THYSSENKRUPP & NITROGÉNMŰVEK

Real-time product quality prediction of solid fertilizers

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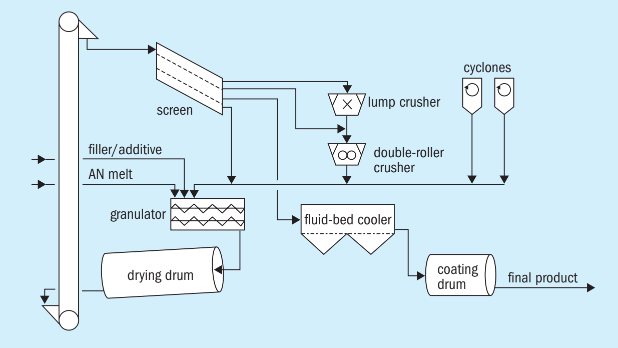
Fig. 1: The uhde® AN/CAN granulation process



Source: tkIS

The production of solid nitrate fertilizers such as calcium ammonium nitrate (CAN) and ammonium nitrate (AN) with uniform product quality is a complex task. The last step in nitrate fertilizer production, granulation (Fig. 1), with its large recycle loop is a particularly complicated system, depending on multiple variables with a high degree of variance. The following parameters all influence product quality:

- nitrogen content;
- moisture content of the product;
- particle size distribution;
- grain hardness;
- coating quality;
- friability;
- caking tendency of the product.

The product quality of nitrate fertilizers depends on a wide range of process and feedstock parameters including but not limited to the following:

- chemical composition and particle size distribution of the filler;
- climatic conditions;
- concentration, temperature and pH value of the AN melt;
- recycle rate of different solid fractions;
- temperature, humidity and amount of air to the dryer;
- the type and amount of additives;
- the frequency of revolutions adjusted for the granulation and drying drum.

This non-exhaustive list illustrates the complexity of quality control in solid fertilizer plants. The challenge is increased by the fact that there is always a time delay between cause and effect, as the intermediate streams are run in a recycle loop and the residence time in this loop is quite high. The lack of reliable online measurement methods for main product quality parameters, e.g., composition, granulometry and moisture content, also causes a time delay, as laboratory analyses have to be performed for accurate measurements. During the time taken to carry out the laboratory analyses, from sampling until knowledge of the results, production continues and off-spec product may have already accumulated by the time the operators are notified of deviations in product quality.

Furthermore, continuous monitoring of product quality is not possible if product quality is only determined by laboratory analysis, which represents product quality at a specific time.

The interdependencies between the process parameters measured by the DCS and the resulting product quality are also highly complex. Even with experienced personnel off-spec product cannot be fully eliminated, thus reducing the profit of the fertilizer producer. Additionally, off-spec product potentially harms good batches of product depending on storage procedures in place. Therefore, identifying off-spec production as early as possible and taking corrective countermeasures is beneficial for production.

Besides the operational challenges, the need for laboratory measurements requires resources for sampling and analysis by skilled personnel and therefore incurs operational expenses.

Machine learning as a solution

To solve these challenges, thyssenkrupp Industrial Solutions – Business Unit Uhde (tk Uhde) has developed a method for quality prediction based on state-of-the-art machine learning algorithms and successfully implemented it together with Nitrogénművek Zrt (NZRT) in a tk Uhde pugmill granulation plant.

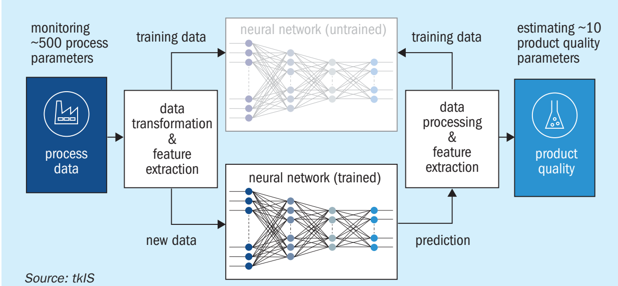
Combining its domain expertise in combination with a machine learning approach, tk Uhde has developed a soft sensor based on artificial intelligence (AI). The soft sensor is able to calculate product quality from DCS data in real time and to maximise the yield of high-quality product from CAN/AN-production plants.

Neural network models were trained with historical data in order to predict quality parameters of the solid nitrate fertilizer.

After initial training, the model was rolled out and now predicts almost instantaneously the quality parameters based on live process data coming from the DCS. Comparisons with laboratory test results show the high accuracy of the model. The offered insights regarding the expected product quality enable the operator to take measures to avoid off-spec material immediately without the delay of laboratory tests and thus maximising the yield of the production facilities. This approach can be adapted to other solid fertilizer productions and other processes with complicated interdependencies between product quality and process parameters.

Additional features like forward predictions or quality calculations in the start-up phase are currently under development. The ability to look ahead will help to minimise the inherent time delay between cause and effect of the recycle loop. In addition, it will allow timely countermeasures to be initiated to avoid off-spec production. The start-up phase is one of the most challenging periods of production and the precise knowledge of acceptable product quality is therefore of high value to the plant operator.

Fig. 2: AI model for quality prediction[1]



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AI model

The complex relationship between process parameters and the resulting product quality in solid fertilizer production make this process particularly suitable for AI-based approaches.

As shown in Fig. 2, an artificial neural network (ANN) is a collection of connected computational units (i.e. nodes) ordered in layers, which receive input signals from nodes in front of them. The signals are processed and passed to the nodes behind them. The output of each node is the value of a non-linear function of the sum of its inputs. Each node has a weight attached which is adapted during the training procedure.

All ANN have an input and an output layer and possibly multiple hidden layers in-between. More sophisticated network architectures like recurrent neural networks (RNN) allow connections of nodes to previous layers or themselves. Such network architectures are well suited to learn contextual behaviour or temporal sequences.

In the present study, a model based on recurrent neural networks has been developed, which links the measured process data from the last 45 minutes to the

Fig. 3: Comparison of soft sensor data and laboratory results

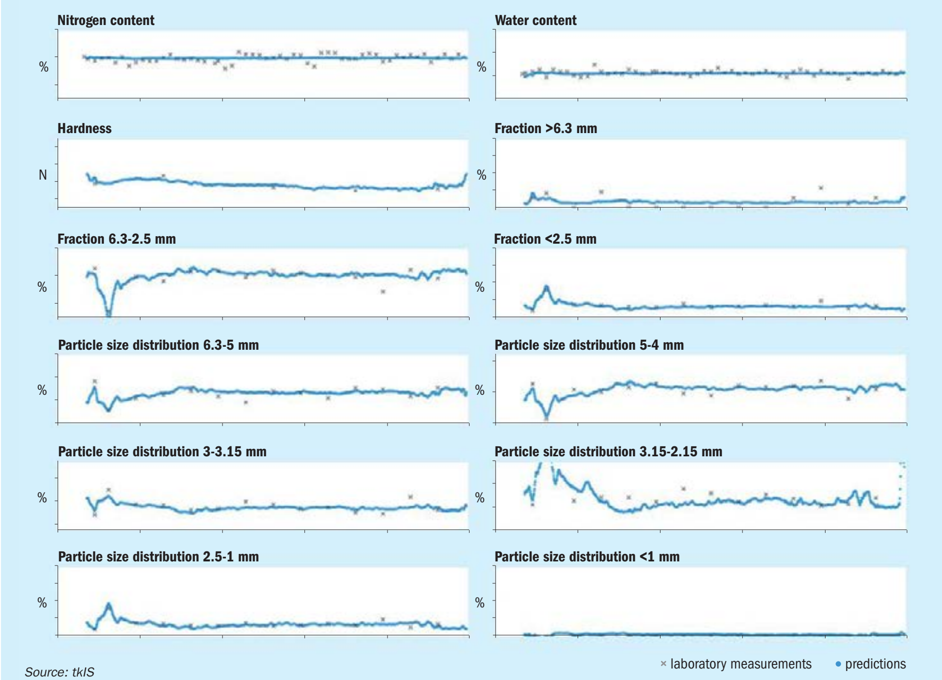

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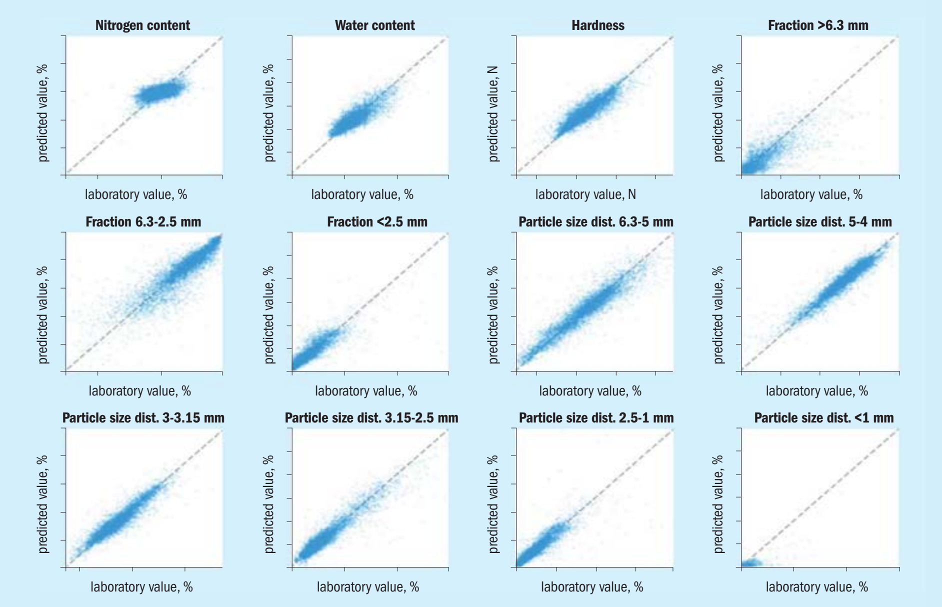
Fig. 4: **Prediction accuracy of the AI-based soft sensor**



Source: tkIS

currently expected product quality. The model takes approximately 500 process parameters as input and outputs a prediction about approximately 10 product quality parameters. The predicted parameters are the nitrogen content, product humidity, particle size distributions and hardness of the granules.

Over a period of four years, an extensive dataset was collected which consists of data of almost 1,600 process parameters and their related product quality measurements. In order to reduce the model complexity, the initial number of input process parameters could be reduced to 500 by carefully analysing and excluding parameters which are not correlated to the product quality or did not show any impact on the model performance.

The model is trained with the objective to optimally predict the product quality. The weights of the nodes in the RNN are iteratively adjusted in the training process to yield a prediction which deviates minimally from the measured product quality in the historical dataset.

In the reference project historical data was used of the installed sensors, actuators and the laboratory data of the product to set up and train a neural network. The trained neural network gives in-situ feedback to the operator about the expected quality of the product (e.g. hardness, nitrogen content, humidity, particle size distribution) and thereby eliminates or at least minimises the time delay between cause (i.e. production process) and effect (i.e. resulting product quality).

Soft sensor and dashboards

The outcome of the procedure described above is a trained model which is applied to make predictions from live process data during plant operation. In the present application, the model is installed on premises at the plant site. It queries the live process data from the plant and continuously makes predictions on resulting product quality.

The trained neural network is continuously fed with live input data of the plant and predicts the expected quality figures without delay. If the plant data change, the neural network automatically provides an updated estimation of the product quality. While the measurements from the laboratory analyses are only available at distinct points in time and with an additional delay after sample collection, the AI model delivers its predictions continuously at any point in time and with almost no time delay. Thus, the operator knows without a delay that the expected quality deviates from the desired ranges and can act in accordance with the suggestions of the model. Thereby, the amount of off-spec product will be reduced, and the yield of high-quality product will be maximised.

In addition, the AI-based soft sensor offers the unique advantage of being adaptive: As operating conditions of the plant change over time, the model will continuously learn from new data and thus can automatically adapt to any future conditions.

All results as well as the underlying process are visualised in web dashboards, which are fully customisable and can be adapted to customer needs. Furthermore, they allow process data to be queried and analysed and provide predictions at any point of time.

Table 1: **Relative prediction accuracy of main product quality parameters**

Parameter	Relative prediction accuracy, %
Nitrogen content	99.7
Water content	92.8
Hardness	96.6

Source: tkIS

Fig. 3 shows product quality over a time range of five days in NZRT's pugmill granulation plant designed by tk Uhde. The grey markers indicate the measured results of the laboratory analysis at the timestamps of sample collection. The multitude of blue points show the continuous predictions of the AI-based model.

As can be seen in Fig. 3, the general trend of the product quality parameters is well described by the model. To further discuss the accuracy of the results of the implemented soft sensor in NZRT's pugmill granulation plant, the predicted values are plotted versus the laboratory values in Fig. 4. In the ideal scenario without any measurement uncertainties and at perfect prediction precision, all values would reside exactly on the diagonal line. Measurement uncertainties as well as model prediction errors cause a deviation from the diagonal. As shown, most parameters, especially main product quality parameter like nitrogen content, humidity, hardness, and product particle size fraction, can be predicted very well. Currently, only oversize and fines fraction show slightly larger deviations.

As shown in Table 1 the AI-based soft sensor reaches an accuracy of 92% to more than 99% for the main product quality parameters as the relative prediction uncertainty ranges between 0.3 and 7.2%.

The soft sensor does not control any actuators or set any process parameters. It is essentially a tool which is reading data and estimating the product quality, i.e. an assistance system for the operator.

The operator always stays in full control of the process. Further soft sensor functions like forecasting in continuous operation or quality prediction during start-ups as well as extended dashboard functions are still under development.

Digital services offered by tk Uhde

For tk Uhde, digitalisation is a promising tool that can bring specific benefits to customers:

- extended plant uptime;
- increased production;
- enhanced efficiency;
- better maintenance planning;
- improved safety.

Any digital solution proposed by tk Uhde will optimise the plant in its lifecycle and increases the profit. Depending on the type of plant or process, this solution can be, for example, a statistical data evaluation, a digital twin of the plant or a process, or an operator training simulator[1,2]. Added value is created by combining state of the art data analytics methods with tk Uhde' expert know-how as process licensor and EPC contractor[3].

Fig. 5 is a schematic showing the interaction between the fertilizer producer and tk Uhde. Different ways exist to extract recommendations from process data and several approaches exist to combine artificial and human intelligence and hence expert know-how. A selection is made depending on the process and the situation:

- Model-driven approach: Physics-based models and simulations are combined with real-time data analytics (e.g., digital twin).
- Expert-driven approach: Known correlations, specifications and patterns are used as guiding principles for learning algorithms (e.g., statistical data analysis for trip prevention).
- Data-driven approach: Generic analytics and machine learning methods are employed, followed by expert interpretation of the results (e.g., neural network-based machine learning tools)[3].

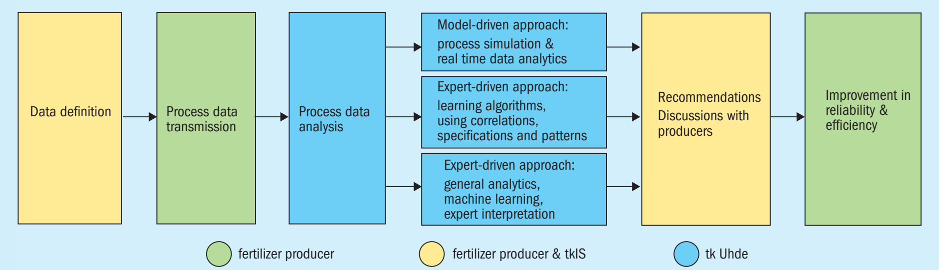
To select the best method applicable to a task, both technology expertise as well as digital know-how is required and provided. tk Uhde experts guide the plant owner through this process.

Digital products and services provided by tk Uhde combine the vast engineering and process expertise gathered as EPC contractor during decades of engineering and commissioning of process plants worldwide with state-of-the-art data-driven methods and artificial intelligence. With the best digital services, tk Uhde helps to analyse, stabilise, and optimise the plant during its lifetime and supports a safe operation[3]. ■

References

1. Franz J.: "Optimisation of fertilizer plants by digitalisation and automation", GPCA Fertilizer Convention, Muscat, Oman (2019).
2. El Hawary T.: "Plant data assessment by statistical and process analytics methods", AFA Operation & Maintenance in Fertilizer Industry Workshop, Muscat, Oman (2018).
3. Rodermund K.D and Poschlad K: Digitalization solutions for the fertilizer industry, Fertilizer Focus (May/June 2021).

Fig. 5: **Information flow between fertilizer producer and tk Uhde for process modelling**[3]



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