Recenzované výzkumné články

The Use of Data Mining for the Optimization of the Control Model of the Reheating Furnace

Využití data miningu k optimalizaci řídicího modelu ohřívací pece

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This paper focuses on a brief overview of theoretical and methodological solutions of Data Mining that are used for the Optimization of the Control Model of the Reheating Furnace. It is also mentioned the applicability of outputs in practice, especially in the context of the changing requirements of data processing related with the increasing manifestations of the vision Industry 4.0, which places great emphasis on the extraction of information and knowledge, which often remain hidden in the operating data. The use of wealth that is often hidden in operating data (for example, the correlation between variables, but also indications of technological inconvenience or errors in non-automated data collection and recording) is a basic prerequisite for the implementation of Industry 4.0 principles. The usability of modeling is also important in business practice outside the metallurgical field.

***Key words**: artificial intelligence; data mining; data processing; modeling*

Tento příspěvek se zaměřuje na stručný přehled teoretických a metodologických řešení sběru dat, která se používají pro optimalizaci řídicího modelu ohřívací pece. Uvádí se také použitelnost výstupů v praxi, zejména v kontextu měnících se požadavků na zpracování dat souvisejícími se stále častěji se uplatňujícím konceptem Průmyslu 4.0 založeným na získávání informací a znalostí, které často zůstávají skryté v provozních datech. Použití bohatství, které se právě často skrývá v provozních datech (například korelace mezi proměnnými, ale také náznaky technologické nekázně, nebo chyby v neautomatizovaném sběru a zaznamenávání dat), je základním předpokladem pro implementaci zásad Industry 4.0. Použitelnost modelování je také důležitá v obchodní praxi mimo oblast metalurgie. Článek zmiňuje problematiku nástrojů umělé inteligence, jsou zde stručně popsány právě ty, které lze s úspěchem využít při jednotlivých fázích procesu zpracování dat, zejména jde o nástroje hlubokého učení (tzv. deep learning – specificky pak možnosti analýzy textových informací, analýzy mluveného slova, analýza obrazu a simulace chytrého chování), dale je zde popsána možnost využití umělých neuronových sítí při vytváření modelů dynamických soustav (například EKF – tzv. Kalmanův filtr, dále DNN´s, což je hluboká neuronová síť používaná s úspěchem pro rozpoznávání mluvené řeči). Zajímavý pak je příklad využití umělé neuronové sítě pro predikci teploty v konkrétní ohřívací peci, který zachycuje, jak dokáže model, při jehož vytvoření byla využita právě umělá neuronová síť, predikovat teplotu pecního prostředí. S ohledem na to, že teplotu v peci nelze bez relativně vysokých nákladů (ty jsou dány náklady na termočlánky s omezenou životností, či jiné měřící nástroje a náklady na samotné měření) spolehlivě určit, je vhodné ji predikovat a k tomu právě takto vzniklý model může sloužit. Průběh teploty v ohřívací peci je například u normalizačního žíhání ve slévárnách dán technologickým předpisem a jeho nedodržení (příliš rychlé/pomalé ohřátí, nedodržená doba výdrže apod.) mohou mít zásadní vliv na kvalitu výsledného výrobku. Jedná-li se o pec pro předehřívání polotovarů pro další zpracování, může mít nižší/vyšší teplota polotovaru, než je dáno předpisem, taktéž vliv na kvalitu výrobku a výrazně také může ovlivnit životnost následné technologie (např. vyšším opotřebením válců či dopravníku).

***Klíčová slova**: umělá inteligence; data mining; zpracování dat; modelování*

Data mining is a general term for various methods of data analysis, often using artificial intelligence. The process of data mining is based on tabulated or otherwise arranged usually blind dates. It ends by finding of knowledge (patterns) contained in these data, which are expressed in a simpler and clearer form, and which can be used easily in dealing with future situations than the original data.

Monitoring and control systems collect for the purpose of monitoring a number of operational data. These systems construct their databases as simply as possible; each trend is usually stored in a separate table. Data in the tables are stored according to two basic principles, either periodically after a preset time interval or after a certain event - change of a variable value. Many systems use

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ISSN 0018-8069

their own mechanisms for storing data that combine both periodic data storage and storage management using a change of value. These data must be preprocessed before deploying data mining [1].

In that connection the question arises, how to further process the obtained data so that the knowledge hidden there can be made usable in order to optimize individual production processes, or the entire production process. Just here not only the conventional methods of data analysis, identification and modeling are applied, but use of artificial intelligence tools is also assumed.

In business practice, a very recent connection of process management, its models and prediction with higher levels production management is emphasized, especially in the field of process management, its identification, description, hierarchy and classification, so that it is possible to create the connection between the technological processes at the basic level and processes at the managerial level controls. Attention should be paid to the interconnection of SCADA / HMI systems and ERP systems. This connection further enables focusing on creation of hybrid models of dynamic systems. Dynamic systems here are understood as systems in the sense as broad as possible, it means that they are understood by the operational analysis. The research concept in the framework of further research will be focused on describing the same object from the widest possible point of view and from various aspects. More information is mentioned in the following chapter.

1. Artificial intelligence tools that are usable in data processing and analysis and modeling of behavior of dynamic systems

In recent years, the subject of big data, data mining, artificial intelligence, deep-learning, neural networks etc. is discussed a lot. As mentioned in the previous chapter, this is not a completely new topic, but it is definitely the theme that is very up to date and its further development and massive use in practice can be expected.

1.1 Deep learning

Simply said, deep learning applications are not programmed, but they are trained using real big data on how to behave in different situations. But this is not easy because they are prone to erroneous interpretations so they need a team of experienced specialists [2]. At least 4 typical areas are existing where a duel of top scientific workplaces is visible and significant progress can be made almost every day. These fields are particularly the following:

Text Information Analysis

Deep-learning moves the text analysis towards "understanding" the significance of the document being examined. The process that leads to this result is not quite simple. This means creating the database (corpus) as large as possible of text documents, for which there is systematically described content (in the background there is a vector description of the language indicating the most frequent occurrence of words and allowing them to estimate their order). A system that knows what is written in the text can then solve the situation when the same or similar sentence appears in a completely different context. The problem is, of course, very complicated. Analysis still does not function for 100% of cases. It can be documented, for example, in a commonly used automated translation based on a similar content classification for different languages [3].

Spoken Word Analysis

It is still a long way from understanding the text document to the ability to listen and to talk. China's Internet service provider Baidu (the equivalent of Google) probably passed the longest part of that way, saying that his latest DeepSpeech 2 mobile application, used by a personal assistant called Duer, understands the spoken word even better than a human being [3]. Even under difficult conditions, it is able to interpret correctly approx. 95% of the words.

Also here, the artificial intelligence had to learn to understand at first, by having the chance to compare the sound and text of the same content on large data. In addition, the soundtrack was purposefully distorted and masked by other sounds. Duer, except English, knows also most of the Chinese dialects, so may become a useful help for the communication of Chinese people between themselves. Andrew Ng, the head of deep-learning research in Baidu, says that the era when "we all use voice recognition to manage things around us all the time" is coming very fast.

Image Recognition

This discipline started with the recognition of printed text letters. This was reached with a respectable success before the arrival of deep learning. The analysis of the hand-written text seemed to be a much more difficult task. And machines can do even this with the help of neural networks and they can proceed further. Perhaps the best-known higher-level application we are meeting every day is the recognition of peoples´ faces. Google and Facebook went the farthest in this field. Facebook is trying to get face recognition in the slightest way, nevertheless, this function is in the center of general interest.

Deep learning is taking place at several levels. Even the current advanced technologies do not manage yet the analyses of the entire photo in detail so it is necessary to identify first the places we are interested in (it is similar to the exploring of satellite photos by secret). At the highest levels, the physiological data are detected that are uniquely identifying every single person. The last item for filling in is the assignment of personal information. One photo on Facebook (or elsewhere), to which someone has added names of people, is enough - and that’s it. Facebook of today knows the faces of millions of people.

It has the largest similar databases in the world. In this case, no State Security Service can be compared [4].

Simulation of Smart Behavior

The first thing that may occur in connection with the previous item, is how the image analysis of the self-controlled car system must be done. Of course, it distinguishes different objects, though not in such detail. But it will be certainly important for how fast those objects are moving and whether they are approaching. Car self-control elements are becoming quite common (parking, highway driving, etc.) and in the near future, they can cause loss of their jobs to professional drivers. Very probably similar systems will be found in common cars, too. For example, Toyota plans to use in all new cars its anti-collision system, which takes over critical driving, in 2017, and from 2020 the sale of fully self-controlled cars. Though the ideas about self-controlled cars are very interesting, let's leave them to others.

1.2 Use of neural networks and other artificial intelligence elements in modeling

A very interesting view of the problem can be found in the article "New approach to the application of a neural network in a nonlinear dynamic model" [5], which deals with the use of a radial base neural network (RBF-NN) for emulating the expanded Kalman filter (EKF) at data assimilation. The dynamic model studied here is primarily used to predict weather development, but with respect to the same principles, it would be analogously usable in modeling, e.g. in the field of behavior if the heating furnace in the metallurgical industry. Although this model is simple, it represents some atmospheric movements, such as gravitational waves. In the literature it was demonstrated that the ability of EKF of following the nonlinear models depends on the frequency and accuracy of observations and model errors. Artificial neural network (ANN) is an alternative solution to the use of conventional methods (e.g. regression analysis, or time series analysis).

Deep Neural Networks (DNNs) have been very successful in various applications, such as in object recognition applications [6] and speech recognition [7]. Other works also show that neural networks can be successfully used in many cases of processing of human speech. They also allow the detection of paraphrases and the detection of inserted words [8]. In the field of statistical machine translation, the use of deep neural networks has begun to show promising results. Schwenk [9] also summarizes the successful use of direct neural networks in the systems based on statistical machine translations. Within the frame of this research line using neural networks for statistical machine translation, the so-called "Novel neural networks", which can be used as a part of commonly used translation systems, are gradually starting to establish themselves, too.

Despite their flexibility and performance, DNNs can be used only for the problems, the inputs and targets of which can be reliably encoded by the fixed-length vectors. This is a significant limitation because many important problems are best expressed by sequences, the lengths of which are not known at first. Speech recognition and machine translation are, for example, sequential problems. Thus, it is clear that a method that is independent of the domain, and which learns to map sequences into sequences, would be useful.

Figure 1 shows the use of an artificial neural network to predict the temperature in a heating furnace. It captures how a model which was created by the artificial neural network can predict the furnace temperature [10]. The furnace temperature cannot be reliably measured without relatively high costs (it is limited the due lifetime of thermocouples or other measuring instruments and the costs of measurement itself), and that's why it is advisable to predict the temperature by using the model created by ANN. The temperature curve is given by technological instruction (for example during standardization annealing in the foundry) and non-compliance (too fast / slow heating, or continuous time, etc.) can cause a significant effect on the quality of the final product. In the case of a heating furnace (the lower / higher temperature of the workpiece) can not only affect the quality of the product and significantly affect the lifetime of the subsequent technology [11].

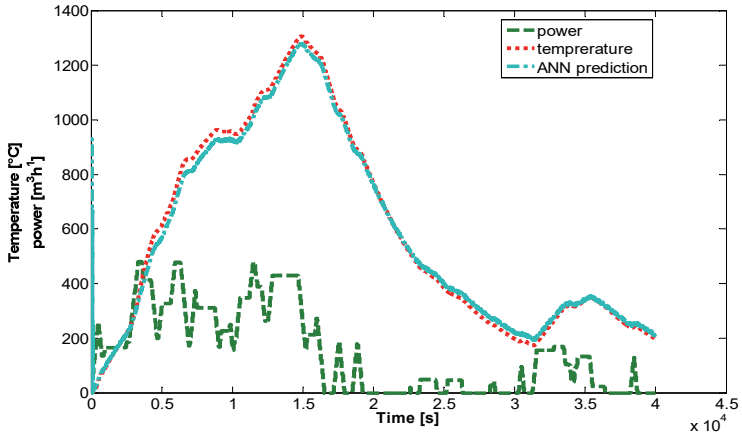

Fig. 1 The example of using an artificial neural network for prediction of the temperature in the furnace. Source: our own processing
Obr. 1 Příklad využití umělé neuronové sítě pro predikci teploty v peci. Zdroj: vlastní zpracování

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ISSN 0018-8069

Conclusions

In order to be used in process control of the metallurgy production, the artificial intelligence tools must be capable of processing and analysing a large amount of technological data in a short time, and that's why it is also very important to use data mining tools, so that the data collected in technological units are good and consistent, and the machine learning process runs efficiently and without unnecessary mistakes, which needs to be ensured in the context of further learning.

In this process the data preparation is essential – it is an important issue for data storing and data mining, as real-world data tend to be incomplete, noisy, and inconsistent. Data preparation includes data cleaning, data integration, data transformation, and data reduction. Data cleaning routines can be used to fill in the missing values, to smooth the noisy data, to identify outliers and to correct the data inconsistencies. Data integration combines data from multiple sources to form a coherent data store. Metadata, correlation analysis, data conflict detection, and the resolution of semantic heterogeneity contribute to the smooth data integration. Data transformation routines adapt the data to appropriate forms for mining. For example, data attributes can be normalized so as to fall between a small range, such as from 0 to 1.0. Data reduction techniques, such as data cube aggregation, dimension reduction, data compression, numerosity reduction, and discretization, can be used to obtain a reduced representation of the data while minimizing the loss of information content. Concept hierarchies organize the values of attributes or dimensions into gradual levels of abstraction. They are a form of discretization that is particularly useful in multilevel mining. Automatic generation of concept hierarchies for categorical data may be based on the number of distinct values of the attributes defining the hierarchy. For numeric data, such techniques as data segmentation by partition rules, histogram analysis, and clustering analysis can be used. Although several methods of data preparation have been developed, the data preparation remains an active and important area of research.

When searching for available information and usable tools, the commercial tools have been identified, but also the ones, which were available and free of charge. By evaluating the suitability of these tools the Tensor Flow is considered as a very promising tool developed for deep learning application.

Deep learning is used in most cases to recognize images or textual analyses of various sources (such as the web). Its principle is based on the cascading recognition of certain patterns (typically facial recognition, plant or animal recognition according to their characteristic features). In technical practice, commonly used models of systems are linearized. Non-linearities, or different responses of dynamic systems to the input impulses under different conditions (e.g., different operating points, temperatures, pressures, etc.) lead to a very dynamic behavior of these systems. The principles of deep learning can categorize these different behaviors and in his way it can create a model of the behavior of a particular technical system based on the learned neural networks that will be activated when a behavioral pattern of input data is found.

Acknowledgments

This article was supported by the specific university researches No. SP2017/38 and No. SP2017/63.

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