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PREDICTIVE DYNAMIC POWER DEMAND CONTROL IN AN EAF STEEL PLANT

DYNAMICZNA PREDYKCJA STEROWANIA ZAPOTRZEBOWANIEM MOCY W STALOWNI ELEKTRYCZNEJ

The demand portion of the electricity bill presents a considerable part of overall energy cost in high-load industrial installations such as electric arc furnace (EAF) steel plants. In order to keep cost at an acceptable level, power demand control is applied to avoid exceeding the contracted demand target while optimising load-shedding for the best possible energy utilisation and productivity. Numerous practical solutions addressing the first aim are already available. Optimised energy utilisation in demand control for electric steel plants cannot be achieved by conventional methods due to the erratic load characteristic of EAFs.

This paper deals with the development and installation of an innovative predictive dynamic power demand controller at the steel plant of ArcelorMittal Hamburg. Models describing the electric load of the EAF in its various states of the production cycle, the ladle furnace and the so-called basic load, comprising all other plant equipment including the rolling mill, are developed and utilised to predict the oncoming electric load situation of the plant for the timeframe relevant to the power demand controller. Thereupon, a power demand control algorithm avoiding unnecessary load-shedding and achieving more constant energy insertion into the melt is designed and will be verified by practical installation.

Keywords: Power Demand Control, Electric Arc Furnace, Electric Load Prediction

Znaczna część zużycia energii elektrycznej w przemyśle stalowniczym przypada na wysoko-napięciowe urządzenia elektryczne, takie jak stalowniczy piec łukowy (EAF). Aby utrzymać wydatki na energię na określonym poziomie oraz uzyskać jak najlepszą wydajność energetyczną oraz produktywność, zużycie energii elektrycznej podlega stałej kontroli tak, aby mieściło się w wyznaczonych granicach. Optymalizacja zużycia energii w elektrostalowni nie jest możliwa do osiągnięcia konwencjonalnymi metodami z powodu zmiennej charakterystyki EAF.

W artykule przedstawiono prace związane z wprowadzeniem innowacyjnej metody ciągłego sterowania zużyciem energii w stalowni ArcelorMittal w Hamburgu. Opracowano model opisujący zapotrzebowanie na energię elektryczną pieca łukowego w różnych stanach technologicznych, zapotrzebowanie piecokadzi oraz innych urządzeń zawierających pozostałe wyposażenie zakładu, włączając walcownię. Model został zastosowany do przewidywania zapotrzebowania na energię elektryczną zakładu w odcinkach czasowych odpowiednio do zapotrzebowania na energię przez sterownik. Jak tylko algorytm zapotrzebowania na energię nie będzie wymagał zbędnych skoków obciążenia i osiągnie bardziej stabilne warunki energetyczne zostanie wdrożony do sterowania energią topienia oraz zostanie zweryfikowany w rzeczywistych warunkach pracy.

1. Introduction

Industrial installations with a nominal power greater than a certain limit value (e.g. in Germany this value is 30 kW) are not only charged by their energy supplier for the amount of electric energy that has been utilised but also for the power drawn. This is to represent that the power supplier has to ensure a certain value of power to be available to the installation at any time. This power limit – usually called demand target – is agreed

upon in the energy supply contract. As a control mechanism, the average power drawn by the plant is determined in regular intervals called demand periods. In the case considered in this paper, the demand period is 15 min. As the average power values can vary depending on the offset of these demand intervals in relation to the load development in the plant, the power supplier sends a synchronising signal at the onset of every demand period. This way, actions to observe the actual power util-

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isation in the demand interval and eventually to plan load-switching in a way to meet the demand target can be carried out at the plant site. The latter is especially important because exceeding the contracted demand target means that the demand portion of the electricity bill is amended by the corresponding higher average power value for the whole billing period, which can be as long as a year. Amendments are made retroactively, causing extensive extra cost. Power demand control is applied to address this issue.

Usual high-load installations have a rather constant load characteristic, meaning there are no or little load variations. In these cases, power demand control can be based on the assumption that the power drawn by the plant does not vary considerably during the individual demand periods. This simplifies the optimisation of switching actions as there are almost no unpredictable events to allow energy for. On this basis, numerous more or less sophisticated solutions are readily available on the market [1].

In an EAF steel plant, the situation is different. Several loads are present here which do exhibit highly erratic behaviour. Therefore, the above mentioned assumption of constant power levels cannot be used for efficient power demand control. This is the starting point for the innovative predictive power demand control algorithm presented in this paper. It is shown how simple but effective models can be derived to facilitate load prediction for a steel plant and especially to estimate the remaining power-on-time of the EAF until tapping. Using these predictive models, a new power demand control algorithm is developed and implemented at the steel plant of ArcelorMittal Hamburg.

This steel plant is a typical mini mill equipped with an AC EAF, a ladle furnace, a continuous caster and a rolling mill. Additionally, a direct reduction plant is installed at the site such that the EAF can be fed with directly reduced iron (DRI) [2].

2. Characteristics of electrical loads in the steel plant

The EAF in the steel plant has a nominal power of 120 MVA that is switchable in steps of about 5 MW by the supplying transformer, which is equipped with an on-load tap switch. During a heat, the active power drawn by the EAF varies considerably, firstly due to the stochastic behaviour of the burning arc and secondly because of the varying conditions the melt goes through (i.e. foaming slag, DRI feeding etc). Fig. 1 shows a typical plot of the EAF's active power during a heat.

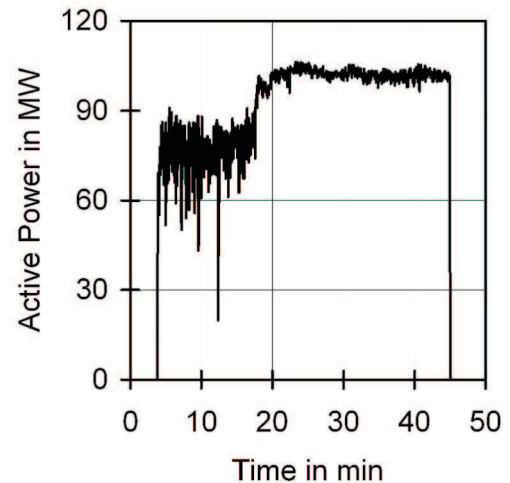


Fig. 1. Typical plot of the EAF's active power during a one-basket-heat

In further investigations, it can be shown that there are three relevant stages in each heat that can be quantified by the total specific energy inserted (e.g. 0 – 100 kWh/t, 100 – 300 kWh/t and > 300 kWh/t), as described in [3].

Moreover, in the steel plant considered, four different types of heats are processed, ranging from 100% DRI-heats over one-basket- up to three-basket-heats. For the load characteristics of the first basket of multi-basket-heats, it can be said that it is comparable to the one of a one-basket-heat up to the point when subsequent baskets are charged. After that, the meltdown of these additional scrap baskets happens much more uniformly with less variation in active power, as shown in Fig. 2. However, as a result of the multiple scrap-charging and meltdown phases in multi-basket-heats, there hardly ever occurs a case where the EAF runs through a complete demand period at full power. Consequently, utilised energy falls below the demand target in the majority of cases even with a standard power demand controller, not leaving much potential for optimising energy utilisation. Therefore, the active power characteristics of multi-basket-heats are not investigated in more detail.

In order to predict the near-future power demand of the EAF, a model describing to some part the stochastic behaviour as well as correctly estimating the long-term mean value needs to be found. It can be shown that the following equation meets these requirements:

$$\bar{P}_{elEAF} = 0.5 \cdot P_{elEAFactual} + 0.5 \cdot \bar{P}_{elEAF}, \quad (1)$$

where \bar{P}_{elEAF} is a general mean active power value that is continuously determined in runtime, dependent on the actual melting progress and transformer tap. Averaging follows a PT₁-algorithm with a time constant of 170 min

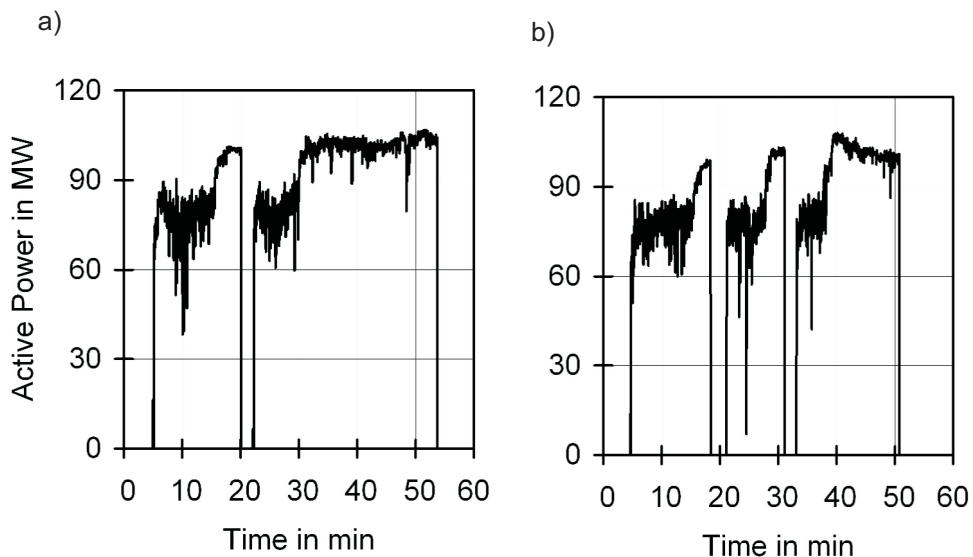


Fig. 2. Typical plot of the EAF’s active power during a heat, a) two scrap baskets, b) three scrap baskets

(roughly 3 heats). Thus, it well represents the required long-term mean value, whereas the actual active power value of the EAF ($P_{el\ EAF\ actual}$ in the above equation) represents the stochastic momentary deviations from the average power.

Fig. 3 shows the result of equation (1) for a 25-minute-section of a one-basket-heat. The curves show similar characteristics, although the simulated values do not exhibit as much stochastic deviations as the actual values. Nevertheless, the mean values of both curves (102.3 MW actual vs. 101.8 MW simulated) are almost identical, confirming that this kind of model is suitable for predicting the near-future (i.e. the remaining portion of the demand period) development of the EAF’s active power in case the EAF is running amidst a heat. In cases where the EAF is about to be tapped within the current demand period, a different approach has to be followed, allowing for the prediction of the remaining power-on-time. This is described in chapter 3.

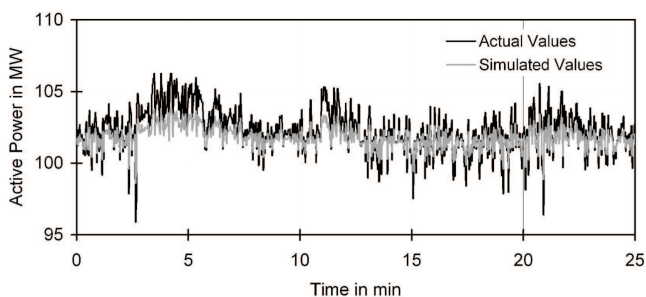


Fig. 3. Comparison between actual and simulated values of EAF active power

The ladle furnace, as a second major electrical load in the steel plant, has a nominal power of 25 MVA and is

supplied by a tap-switchable transformer like the EAF. However, as there is no melting performed within the ladle furnace, its active power consumption curve shows less stochastic behaviour than the EAF’s and runs more smoothly, as shown in Fig. 4.

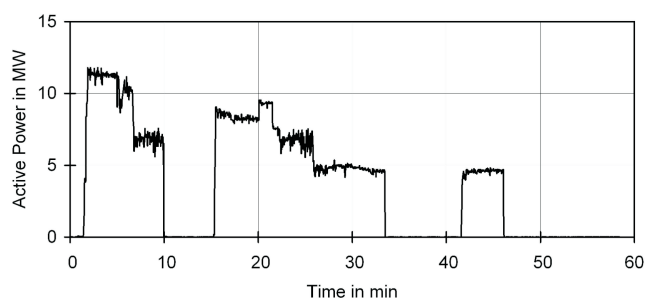


Fig. 4. Typical plot of the ladle furnace’s active power

In addition to the step-shaped changes in active power caused by the ladle furnace’s transformer tap switch, the electrical load of the ladle furnace is characterised by its variable on and off times, which are due to the alloying and purifying processes performed in the ladle furnace and to the short reheating phases necessary for delivering the melt to the caster at the right temperature. As control of these processes is carried out independently of the process control system that the power demand controller has access to, there are no process variables available to determine the moments of engaging and disengaging of the ladle furnace. Thus, modelling the ladle furnace’s active power for a whole demand period or any time frame in advance is hardly accomplishable. Instead, the maximum active power drawn during the last 24 hours is taken as a “worst case”. If the ladle furnace is on, the later described power demand control algorithm

allows for an amount of energy corresponding to this maximum load until the end of the demand period.

Having said that the variable on and off times of ladle furnace operation hinder load prediction, actively postponing the engaging of the ladle furnace presents a means for controlling the power demand of the overall steel plant, which is described in more detail in chapter 4.

The third electrical load to be characterised here, the so-called basic load, comprises the remaining plant equipment, most importantly the casting implements and the two-train rolling mill. As with the ladle furnace, there is also no process data available concerning operation of these installations to base any precise modelling or prediction on. Merely the actual electric power drawn can be determined from the electric meter connected to the power demand controller.

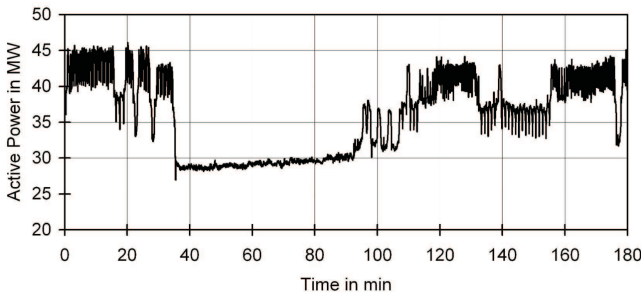


Fig. 5. Typical plot of the basic load's active power

Fig. 5 shows the various load levels of the basic load ranging from around 25 MW up to about 45 MW. Each of these load levels relates to a certain state of the rolling mill (i.e. off, one or two trains running) and other plant equipment. Not having access to the corresponding control systems and therefore not being able to determine the exact moment when installations are going to be engaged or disengaged, it is unfeasible to predict the exact run of the oncoming load curve for the basic load. It can also be shown that even if the oncoming switching were known, the load levels, each one regarded as a different time series process, cannot be described or modelled by time series analysis due to their highly erratic characteristics. However, during practical measurements, a model similar to equation (1) is used and results show that it allows for a prediction of the basic load's oncoming power levels good enough to serve as a basis for the predictive power demand control algorithm.

3. Prediction of the EAF's remaining power-on-time

As said before, the key issue in developing a predictive power demand controller is the prediction of the EAF's remaining power-on-time until tapping. In [3], a

physical energy model is derived to fulfil this task. It is based on the assumption that the total amount of electric energy required for the melt is determined by the charged amounts of scrap and DRI as well as by their respective specific energy requirements. Using an estimation for the near-future active electric power and keeping track of the amount of electric energy already inserted into the melt, the remaining time until tapping Δt can then be expressed by the model

$$\Delta t(t) = \frac{am_{Scrap}(t) + bm_{DRI}(t) - \int_0^t P_{elEAFactual}(\tau)d\tau}{\tilde{P}_{elEAF}}, \quad (2)$$

where a and b represent the before-mentioned specific energy coefficients for scrap and DRI, which are adapted after each heat to allow for slow changes in process parameters. The estimated total scrap and DRI tonnages m_{Scrap} and m_{DRI} are marked as time dependent in the above equation because their corresponding values are adjusted during the course of the heat to improve prediction accuracy towards tapping. $m_{Scrap}(t)$ is updated whenever subsequent baskets are charged. The time-dependency of $m_{DRI}(t)$ accommodates the fact that the final amount of DRI is not known at the beginning of a heat and can therefore only be estimated using empirical values from past processes. Thus, at the onset of the melting process, a statistically estimated quantity of DRI (i.e. the mean value of total DRI in the last 100 heats) is used for calculating the remaining power-on-time. In the steel plant considered here, a characteristic drop in the DRI feeding rate occurs in the last minutes of the heat.

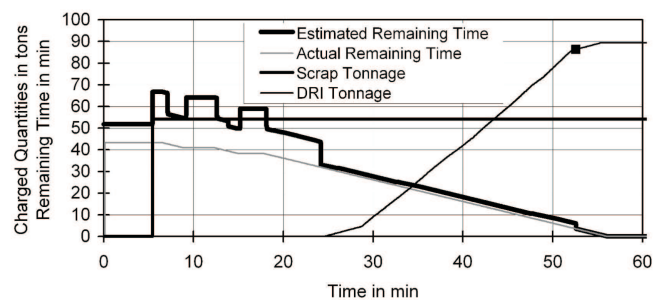


Fig. 6. Estimated and actual remaining power-on-time and charged quantities during a one-basket-heat

Measurements show that after this drop is detected, only 6 to 8 tons of DRI are fed into the EAF. Consequently, the total amount of DRI $m_{DRI}(t)$ can then be updated to the amount of DRI already charged up to that moment plus the statistically estimated remainder, which is again a mean value determined from the last 100 processed heats. Fig. 6 shows the development of the estimated remaining power-on-time during a one-basket-heat.

The estimated remaining power-on-time curve in Fig. 6 shows the above described algorithm in effect. At the beginning of the heat (at about 6 min), an estimate is made that is much larger than the actual remaining time. This is due to the fact that melting starts at a low power level, resulting in a relatively long remaining time estimate according to equation (2). The following step-shaped alterations in the curve emerge because the EAF's active power is changed according to control diagrams that set particular transformer taps depending on the actual melt progress. By about 24 min, the highest transformer tap is reached and the estimate curve almost coincides with the actual remaining time curve. Finally, at 52 min, the characteristic drop in the DRI feeding rate occurs (indicated on the respective curve with a black square), and the estimate is again updated to reach even better accuracy. From that moment up to tapping, estimated and actual remaining time curves run equally.

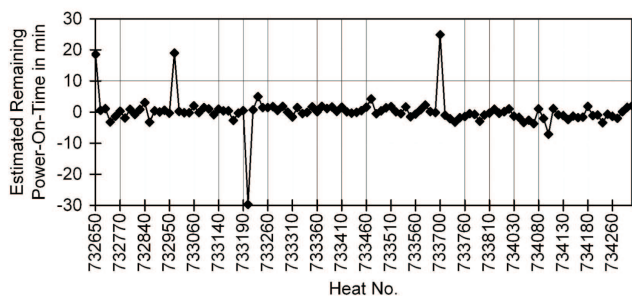


Fig. 7. Estimated remaining power-on-time at tapping over 110 one-basket-heats

Fig. 7 shows the result of similar measurements over two weeks. Exemplarily, the achieved estimation accuracy at tapping is only depicted for one-basket-heats, as they account for the largest number of heats processed during the experiment period. Statistically, the measurements show a mean estimation accuracy of -0.7 min, -0.1 min and -4.0 min for 100% DRI-, one-basket- and two-basket-heats respectively, accuracy meaning the difference between estimated and actual remaining power-on-time at the end of the corresponding heat. The minus signs imply that the estimated times show a slight tendency to predict tapping a little earlier than it actually occurs; this is confirmed by the graph in Fig. 7, which – on average – runs slightly below the zero line. The few outliers in the curve give a hint that there can occasionally be unusual processes that lead to inappropriate estimation results. However, these deviations from the ordinary have to be taken into account.

For the overall power demand strategy, this means that a superordinate controller must ensure that the demand target is not exceeded even in cases where the prediction of EAF tapping is unusable due to unpredictable incidents. For the cases when a heat runs smoothly and remaining time prediction is feasible, the estimated re-

maining time cannot be taken as such but must be provided with a safety buffer time. That is because a tapping after the predicted moment results in more energy than presumed being drawn by the EAF, which might lead to unwanted load-shedding or even shut-off. The other way around, if tapping occurs earlier than predicted, the only consequence is that the amount of electrical energy that was allotted to the EAF in the current demand period is not completely used up. Thus, a buffer the size of the respective standard deviation is added to the estimated remaining time to allow for the unavoidable variation in estimation accuracy that is mentioned above. This way, assuming a Gaussian distribution, actual tapping lies within the predicted time frame for 84 % of the cases.

3.1. Demand Control Strategy

The above described models render it possible for the predictive power demand controller to calculate estimates for a number of parameters. These are the remaining power-on-time until tapping of the EAF, the electric energy the EAF will consume during the actual demand period and in total until tapping and the electric energy the ladle furnace and the basic load will utilise in the demand period. Moreover, the power demand controller monitors the remaining time until onset of the next demand period and the total remaining electric energy to meet the demand target.

Having these parameters at hand, the following rules of action are carried out along a decision tree in order to optimise energy utilisation. This is depicted in Fig. 8.

First, it is decided whether tapping is estimated in the current demand period. The outcome of this decision determines which amount of electric energy is allotted to the EAF: Either the total remaining energy until tapping or until the end of the demand period. In the first case, EAF transformer tap switching is avoided as far as possible, such that the EAF is allowed to finish off the actual heat without being interrupted by power demand control. In avoiding these control actions shortly before tapping, eventually a higher productivity can be achieved as tapping is reached as fast as possible at the highest possible power level. If the EAF is unnecessarily stepped down shortly before the end of the heat, tapping might be drawn into the next demand period, increasing tap-to-tap time. In the second case, i.e. tapping is not imminent in the actual demand period, the focus lies on providing for a constant energy insertion into the melt. Thus, on recognition that the demand target will be exceeded at the current load level, the EAF is switched down in small steps early in the demand period in order to avoid severe control actions towards the end. If load levels then develop in such a way that the demand target will not be reached, the EAF is stepped up again.

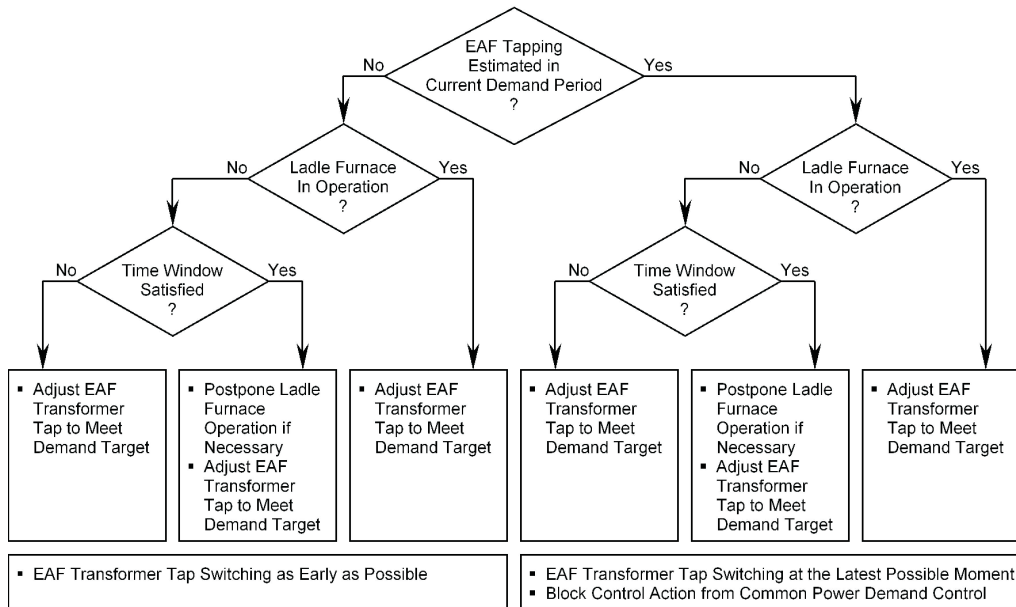


Fig. 8. Decision tree for the predictive power demand control algorithm

To support the afore-mentioned objectives, the ladle furnace is used as an actuator to the power demand controller to some extent. It can serve to free a certain amount of energy that can in turn be used to let the EAF run through the actual demand period without load-shedding or allow it to finish off the current heat within the demand period. Both are desirable features in order to optimise energy insertion into the melt while meeting the demand target. This functionality is incorporated into the decision tree by observing whether the ladle furnace is in operation during an adjustable time window of about 1,5 min towards the end of the demand period. If it is off and the remaining total energy in the demand period does not allow for it to be switched on without necessitating load-shedding in the oncoming minutes, the power demand controller tries to postpone engaging into the next demand period. This is realised by displaying a corresponding message in the control room such that the operator can then either follow the demand controller's suggestion or override the suggestion if ladle furnace operation is imperative instantly in order not to interrupt the casting process.

4. Implementation

The commercial power demand control solution installed in the steel plant consists of an embedded PC and a software package for visualisation, parameterisation and data archiving. The embedded PC carries out a parametrically adjustable common power demand con-

trol strategy. Therefore, it is interlinked with the load switching actuators and relays of the steel plant in an electric control cabinet. Moreover, it is connected to the counter impulses and synchronising signals from the electric meters and to the plant's process control system through a serial interface. The embedded PC is also linked to an industrial PC via ethernet. This industrial PC runs the corresponding software package and the newly developed power demand control algorithm, which is implemented as a Visual C++ programme. Both applications can interchange data on the PC via OPC (Object linking and embedding for Process Control). Fig. 9 depicts this setup.

The above implementation extends the commercial power demand control solution by the previously discussed predictive functionalities. The new power demand control programme is fed with the necessary process data and can transmit its output parameters (i.e. EAF transformer tap, bit-information whether tapping is imminent, and bit-information whether ladle furnace switch-on should be postponed) back to the commercial software through the OPC interface. At the same time, the required superordinate controller to ensure safe operation of the overall power demand strategy even in cases of erroneous load prediction is constituted. This is because the new power demand controller's output is not directly fed through to the embedded PC. Instead, these output parameters are supervised by the intelligent algorithms in the commercial solution software and possibly altered before transmission to the embedded PC, where the corresponding switching actions are carried out.

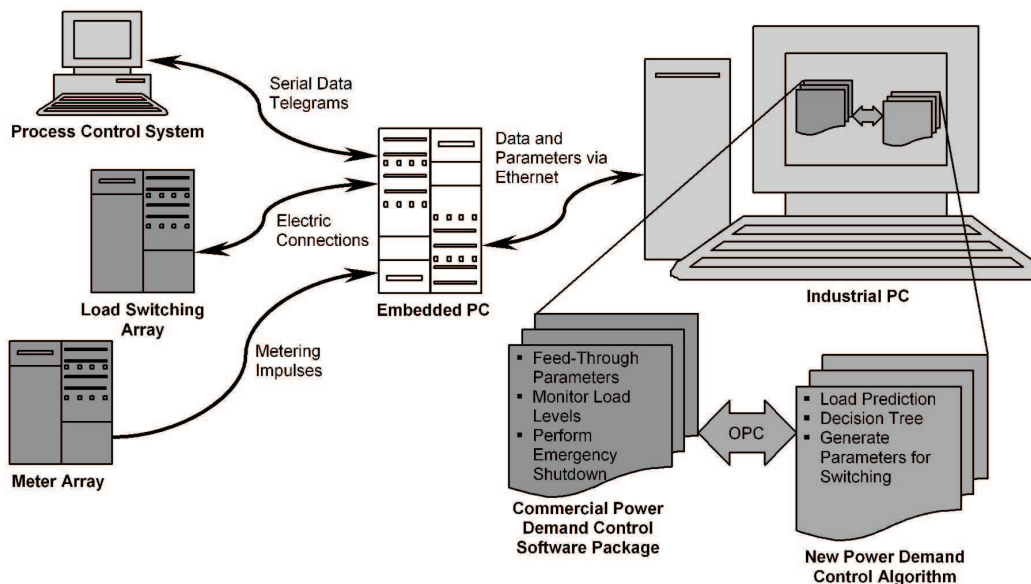


Fig. 9. Schematic of the implementation setup in the steel plant

This setup has been in operation for several weeks in the steel plant considered here. However, the output from the new power demand programme has not been actively used so far, because the overall system is still undergoing thorough plausibility checks and intensive testing for stable operation. Future works will include the activation as intended and an analysis of results to finally evaluate the achieved optimisation in power utilisation.

5. Conclusion

In the previous paragraphs, an innovative strategy for power demand control in EAF steel plants is set out. First, the plant is broken down into its major electric loads. For each of these loads, a suitable model to describe the corresponding load characteristics is identified. In case of the EAF, it is shown that the load model must be supplemented by a model for prediction of the remaining power on time in order to estimate the oncoming electric load situation during the actual demand period. Analysing long-term measurements under real-time conditions, it is verified that the prediction models yield reasonable accuracy. This is especially the case due to the adaptive behaviour of these models.

Second, a new power demand control algorithm is formulated as a set of rules following a decision tree, incorporating the ladle furnace as an actuator for the

controller. This concept not only optimises energy utilisation as a whole, but it also aims at process-specific objectives, i.e. a more constant energy insertion into the melt and shorter tap-to-tap times.

Finally, the newly developed algorithm is installed at the steel plant of ArcelorMittal Hamburg and incorporated into an existing parametrically adjustable power demand solution. Due to time-consuming plausibility and stability tests, the arrangement has not been tested actively so far, but preliminary results show considerable promise for meeting the above-mentioned optimisation objectives.

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