AI Kiln Solution For Optimized Control
How To Reduce Energy Consumption And Emissions In The Clinker Process

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***Abstract* - Cement production represents a core element of our building materials industry not only historically, but also currently and in the future. It not only supports our infrastructure, but also makes modern civilization as we know it possible. For this reason, the demand for cement will continue to double in the near future.**

A core element of cement production is the clinker process in a rotary kiln. This process is both energy-intensive and difficult to control. Due to harsh environmental conditions and high temperatures, there are few meaningful measurements within the process. In addition, there are complex influencing process factors such as input raw materials and variable fuels. The fuels in particular lead to increased environmental pollution through exhaust gases.

Thus, the cement industry is currently facing major challenges in the production of clinker in rotary kilns. Some of these are monitoring kiln operation, accurate measurement of zone temperature, reducing emission and fuel consumption.

A highly qualified development team and a cement manufacturer has addressed these challenges together and has developed and tested in real environment an artificial intelligence-based control algorithm for the rotary kiln in a pilot project. This control algorithm, based on Artificial neural networks (ANNs) indicates changes in the rotary kiln process at an early stage, based on the input parameters, and makes suggestions for action to optimize the control of the process. Thus, not only can the process run in an optimal range, but also fuels and emissions can be reduced. This solution is part of cement specific software and platform solution.

I. Introduction

The production of cement and its use has a 2000-year tradition. It is an essential component for society and represents an integral point of infrastructural development of mankind. Despite this importance, industrial production has taken place only since the middle of the 19th century. In the middle of the 19th century, shaft furnaces were first used for production, which were later replaced by rotary kilns. Today, rotary kilns can be found as standard equipment worldwide. Today's annual global cement production has reached 2.8 billion tons and is and is expected to increase to about 4 billion tons per year. Major growth will be in countries located in Asia, as well as in regions such as the Middle East and North Africa. Based on this potential, cement production has undergone a highly dynamic development over the last 20 years. [2]

In addition to this development, the cement industry is simultaneously facing extensive challenges such as cost increases in energy supply, requirements to reduce CO_2 emissions, and the supply of raw materials in sufficient quality and quantity. For such complex requirements and best possible process control, automation or digitalization is often used as a solution approach in the raw materials industry.

The automation of the cement kiln is a very difficult problem because the processes involved, both chemical and physical, are simple in theory but complex in practice. This is especially the case when commercial aspects such as quality and cost of production costs are taken into account. The production of cement and its main component, clinker, has a number of conflicting objectives: Maximize production, minimize costs, and maximize efficiency while meeting minimum quality requirements. All these optimizations must take place within various environmental, thermodynamic and mechanical constraints [2].

This tension field and additional to it, cement rotary kilns are complex to control due to time-varying nonlinear behavior of their parameters. This is partly due to the poor quality of the measurements in the harsh environment of the cement production cement production process. Therefore, the control is usually limited to some simple control loops for the secondary variables, and the control of the primary variables and the selection of the operating conditions are the responsibility of the kiln operator. Different technologies for advanced process control (APC) have been developed over the last twenty years for the cement industry, being fuzzy logic, expert systems and rudimentary approaches of artificial intelligence, the most widespread form of technology applied to kiln control [2], [3]. However, the current APC systems have limited performance for kiln control and require excessive retuning.

A big team around the authors together with cement manufacturers, has also addressed this problem and chosen a new approach. Through new technological developments, especially in artificial intelligence, an innovative solution has been developed, in particular by means of artificial neural networks (ANN). Based on historical data and current process information, this solution calculates an outlook on changes in the clinker process in the rotary kiln. In this way, negative process changes can be counteracted at an early stage and the clinker process can be kept in the optimum process engineering range. This leads not only to increased process reliability, but also to reduced fuel consumption and thus to significantly lower emissions. Thus, the necessary process quality can be maintained and, on the other hand, the ever-increasing environmental requirements for cement plants can be met in cement production.

The here described AI solution is integrated into a digital platform specific to the cement industry. In addition to a variety of functionalities such as asset health analytics, KPI analysis and reporting, the platform and software offers an open- or closed-loop variant of the AI Kiln Control solution. In the open-loop variant, the operator receives early information about changes in the firing process in the rotary kiln and calculated suggestions for countermeasures. In the closed-loop variant, the instructions for action are implemented directly with a notice.

II. Cement Production Description

The basic process in a cement production plant is burning a mixture of raw material containing Carbonates and Silicates in a kiln to produce solid oxides, clinker, which is then cooled and milled to make the cement dust. Fig. 1 shows the structure of a rotary kiln with the most important variables used for control purposes in a simplified way [3].

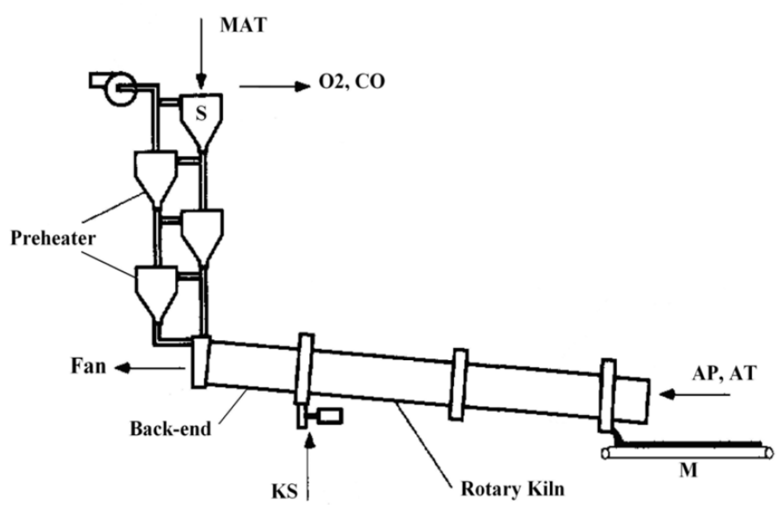

Fig. 1. A rotary kiln plant (according to [3])

The thermodynamic processes for clinker production are the preheating and calcination of the raw meal, followed by the endothermic and exothermic sintering processes, which produce the various clinker complexes such as calcium silicates. Each of these processes requires fairly specific thermodynamic and metallurgical conditions for the process to take place. These processes, called burning processes, take place in three main parts: Preheater, Kiln and Cooler.

Reducing energy consumption is a key objective in these processes. The preheater is used to utilize as much of the energy from the kiln as possible before it is released to the atmosphere. The heat extracted from the kiln by a fan is used to dry the raw meal and break up silicates, as well as to partially calcine the carbonates present in the material, which are then fed to the kiln. The kiln is a huge cylindrical tunnel that rotates around its axis at a pitch of about 4 percent. The mixture of crushed, preheated raw material is fed into the kiln from its rear end. The air, known as secondary air, is blown in from the other end of the tunnel, i.e. in counterflow. The raw material is conveyed through the kiln at a very low speed.

In the center of the furnace is the firing zone, where gas burners are placed to create a specific temperature profile. In an oven, the back end is responsible for the calcification of the flour before the main baking. Therefore, if the temperature of the back end is above the acceptable range, baking is performed before entering the firing zone, and vice versa if the temperature is lower. In the firing zone, the high temperature melts the calcified flour. Then the main chemical reactions take place between the silicates and the oxygen in the air. Part of the combustion gases is the co-gas produced here. Finally, the cement crystals are formed and leave the kiln as clinker. The initial clinker has a temperature of about 1000 to 1200 °C and should be cooled before it is fed into the clinker silo. In the production line, water is used to cool the clinker. The cooling of the clinker also has a great influence on its quality.

III. PROBLEM STATEMENT: KILN CONTROL AND QUALITY CLINKER PRODUCTION

The primary control objective in the industry is to achieve an optimum balance between quality and production, and this is also the case in the cement industry. Clinker quality is determined primarily by the characteristics of the kiln charge and the thermodynamic conditions. Therefore, a stable control of the chemical composition of the kiln charge and the thermodynamic profile of the plant is an essential requirement. Deviations in certain chemical compositions of the flour can be a major source of disturbance, as they can affect the combustibility and, consequently, the firing characteristics and thus the thermodynamics of the process.

The thermodynamic profile includes the temperature curve as well as the values of gases and mass contents along the kiln. In order to achieve these objectives, some effective process variables were chosen as input and output variables for the control scenario. It must be mentioned that although the temperature of the burning zone is one of the most important factors for the clinker quality, but unfortunately the real data for this part of the kiln were not available, so the backend temperature was used instead.

Based on the main objective of kiln control is to produce a desired quality of clinker with minimum energy consumption. There are several control loops to be maintained in order to achieve the desired clinker. Kiln control strategies involve maintaining the burning zone (BZT) of the kiln at the desired temperature based on the burning requirements of the raw material. Maintaining the draft conditions (O_2) required for the fuel burning are also of much importance and separate control group are designed in order to maintain airflow in the kiln.

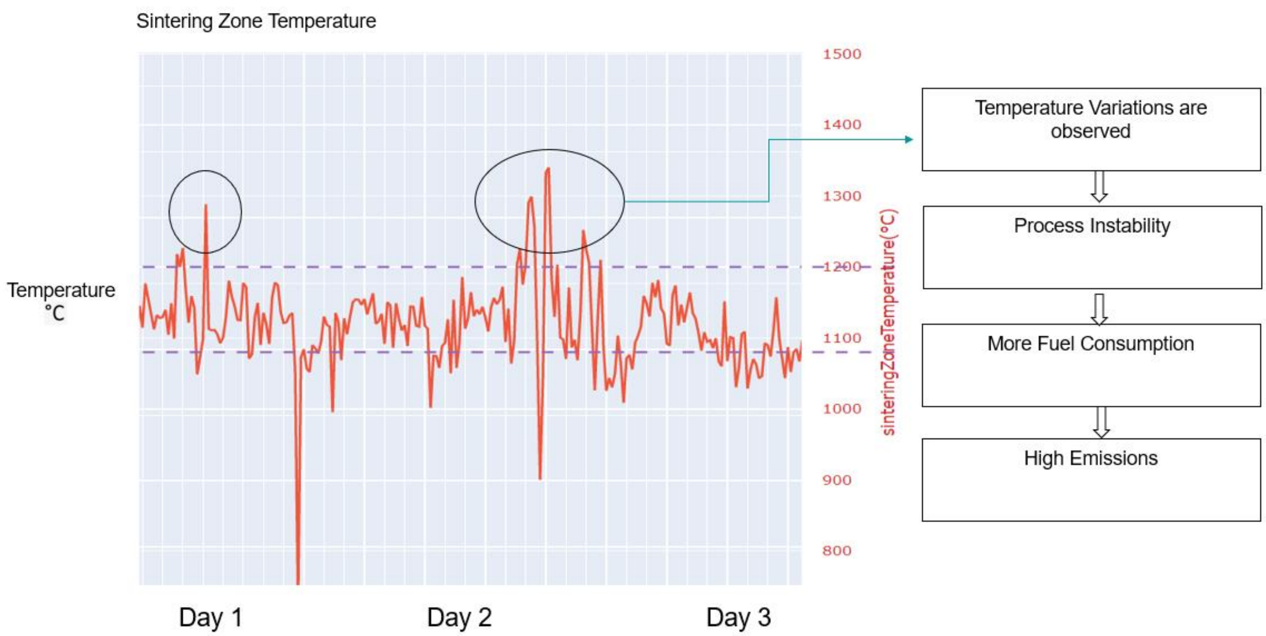

Fig. 2. Examples of difficulties in the clinker process

Fig. 2 shows only an excerpt from the extensive factors influencing the clinker process in the rotary kiln. The key points shown in the figure are explained in more detail below.

Temperature Variations - One of the challenges in kiln control is that the central parameter for monitoring kiln operation, known as the sintering zone temperature, cannot be measured accurately. Therefore, kiln control currently heavily depends on deep expert knowledge and broad experience to avoid instable system states and unplanned downtimes.

Emission - CO is a poisonous gas released in combustion and NOx also produced during clinkerisation process. CO and NOx are pollutants (greenhouse gases) and needs to be measured, monitored, and controlled in line with the statutory environmental obligations. Gradual increase and reaching threshold in CO level will cause kiln shutdown resulting in production loss. Increase in CO results in low fuel efficiency.

Fuel Consumption - Most of the operators works on their comfort level and set the parameters like fuel rate to a level based on their experience, it is observed that the fuel consumption was always at highest value leading to more fuel consumption.

Available control system infrastructure - The present available control solution in the plants are normally static in nature and entire logic is built on mathematical model. The entire engineering model/physics model is built based on the expert knowledge. Any changes in the fuel, chemical composition, control system leads system to underperform, and entire logic needs to be built again.

The problem has developed into an underspecified multivariable control, i.e. more control variables than control variables. Variables. This fact implies that there is more than one solution for every problem. But within constraints, one solution will generally be more optimal than others. [2]

A. Comparison of Kiln Controls

Based on the main process engineering problems presented earlier, it is necessary to understand the basic behavior of the most critical process, the rotary kiln in cement production. It is known that the different parameters of the kiln react differently to changes in the control parameters, some are sensitive, others do not react at all. In addition, some parameters have linear characteristics, while others behave nonlinearly. These significant differences require a differentiated approach to improve the control strategy. AI technology is designed to handle linear and nonlinear behavior in a complex environment where numerous dependencies determine the engineering process.

The main difference between a data-centric solution and traditional expert systems is the development of a dedicated machine learning-based kiln model that provides more accurate insights into future kiln process trends than traditional approaches, which are usually based on a generic mathematical toolbox and a simple aggregation of recent historical data. APC (Advanced Process Control) is widely used to improve kiln and mill control. However, in practice, the limitations of the current APC approach also become apparent. For instance, a typical fuzzy logic is not able to cover all operating scenarios and is very sensitive to operational changes. A typical MPC (Model Predictive Control) uses linear models in most cases and any change in equipment leads to a completely new setting of the model.

By incorporating long-term data sets for training, the trained models can learn from the past and establish correlations between parameters and time, and between actions and outcomes. This knowledge, accumulated in the models, forms the basis for better control performance.

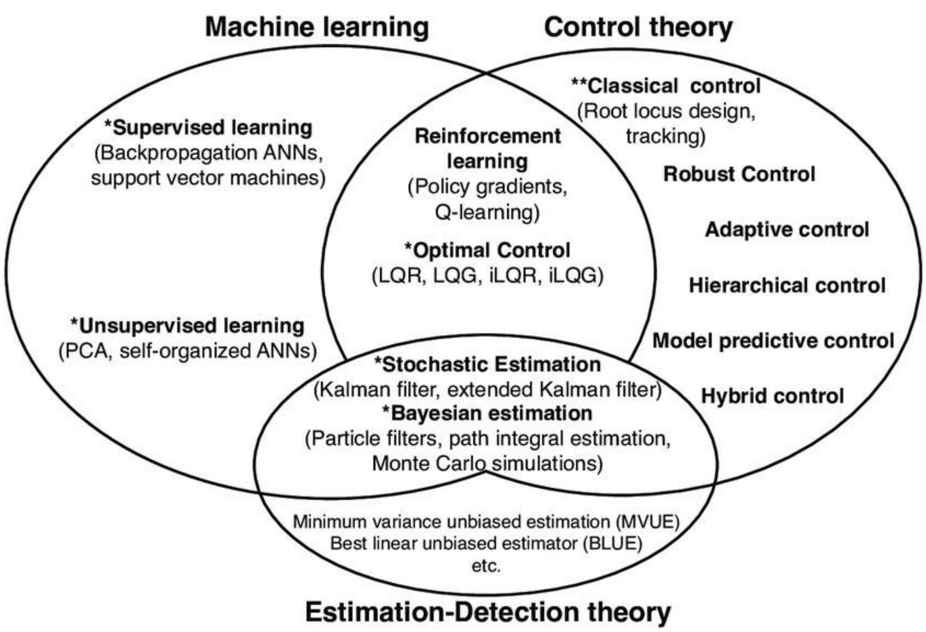

Fig. 3. Overlap zones of different technologies for control logics [1]

IV. AI KILN CONTROL SOLUTION

The main technical difference of the solution from the previously described solutions is the development of a dedicated machine learning based kiln model that leads to more accurate insights into the future trends of the burning process than conventional approaches, which are usually based on a generic mathematical toolbox and a simple aggregation of recent historical data. The solution is developed based on the standard kiln model, which is adapted and extended to meet the required use cases.

The intelligent control system application will run on an external server and will be connected to the existing control system via OPC DA communication. Sensor data will be collected via an OPC DA gateway/data input service and archived in a time series database. Historical information will be processed by the AI Kiln Model to forecast key parameters. The final setpoints resulting from the closed loop algorithm are transmitted to the control system via OPC DA communication. The developed solution consists of several subcomponents (Fig.4), which in interaction enable the successful solution:

- ***Control system:*** A control system manages, commands, directs, or regulates the behavior of other devices or systems using control loops
- ***Sensor data:*** Sensor data is the output of a device that detects and responds to some type of input from the physical environment. The output may be used to provide information or input to another system or to guide a process.
- ***OPC UA/DA:*** OPC is the interoperability standard for the secure and reliable exchange of data in the industrial automation space and in other industries. It is platform independent and ensures the seamless flow of information among devices from multiple vendors. The standard solution includes the OPC gateway software, OPC server can be provided as an option
- ***Data Ingestion service***: Data ingestion is the transportation of data from assorted sources to a storage medium where it can be accessed, used, and analyzed
- ***Influx DB:*** InfluxDB is an open-source time series database optimized for fast, high-availability storage and retrieval of time series data in fields such as operations monitoring, application metrics, Internet of Things sensor data, and real-time analytics
- ***AI Forecast Model:*** The AI model uses algorithm that forecasts the kiln signals, and the output curve contains the mean, max and min value for the predicted signals. Now the forecasted value and the desired range is given as an input to the Optimization module where the difference between the forecasted and desired is calculated and the also considering the other signals which alters the kiln behavior. The values of the signals are recommended to ensure the kiln stability and the same value is passed on to the decision support and these values are considered as new setpoints and the same has been fed back to the control system through OPC.

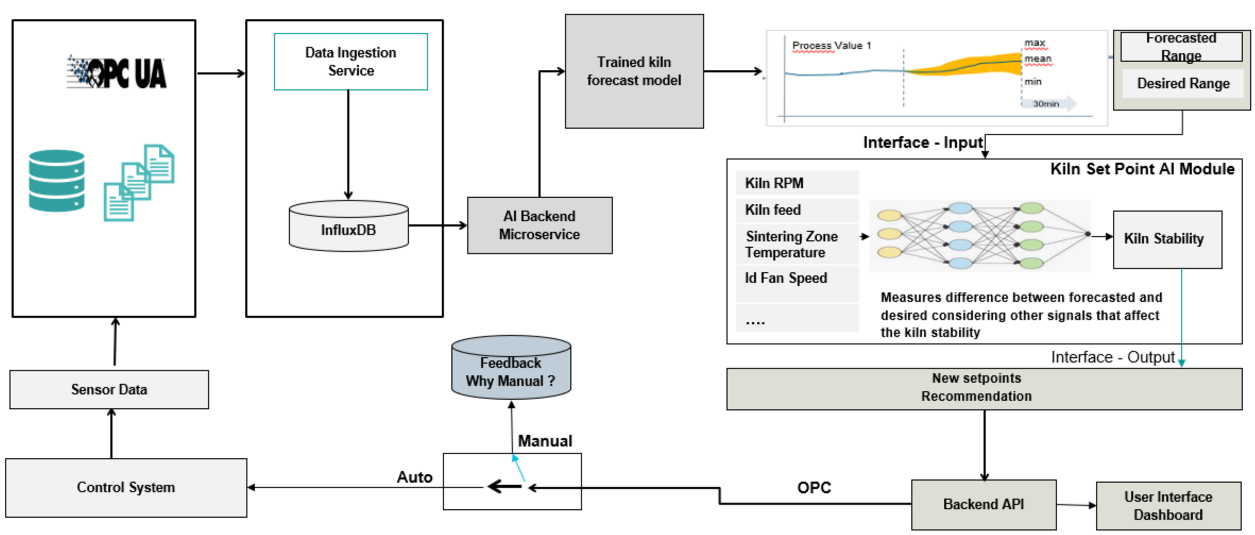

Fig. 4. Conceptional description of the functionalities

A. Ensuring the right decision with the AI Recommendation Module

The Recommendation Module in the solution is used for the final optimization and the feedback of the results, values and proposed actions. Thus, the most important point here is that based on the results of the calculations and analysis, the correct and usable decisions are derived and presented to the operator. Thus, the optimal setpoints from the 19 used parameters is selected. To reach this task of the AI Recommendation Module there a working the main steps.

1) Kiln Parameters prediction: Calculating the results out of 19 parameters.

For the calculation of the Kiln prediction the following parameters are used as examples:

- 4 parameters like Sintering zone temperature,
- Kiln Inlet Temperature,
- Kiln Inlet O2
- Kiln Inlet Nox

These Values are predicted for next 15- and 30-minutes using the before described LSTM model.

2) Business process modelling: Observing the complete process

A business process model is a graphical representation of a business process or workflow and its related sub-processes. Process modeling generates comprehensive, quantitative activity diagrams and flowcharts containing critical insights into the functioning of a given process, including the following:

- Events and activities that occur within a workflow
- Who owns or initiates those events and activities
- Decision points and the different paths workflows can take based on their outcomes
- Devices involved in the process
- Timelines of the overall process and each step in the process
- Success and failure rates of the process

Thus, the results are aligned with the existing running process flows. This evaluation ensures that the results and the instructions derived from them fit into the running business process at all. This prevents results and feedbacks that cannot be implemented or that disrupt the process.

3) Constraints ensuring kiln stability: Upper and lower limit are specified for each recommended parameter

After the comparison of the results with the process parameters, a comparison with the possibilities and limitations of the kiln aggregates takes place. So, whenever any parameter values reach threshold, immediately notification is provided to the operator to take appropriate steps thereby avoiding the disturbances to the kiln. In addition, the mechanical feasibility of the Kiln unit is compared with the results of the analysis, in order to pass on only feasible instructions for action.

4) Operator knowhow: It is a set of 200+ ruleset of operator knowhow and fed to the AI model to gain process knowledge.

Finally, the results are compared with the recorded experiences of the operators. This is an important core element in order to also compare the expert knowledge that has developed over the years with the current results. This is to enable the best possible recommendation of hands. This expert knowledge also increases over time of use and thus also the effectiveness of the matching and thus the operator support.

These four conceptual steps of the recommendation module can also be described as operational as follows

1. Bayesian Optimization builds a probability model of the objective function and uses it to select hyperparameter to evaluate in the true objective function. It is used for Recommending optimum setpoints of control variables in kiln.
2. Control Variables: Kiln RPM, Fuel Rate, ID Fan Speed and Kiln Feed.
   Predicted Parameters: Sintering zone temperature, Kiln Inlet Temperature, Kiln Inlet O2 and Kiln Inlet Nox.
3. 75 minutes of continuous data from control system is fed to LSTM model for accurate prediction.
4. Then this Predictions are given to the optimization algorithm so as to give the best value for control variables to keep the control parameters in best possible value so as to keep the kiln in best possible state.

The conceptual and technical procedure in the Recommondation Module just described is visualized once again in Fig.5. The combination and comparison of the different influencing factors on the holistically considered process of cement production in relation to the rotary kiln ensure that the recommendations for action provide real and realizable added value.

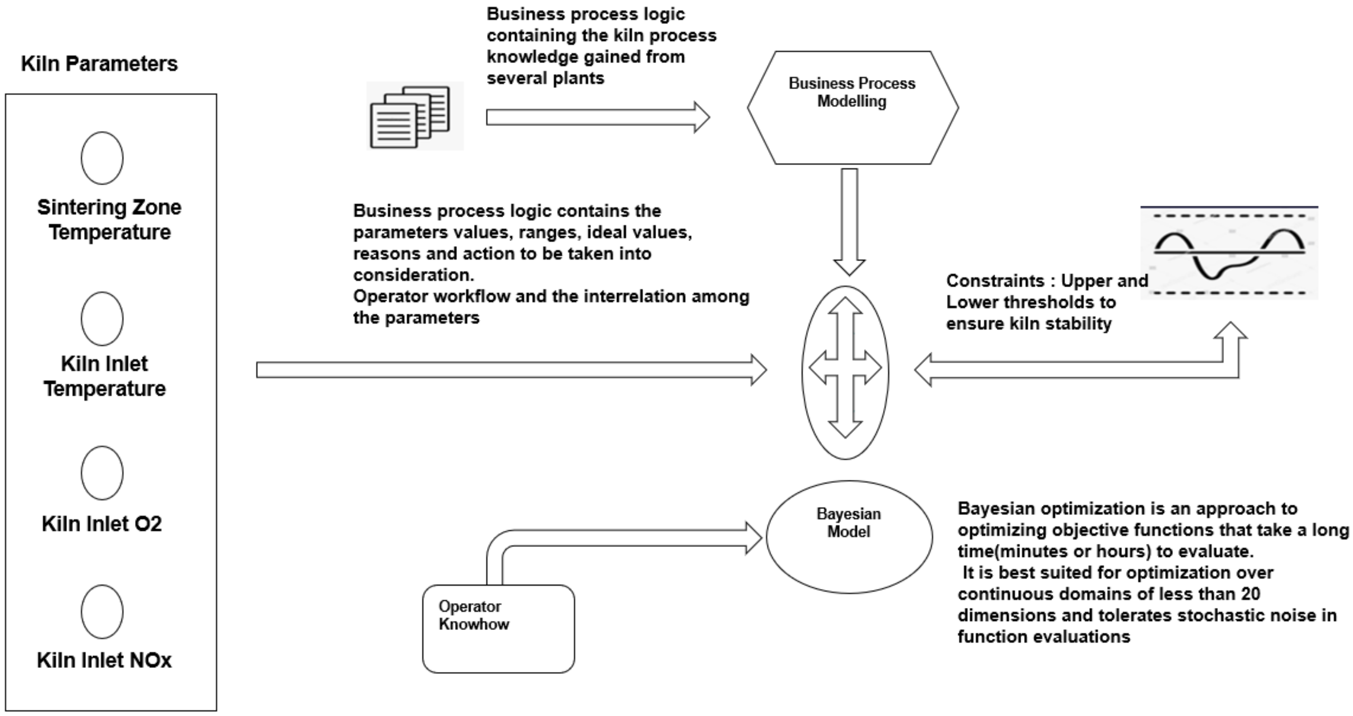

Fig. 5. Conceptional visualization of the Recommendation Module

Based on the technical description of the analytical steps for the generation of results based on characteristic values, the development and step-by-step implementation of the recommendations for action were described. The following describes the results achieved and improvements made to our solution at the customer's site

V. Result and Benefits

As described in Section 3, the kiln is one of the most important pieces of equipment in cement production. In addition, cement production is a pyroprocess that requires large amounts of heat. Thus, attention should be paid to both the process of heat generation and the consumption of fuels to ensure optimization of the process. In addition to reducing heat consumption, optimizing a pyro process has other benefits, such as avoiding global warming and maintaining the mechanical integrity of the equipment. In order to be able to evaluate the presented results in the right relation it is also necessary to establish the correlation with the studied real system. The studied kiln had a capacity of 8250 tpd clinker and a specific heat consumption of 845 kcal/kg clinker. During the study, a total of 19 kiln parameters were considered. After the optimization analysis, the heat consumption was reduced to 823.03 kcal/Kg clinker.

The overall benefit of AI kiln predictive solution operations AI kiln is measured in terms of kiln stability, kiln parameter prediction approximation, kiln parameter optimal recommendation and keeping emissions under control.

- Temperature predictions, such as furnace inlet temperature and sintering zone temperature, are approximated to actual values.
- Non-linear parameters such as kiln inlet O2, kiln inlet NOx, kiln main drive current is also convergent in nature.

In order to evaluate the performance of the algorithm in comparison to real operation, the real data is compared with the results of the AI Kiln Control Solution in Fig. 6. Here, the temperature is plotted against time. The direct comparison clearly shows that the measured and calculated values are almost the same. This first indicator shows that the process can be reproduced with a high correlation based on historical data.

Having demonstrated the performance of the AI Kiln Control, the possible savings are shown below using fuel consumption as an example. Fig. 7 shows the consumption of coal over time. The orange curve represents the real process without AI Kiln Control and the blue curve the consumption with the AI Kiln Control solution. The action instructions that led to the savings were created using the Bayesian Model described above within the Recommendation Module. In this example, 5 to 20 tpd were saved based on the plant process parameters.

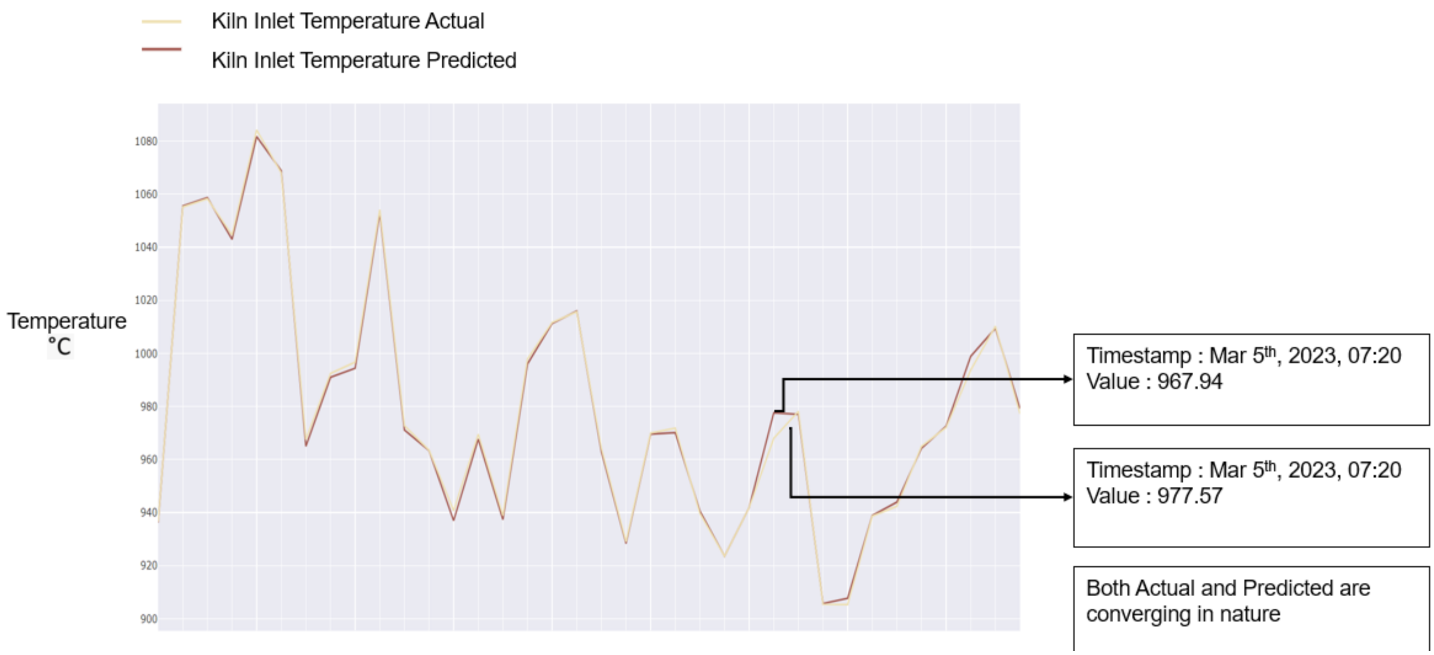

Fig. 6. Kiln Inlet Temperature (Actual vs Forecasted)

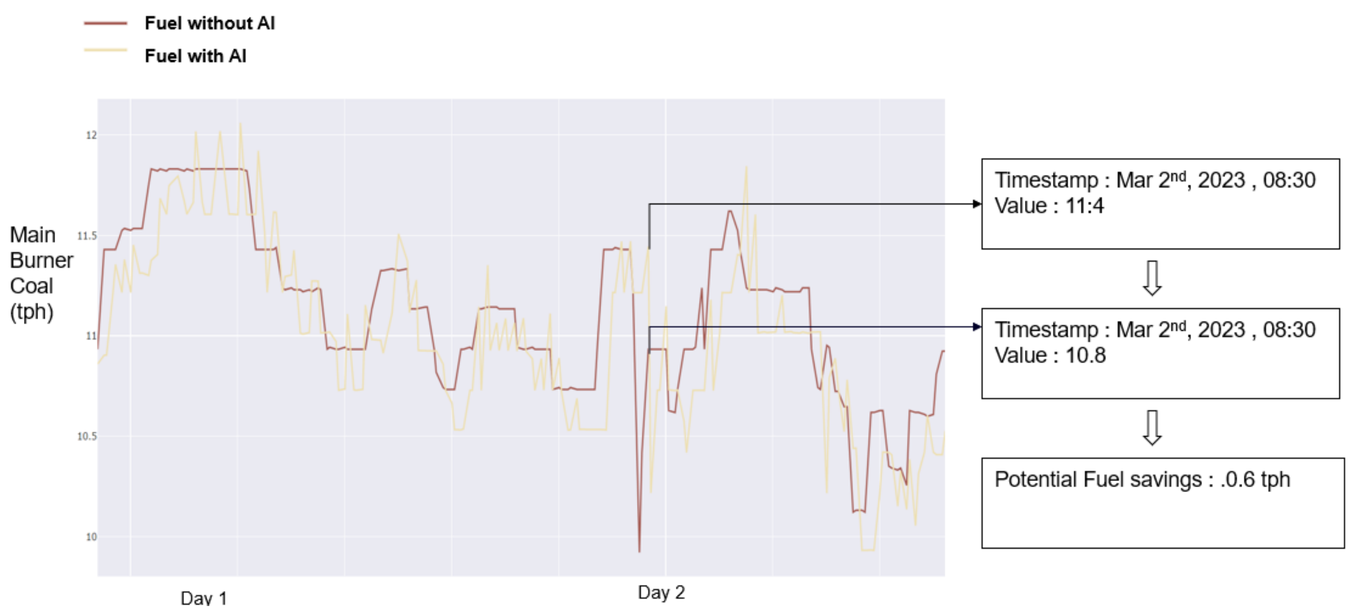

Fig. 6 - A major reduction in heat consumption

In addition to the two examples shown visually, two further examples of calculations that show the savings achieved with AI Kiln Control are shown below.

TABLE 1

RESULTS OF THE KILN PROCESS BEFORE AND AFTER USING THE AI KILN CONTROL SOLUTION

Before AI Kiln Optimization		**After AI Kiln Optimization**	
Duration of Kiln considered (hours)	24	Duration of Kiln considered (hours)	24
Average Kiln Feed (tph)	505	Average Kiln Feed (tph)	505

Coal (Actual) used in Kiln per hour(kg)	13110	Coal (Actual) used in Kiln per hour(kg)	12100
Coal used at the calciner per hour(kg)	25000	Coal used at the calciner per hour(kg)	25000
Total coal used per hour(kg)	13110 + 25000 = 38100	Total coal used per hour(kg)	12110 + 25000 = 37100
Total coal used per day(kg)	38100 * 24 = 914640	Total coal used per day(kg)	37100 * 24 = 890400
Kiln feed per day(tpd)	12120	Kiln feed per day(tpd)	12120
Production(tpd) = (Kiln feed /1.6)	7575	Production(tpd) = (Kiln feed /1.6)	7575
Specific heat (cal)	7000	Specific heat (cal)	7000
Result	845 kcal/kg of clinker	Result	822 kcal/kg of clinker

Within this example, a reduction in heat consumption from 845 kcal/kg of clinker to 822 kcal/kg of clinker was achieved. Building on this success, the reduction in CO2 emissions based on the savings is also presented. As stated above, reduction in heat consumption achieved using reduction in fuel savings that significantly reduced CO2 emission. The emissions correlating to the decreasing fuel are listed as an example in Table 2.

TABLE 2

EXAMPLE OF REDUCED CO2 EMISSIONS THROUGH AI KILN CONTROL SOLUTION

Coal savings(tpd)	Reduction in Heat consumption (kcal/kg of clinker)	Reduction in CO2 emission (MT)
6	4	9.6
8	6	12.8
10	8	18
12	10	21.6
15	12	27
20	16	36

In this example, a pilot project demonstrated that as the amount of fuel saved, emissions are also reduced. In addition to these energetically advantageous savings, lower fuel utilization also results in a lower machine load due to lower maximum temperatures. This results in less wear and therefore less maintenance-related downtime.

Among a variety of advantages of AI Kiln Control solution, the three main benefits for the cement industry are:

- Early detection of critical trends to prevent pyro process instability in clinker burning kilns and higher process reliability
- Significant fuel savings and reduction in CO2 emissions
- Lower heat load on the overall system and thus less wear and tear

This revolutionary next-generation expert system based on artificial intelligence for clinker kiln automation enables high transparency of the clinker and kiln process. In addition, as the database grows over time, so does the solution's knowledge base. This results in an ever-increasing efficiency and improvement of the operation. In this way, the Team and the solution is as a long-term partner for companies in the construction and cement industry, tries to generate an optimization of their operations as well as a contribution to sustainability.

VI. SUMMARY

Cement production is one of the most important building materials industries for our modern society. Thus, this industry not only assumes a responsibility for a resilient raw material supply but also, due to the energy-intensive industry, an important role for a sustainable society of tomorrow. Here, the burning process within rotary kilns for clinker production can be considered separately. This process step in particular is both energetically intensive and responsible for a large number of the emissions generated. In addition, this process is difficult to monitor/optimize due to its complex characteristics.

Siemens Minerals has developed an Artificial Intelligence based solution for the control and optimization of the firing process. This solution uses a predefined set of variables that are analyzed and processed by several machine learning algorithms. The result is compared in another module with the recorded experience values of the operators and the technical limitations of the plant in order to generate the best possible decision and thus result. When integrating this solution, these results are checked by the open loop approach with the operators of the plant to detect inconsistencies and thus also to ensure the performance.

In the fully implemented state of the solution, the customer can access a variety of benefits. These include increased transparency, performance improvements of the rotary kiln process, savings in fuel and emissions, and a variety of other cascading effects. With the AI Kiln Control solution helps customers to optimize their material value chain and achieve tomorrow's sustainability goals.

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