demand processes can be avoided or delayed. The penalties are serious problem, because it can do more than half a price in money for the energy consumption. Today, every company facing the need of lowering its expenses. In words of almost every CEO "Every short term economic return investment has been implemented…", is a major mistake, it is almost certain, that most companies can do significant savings right here, in prediction of power consumption. It is necessary, in this approach, to free of old habits, which says that „every machine has to start at 6 o'clock, and a furnace can start every time it is needed". Also, the additional measuring hardware must be installed. To obtain quality power consumption prediction, the detailed, long-term data has to be available. Predicative power consumption forecast cannot be done over month or year data obtained from the last invoice. No, forecast on daily bases needs at least 10 data samples per hour and if it is needed to control quarter hour power peaks, at least 1 sample per minute is needed. This is also needed to cover all high demand machines with measurement. The last prediction we made, was focused on large automotive company, which producing plastics parts and which carry on many injection moulding machines. In that case, all three main power grid transformers were covered and additional 40 high demand devices. Essentially, injection moulding machines are electric stoves. It is possible to control usage of the device and also control its yield. If there are about 60 control actions per day, 80 % penalties are saved with minor affect to production process. Some penalties could not be avoided, because production yield is higher, than the generated penalty. [1,2]

2. RELATED WORKS

As was mentioned in [3], it is very difficult to predict energy consumption in company or in single building. The total energy consumption respectively money spent, is influenced by many factors, such as ambient weather conditions, building structure and characteristics, the operation of sub-level components like lighting or HVAC systems, occupancy and their behavior and many others. The authors are using advanced methods to predict energy consumption behavior, because they do not have online energy metering. Using simplified engineering methods, statistical methods and artificial intelligence methods to make a behavior model is one of the possibilities but cannot be implemented in large metallurgical companies. There are so many unknown interactions and interferences which restraint a usable mathematical prediction model. The paper research mainly concentrates on applying proposed models to new predicting problems, optimizing model's parameters or input samples for better performance, simplifying the problems or advanced model development, comparing different models under certain conditions. Each proposed model has been developed and has its advantages and disadvantages, and as the authors says, it is difficult to say which one is better without complete comparison under the same circumstances.

Another paper [4] is focused on economic benefits, when Real-Time Electricity Pricing is applied. As the authors claims, "Real-time electricity pricing models can potentially lead to economic and environmental advantages compared to the current common flat rates. In particular, they can provide end users with the opportunity to reduce their electricity expenditures by responding to pricing that varies with different times of the day". The paper deal with possibility of energy consumption scheduling plan, which could have major influence to reduce electricity expenditures by responding to pricing that varies with different times of the day. As can be conclude, these questions are present around a world, not only on the local level.

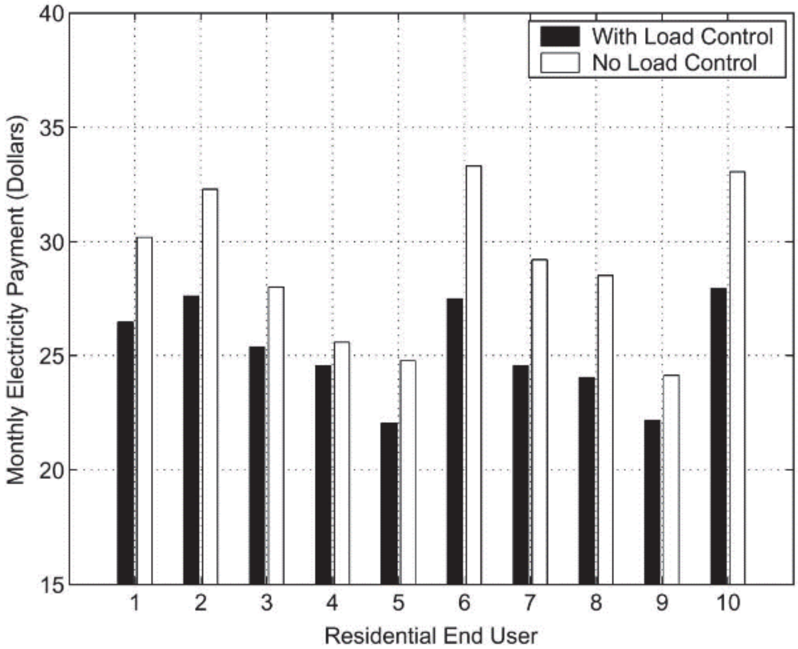

Figure 1 Peak-to-average ratio in aggregated load demand

The basic idea of the paper uses planned operation of the appliances over time. The high energy demand appliances are in operation mode only in low energy price time interval. This can lead to major money savings (**Figure 1**), but this approach doesn't solve penalties.

3. ENERGY CONSUMPTION PREDICTION

As were mentioned in introduction, energy consumption prediction directly depends on data quality we have. For the prediction purposes we are using one-minute data samples acquisition, which is sufficient to most purposes.

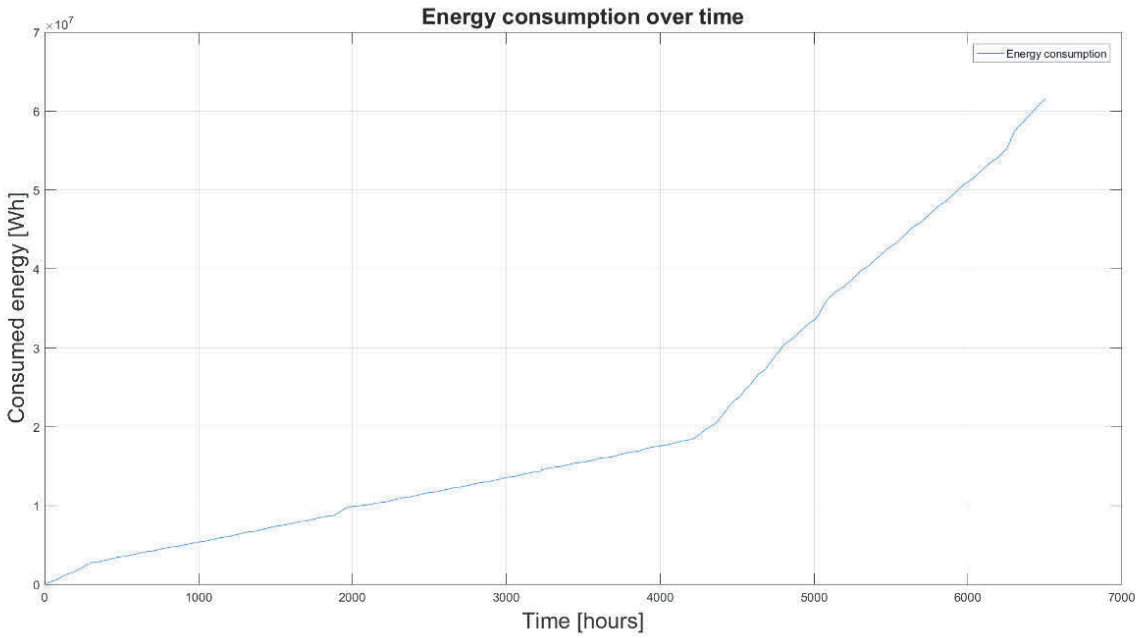

Figure 2 Company's energy consumption over time

In **Figure 2** can be seen company's energy consumption behavior over time with significant seasonal fluctuation. It is obvious, that company use heating system based on electrical energy so significant arise of energy consumption is winter time coming. The goal of the prediction is to determine final amount of consumed energy in the end of fiscal year, or in the specific time e.g. day, week, month. As can be seen, there will be two major assumption end. One before winter season come, and on the end of the year. The ideal prediction model should keep in mind seasonal behavior, but this involve usage of artificial neural network at minimum. [5]

The first tested prediction method was averaging. Averaging is the best method stable systems with periodical energy consumption, *Econs*, behavior. The result of this method is a constant, expressing average energy draw from the grid. Equation is presented in (1). The average power withdraw is then calculated for time span <0; *n*>, where *n* is the final time.

$$avg = \frac{\sum_{t=0}^{n} Econs_t}{n} \quad (1)$$

where:

avg - the average value (W)

Econs - energy withdrawal in time period *t (W)*

n - whole time periods (s)

One main disadvantage, when using averaging is, that the method is prone to ignore faster swing of input data and is very clumsy. There are several methods, how to avoid this unwanted behavior. One method is to take only certain historical data, not all history. As example could be take into account only last two weeks I one-year time span. This approach is very similar to Welch window size estimation and we called it “tail” averaging. Basically, could be resulting equation as in (2). [6]

$$avg_{tail} = \frac{1}{M}\sum_{i=1}^{M} Econs_i \tag{2}$$

where:

avg_{tail} -the average value variant (W)

Econs -Energy withdrawal in time period *t (W)*

M -appropriated period of time (s)

This method takes into account only *M* data samples from the whole set <0; *n*>. The second modification of averaging method is to combine it with (2). The result is not so steady, clumsy with using long time period, but also not so fast changing like with using Welch window.

Moving average method is mainly used in stock market predictions and could be also used in energy consumption prediction. The main difference from avg_{tail} is, that for calculation of certain point it uses not only past data, but also future data relative to the point. We used formula (3).

$$avg_{SMA(t)} = \frac{1}{M}\sum_{i=t-M}^{t+M} Econs_i \tag{3}$$

where:

avg_{SMA} - the moving average value (W)

Econs - energy withdrawal in time period *t (W)*

M - appropriated period of time (s)

t - is a time in desired point (s)

The last tested method for energy consumption prediction was linear regression. Linear regression is a specific case of polynomial regression. The result is a linear equation, respectively straight line, which whose parameters depend on all data point in specific interval. The concordance rate is defined by ***R*** parameter, correlation coefficient, derived from least square method. The linear parameters are calculated from (4). [7,8]

$$a = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{n\sum x_i^2 - (\sum x_i)^2}$$
$$b = \frac{\sum x_i^2 \sum y_i - \sum x_i \sum x_i y_i}{n\sum x_i^2\ (\sum x_i)^2} \tag{4}$$

where:

x_i - the coordinates on time axis in specific time (-)

i - the specific time (s)

y_i - values of *Econs* in specific time *i (W)*

a, b - parameters of the correlation coefficient line R (-)

4. PREDICTION RESULTS

All methods described in chapter 3. where implemented and tested on data set (**Figure 2**). The results are as predicted. The data set has suited running, because there are flat areas, season behavior and initial slope. It is very interesting to observe behavior of every single prediction method, with regard to final consumed energy estimation (**Figure 3**).

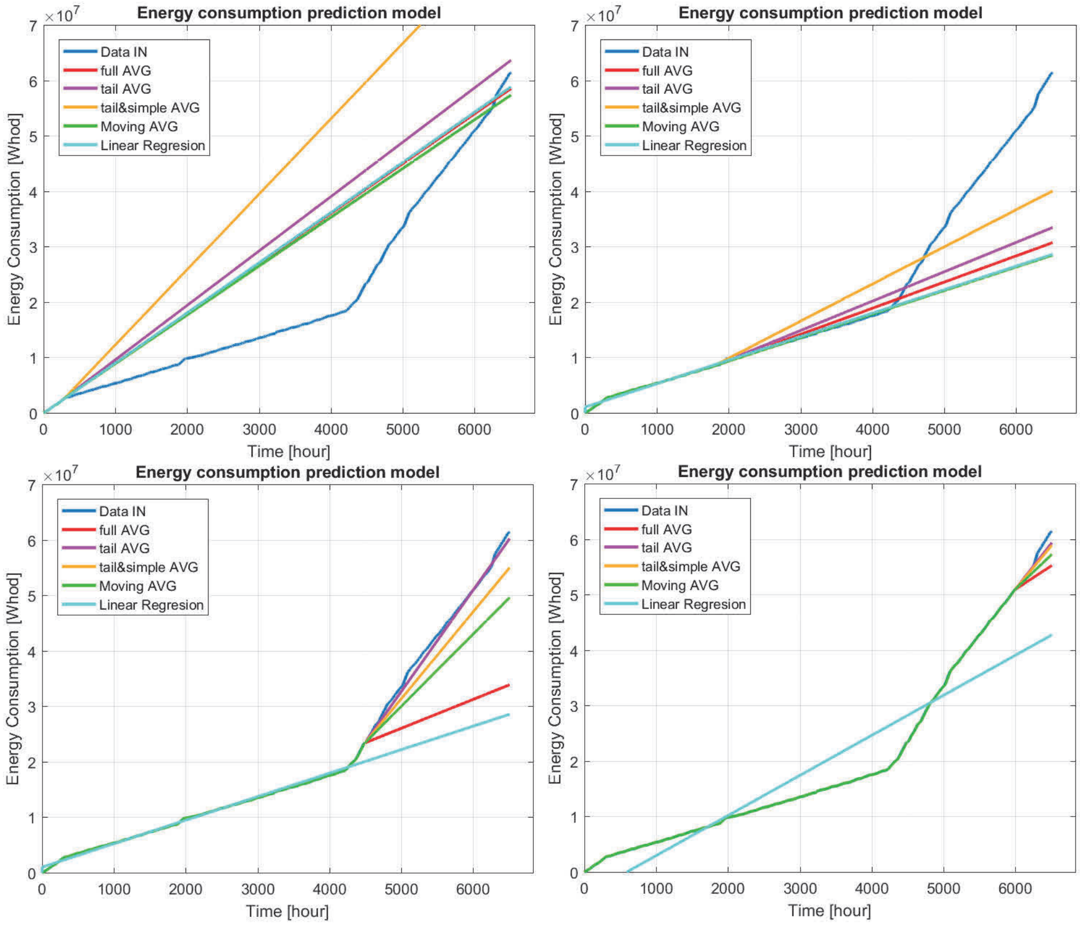

Figure 3 (a,b,c,d) Final energy consumption estimation based on used method type.

The initial slope is always problematic. As can be seen on **Figure 3a**, the estimation is misleading. This is caused by small amount of data point. In the middle of steady state (**Figure 3b**), all estimations are relatively precise, except combination of standard averaging and avg_{tail} (light brown curve). The most important state occurs when the winter season arise (**Figure 3c**). Standard averaging method together with linear regression are misleading. There is a heavy past data influence and it takes a long time to retrieve original running (only averaging method). On the end of time period (**Figure 3d**) has best approximation methods avg_{tail}, avg_{SMA} and combination of standard averaging and avg_{tail}. Linear regression has no capability to return to correctly approximate energy consumption, as well as standard averaging. [9]

5. CONCLUSION

Prediction of energy consumption in metallurgical companies is not an easy task. Seasonal behavior as well as appliances with random running character enforce using advanced algorithms to predict long term energy consumption. This prediction is a key component when forecasting peak energy withdraws, which are source of financial penalties and significantly increase money outcome for energies. There were discussed several methods, suitable for prediction when concerning metallurgical company. Standard household, or SOHOs are quite different, because of natural energy consumption behavior. The next step in prediction process is to implement artificial neural networks into the process. Neural network will recognize type of energy withdraw and assign typical energy consumption curve from the catalog. This will help select proper averaging method, which will eliminate total error to a minimum. Until that we recommend to use not only one prediction method, but whole set and carefully observe final estimation over a time.

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