Digital Services for Alumina Refineries

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Abstract

UC RUSAL makes wide use of digital technologies to monitor and control alumina production processes at the refineries. The best practice technologies used comprise of digital process twins of the production processes, computational fluid dynamic and machine learning models. Digital services are developed by RUSAL Engineering and Technology Center and integrated into the work processes of the refineries. Models of chemical and engineering systems are applied to improve the operating conditions at the alumina refineries, develop production methods for new products and upgrade the existing facilities. Fluid-dynamic and heat and mass balance models help to detect deficiencies, upgrade the design and enhance the efficiency of key process equipment. Computational fluid dynamic is used to improve thickeners, washers, heat exchangers, evaporators and kilns. Machine learning helps to predict particle size distribution of aluminium hydroxide and liquor productivity in the precipitation control system. Projects associated with the implementation of online and real-time measurements are carried out, for example, on the balance of alumina and sodium carbonate in the alumina refinery, balance of soda ash production, upgraded control of the flash trains in the digestion, evaporation and vacuum cooling areas. Currently a digital process twin of the wet grinding area is being developed which involves the use of fill level sensors for the mills, computer vision, and a system of real-time measurements.

Keywords: Alumina production, Digital twins, Computational fluid dynamics, Machine learning, Advanced process control.

1. Introduction

More and more research papers focus on digital technologies and the benefits these can bring in industrial production processes. Mathematical algorithms which are extensively used at alumina refineries are becoming increasingly sophisticated. Thus, well-known Bayer process, as well as Bayer-sintering and sintering methods adopted by UC RUSAL, turn out to be quite challenging from the perspective of applying mathematical algorithms. Though high-level automation systems, e.g. Manufacturing Execution System (MES), Enterprise Resource Planning (ERP), are well elaborated, alumina refineries have some challenges with the quality and lack of data from lower levels in the control hierarchy. The latter is often attributed to limited use of online measurements in the very aggressive and abrasive alkaline and often dense slurries. Insufficient application of measuring instruments and sensors and the complex mathematical models are two major challenges for automation of alumina refineries impeding process control and monitoring as compared with oil, gas or some chemical industries.

2. Mathematical Model as a Service

Traditional PID-based single-loop and cascade control systems have limited application, and are mainly used for some of the simpler control functions. Control of complicated processes requires the use of multi-parameter models, which can predict the behaviour of the object (model predictive control – MPC) under various combinations of impacts [1, 2]. If a good model of an object is available, one needs to select a control technique that can put the object in a required condition within the shortest possible period. An optimal task can be solved using the known methods and rarely needs any special research [3, 4]. Therefore, the most important and least conventional element of the multi-parameter control system is a predictive model of the object, which influences the quality and boundaries of the automation control.

It is desired that the model should consider specific features and parameters of the equipment performance, be reliable even for irregular input data, identify the current condition and dynamics of the controlled object, and predict target parameters under any combination of impacts and disturbances. Increasing computational capabilities and developers' efforts allow generating algorithms that are more complicated; however, the more is complexity of a model the faster it gets outdated, i.e. the consistency between the model and controlled object can be lost. Maintaining the functionality of the complex model requires constant updates thereof throughout the period of use, therefore, a mathematical model can be considered a digital service.

UC RUSAL uses digital technologies to monitor and control alumina production process at the refineries. These include the development of digital twins of the production processes, as well as computational fluid dynamic and machine learning models. Digital services are developed by RUSAL Engineering and Technology Center and integrated into the work processes of the refineries. The present paper discusses some examples thereof.

3. Process Systems Simulation

In the past, specialized software was rarely used to make decisions to modify a production facility or change the alumina production process. Most of the calculations were performed by specialists in different disciplines using simplified algorithms. Such approach did not allow to consider all specifics of the plant or processes resulting in low reliability of calculation results. Generally, only a primary positive effect was evaluated and the secondary effects, often of adverse nature, were disregarded. For this reason, projects could have been associated with significant technological risks and ineffective capital spending, which were revealed only at the stage of actual project realisation.

At present specialized software for simulation of chemical engineering systems plays a significant role in digital transformation of alumina refineries [5, 6]. Due to the possibility of solving tasks with multiple recycle loops, such software enables to calculate the balances of alumina production in very detailed simulations. Consequently, such software applications can provide missing data or unexpected solutions. Implementation of SysCAD digital twins at the refineries along with responsible operators of the twins (both at the refineries and in RUSAL Engineering and Technology Center) allowed for both risk reduction and to assess the possible effects more accurately even at the design stage. Therefore, presently UC RUSAL uses SysCAD process calculations for assessment of investment efficiency.

In terms of process control at the alumina refineries, digital process twins facilitate the assessment of the impact of expected changes in the raw materials subject to availability of reagents or equipment, and help in prompt resolution of process issues. Thus, any risk of unnecessary expenses significantly decreases.

9. Conclusions

Developing and deploying *Digital Services* is a convenient approach of integrating digital process twins into the process environment of the production facility, and also to ensure the further development and servicing to maximise the long term benefits. A comprehensive suite of digital applications, such as digital process twins, computational fluid dynamic models and machine learning models, and their combination, open up new opportunities to improve the performance of alumina refineries. Equipment and process parameters are optimized using models of the process systems. Hydrodynamic and thermophysical models can help to improve the design and develop more reliable control algorithms. Machine learning models are very promising for use as predictive models in the control circuit. Computer processing of the available instrumented process data can be applied to generate new or missing data on the alumina production process (soft sensors or anomaly/deviation detection). Online system of measurement reconciliation can improve the accuracy of process measurements and provide more consistent data for process engineers and other digital systems.

Digital services enable to automate and optimize production processes, improve the data access and transparency, increase the rate and accuracy of data processing, enhance the communication and cooperation between the operators, as well as provide for advanced control and decision-making based on reliable data. Enterprises can use digital services to adjust to changing process conditions and raise competitive capacity of their products.

10. References

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