A Global Study of Green Cement Intelligent Manufacturing Based on Artificial Intelligence

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Abstract: This paper delves into the exploration of artificial intelligence (AI) applications in the cement industry, with a particular emphasis on the manufacturing of green cement. It investigates current situation and difficulties in the cement industry, such as the lack of self-developed software. Then, this paper suggests AI-based solutions to overcome these hurdles. The study discusses three key intelligent manufacturing technologies that have the potential to revolutionize the cement industry. These include the identification of abnormal working conditions, prediction of cement compressive strength, and the application of digital twin technology. Through various case studies, the transformative potential of these technologies is analyzed, providing a comprehensive understanding of their impact on the cement industry. This paper further examines the influence of green low-carbon intelligent manufacturing on China’s cement production capacity. It highlights how the adoption of these technologies can lead to more sustainable and efficient practices in the cement industry. The study concludes with recommendations for the application of AI in cement and other process industries, emphasizing the need for embracing AI to enhance sustainability and efficiency. The overarching aim of this study is to illuminate the prospects of AI in augmenting the sustainability and efficiency of the cement industry, thereby contributing to the broader discourse on AI applications in industrial processes.

Keywords: Cement Industry; Smart Manufacturing; Digital Twin

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1. Introduction

China is moving from a big country of building materials to a strong country of building materials, and has entered a critical stage. The goal of the "14th Five-Year Plan" is to make all the building materials industries reach the level of "Made in China" and "Created in China", so as to realize the strategy of "10th Five-Year Plan" for China's building materials industry to realize the innovation and enhancement, and to go beyond to lead the world. The building materials industry of China in the "Tenth Five-Year Plan" to achieve innovation and enhancement, beyond leading the world building materials industry to undertake the historical mission of the implementation of the strategy [1]. The introduction of artificial intelligence technology is expected to create a new era for the high-quality development of the building materials and cement industry, has been the general trend.

From the series of policies issued by the state, such as the "14th Five-Year" Intelligent Manufacturing Development Plan, "Building Materials Industry Intelligent Manufacturing Digital Transformation Action Plan (2021-2023)", "Carbon Peak Action Program by 2030", ""14th Five-Year"" Energy saving and emission reduction comprehensive work program" and so on can be seen, the traditional manufacturing industry, the number of

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intelligent transformation and upgrading and energy saving and carbon reduction is undoubtedly the national level during the 14th Five-Year Plan to do the big things, is the CPC Central Committee, the State Council made a major strategic plan. In particular, the work program emphasizes "to implement key industry green upgrading project; by 2025, through the implementation of energy saving and carbon reduction actions, cement and other key industries, production capacity and data centers to reach the energy efficiency benchmark level of more than 30%" [2, 3]. The intelligent construction of the cement industry has gradually entered the fast lane, while facing brand new opportunities and challenges. Among them, the chimney-type data silo, the bottom data redundancy, quality data lag, can not provide decision-making support for upper management; In addition, the key core platform and algorithms of the "missing" greatly increased the cost of intelligent manufacturing in China's cement industry, which is not conducive to the transformation and upgrading of the industry. Internet, big data, artificial intelligence and other new-generation information technology will help break through the bottleneck of intelligent manufacturing technology in the cement industry, overcome the core key technologies that constrain the strengthening of the industry chain, and play an important technical support role in pushing the energy-saving and carbon-reducing production of cement and improving quality, as well as upgrading the digitization and intelligence level of the cement industry.[4].

2 The Current Situation and Difficulties of the Cement Industry

The scenarios and issues faced by the cement industry are complex and varied, focusing on the following aspects.

2.1 Intelligent Control Software

Intelligent control software for the cement and building materials industry relies on mature foreign products, and there is a relative lack of domestic self-developed software with weak functions. Foreign mature products are relatively closed, function curing, only meet the industry's routine needs, software license price is very high, debugging is also heavily dependent on foreign engineers, upgrade iteration is slow, it is difficult to respond quickly to new needs, and the core function is not open, APC software to stabilize the control of the main benefits are not obvious enough [5, 6]. Domestic self-developed software functions are relatively weak. With the deepening of the intelligent construction of cement industry, the customization and intelligence degree of intelligent control software is more and more demanding. Dependence on foreign software leads to high cost of intelligent manufacturing in China's cement industry, which is not conducive to the transformation and upgrading of the cement industry. [7]

2.2 Intelligent Control Technology

The development of intelligent control technology in the cement and building materials industry has roughly gone through the process of PID control, expert system, APC control, AI intelligent optimization control, etc. At present, the commonly used intelligent control technology is the expert system, APC software, which only stays in automation, realizes the card-edge control, and relies on the manual operation experience to train and build the single-loop multivariable model control strategy, and the target value is set by the operator manually according to the experience. The target value is set manually by the operator according to his experience, and when the working condition changes or abnormal working condition occurs in the process of operation, the operator can manually intervene in the target value or directly quit the automatic control, which has a low commissioning rate and a poor user experience for the operator. Lacking the functions of online process self-learning and global optimization search, it cannot automatically analyze the best working conditions and automatically set parameters for control, making it difficult to cope with problems such as multi-dimensional linkage control, global optimization control, quality prediction, and identification of abnormal working conditions.

2.3 Production Process

Cement production process is strong, affected by the quality of raw materials, process condition parameters volatility, especially clinker calcination process as the core, with a long time lag, large inertia, strong coupling of the significant characteristics of the control software of the whole working conditions adaptability requirements are very high, the abnormal working conditions identification needs urgent but the research and application results are not good. Based on AI algorithms, video judgment, expert systems and other technologies, abnormal working condition recognition in the chemical industry, automobile driving industry research is quite a lot [8, 9], the cement industry due to the digitalization level, raw material changes, complex working conditions and other multiple factors, the research effect is not good, but the demand is urgent, such as: "pile up the snowman"," The cement industry is not well researched due to multiple factors such as digitization level, raw material changes, complex working conditions, etc. However, there are urgent needs, such as: "snowman", "poor coal", "kiln skin" and other common abnormal working conditions, which seriously restrict the healthy development of the cement industry. [10]

2.4 Critical Parameter

The key parameters of the cement industry are not measurable, and there is a lack of on-line testing and analyzing instruments, and cement quality data are missing. The strength of cement clinker plays a decisive role in cement quality, and at present, the 28-day compressive strength is physically inspected by hand, and there are problems such as large lag. Cement production process has typical process control characteristics, the use of AI algorithms, big data analysis and prediction means to predict the quality data of cement clinker free calcium oxide, 28-day compressive strength, etc., which can help to flexibly adjust the cement grinding ratio, clinker calcination process control, and is of great significance to stabilize the kiln condition and cement quality.

2.5 Visualization Level

The degree of visualization of the whole process of cement production is low, and it is more difficult to realize display, monitoring, management and linkage. Three-dimensional digital twin technology to realize the fusion of virtual and real intelligent production will become an important field of AI empowerment [11], Sinoma Bangye after several years of joint research, based on the process mechanism research and process simulation has been sufficient knowledge accumulation, three-dimensional digital twin also has a certain foundation, based on AI algorithms, process mechanism simulation, thermodynamic diagnosis and other artificial intelligence applications fusion three-dimensional digital twin technology has the feasibility.

3 The Current Situation and Difficulties of the Cement Industry

AI has been put into use and continuously developed in the intelligent manufacturing of green cement. This paper will introduce some important application aspects and development as follow.

3.1 Anomalous Working Condition Identification Technology

More research has been done in various industries in terms of recognizing anomalous working conditions. The application of remote network video surveillance system to the cement calcination industry has matured as early as 2006, Sarah et al. [12] combined deep learning and SVM for high-dimensional and large-scale anomaly data detection. Experimental results show that the proposed model can achieve anomaly detection performance comparable to that of a deep autoencoder, while reducing the training and testing time by 3 and 1000 times, respectively. Zhao et al. [13] utilize multiple deep confidence sub-networks for chemical process fault diagnosis, and validate the superiority of the proposed method by comparing it with PCC and other methods. Wang et al. [14] propose a Deep Brief Networks (DBN) based on a deep confidence network (DBN). Wang et al. [15] propose a health state classification method based on Deep Brief Networks (DBN), and verify the effectiveness of the proposed method by diagnosing the health state of aircraft engines and power transformers. Tran et al. propose an algorithm based on the Taer-Kaiser energy operator and a deep confidence network for reciprocating compressor valve fault identification and diagnosis. Using a two-stage reciprocating air compressor as an experimental case, the proposed method is verified to have high reliability by comparing it with SVM and BP neural network. Sun et al. [16] propose a deep confidence network-based automatic fault detection method and a selfencoder-based fault data generation method using deep neural network to solve the problem of fewer samples of faulty working conditions in the actual production process. Su et al. [17] propose an algorithm based on the ICA and sparse self-encoder-based fault identification and diagnosis algorithm, and the TE process is used as an experimental case to verify the effectiveness of the proposed method. Jing et al. [18] proposed an adaptive CNN for fault identification of gearboxes, and compared it with fully-connected neural network, SVM, and random forest method, which reflects the superior feature extraction and fault identification capability of CNN.

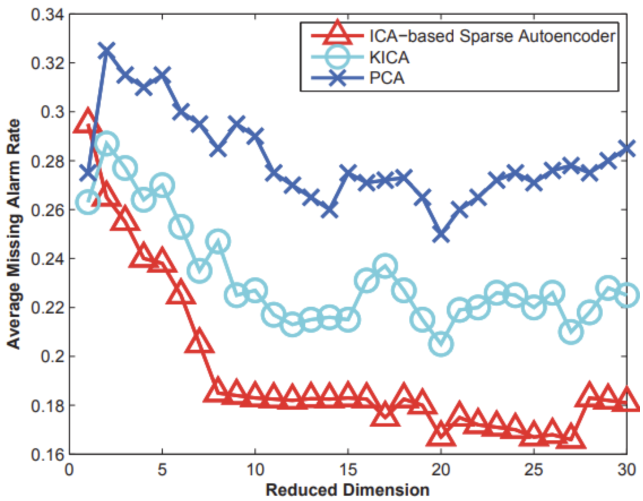

Figure 1 Fault identification and diagnosis algorithm based on ICA and sparse selfencoder

3.2 Cement Compressive Strength Prediction Technology

For cement compressive strength prediction, in 2013, Gupta [19] proposed a neural network model to predict concrete strength at 3d, 7d, and 28d and to create an approximate concrete proportion design. By using this neural network model, the number of test trials can be reduced. In 2016, Mola Abasia et al. [20] used a polynomial neural network to predict zeolite-cement-sand unconfined compressive strength. In their study, they demonstrated that this method has a strong ability to predict the unconfined compressive strength. Chithra et al. [21] predicted the compressive strength of high performance concrete using regression analysis and artificial neural network models. They demonstrated that the artificial neural network model has better results when accuracy is required and complexity is high. Chopra et al. [22] developed a concrete strength prediction model using neural networks and genetic programming. The authors concluded that the neural network model with the training function of the Leffenberg-Marquardt algorithm provides the best predictive tool for concrete strength prediction. In 2017, Khademi et al. [23] compared multiple linear regression, neural networks and adaptive neuro-fuzzy inference systems and showed that neural networks and adaptive neuro-fuzzy inference systems can predict concrete strength at 28d more accurately. In addition, Behnood and Golafshani [24] used a multi-objective optimization method to determine the minimum error and developed a neural network model to evaluate the compressive strength of silica fume concrete. 2019, Wang et al. [25] proposed a wavelet neural network for short-term evaluation of concrete compressive strength.

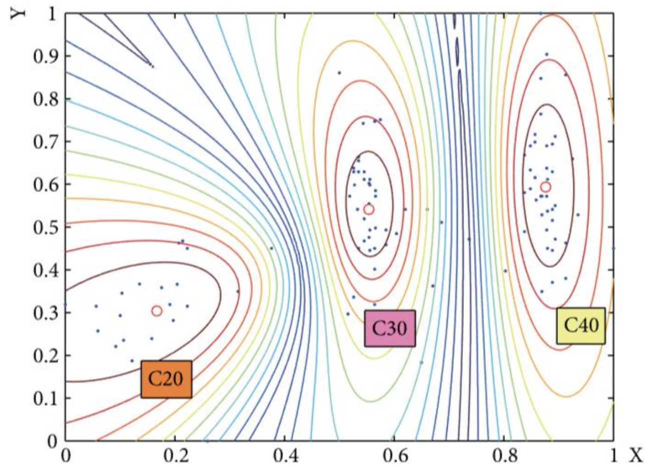

Figure 2 Estimation of specific compression test data based on wavelet neural network modeling

3.3 Digital Twin Technology

At present, digital twin has become one of the research hotspots of intelligent manufacturing. Tao Fei's team [26, 27] proposed the concept of Digital Twin Shop-Floor (DTS) for the interaction and fusion of physical space and virtual space in manufacturing workshop, and divided Digital Twin Shop-Floor into four parts, namely, physical workshop, virtual workshop, workshop service system and workshop twin data, and put forward the operation mechanism and realization method of DTS, but SMEs Due to the lack of ability in developing digital twins and the development advantages are not obvious yet, which leads to the lack of enthusiasm of SMEs to carry out digital twin transformation and upgrading. For this reason Thomas H J et al. [28] established a digital twin-based learning factory to meet the learning needs of SMEs for an easy-to-use, scalable, service-oriented control system based on digital twins. At the same time, in order to consider production employees as part of an integrated control system, Graessler Iris et al. [29] developed an employee-based digital twin production system.

4 Conclusion

China's existing stock of cement clinker production lines of about 1,500, the stock of production lines and new production lines of green low-carbon smart will be the cement enterprises for quality and efficiency, transformation and upgrading of the necessary options. By 2025, more than 30% of the capacity will have a combined clinker energy consumption of ≤100 kgce/t total limit, which will drive about 820 million tons of national capacity to be transformed. The results of the project can also be applied to other process industries, with nearly 5,000 similar industrial kilns (sets) in China, which has a huge market prospect. Based on industrial Internet, big data, cloud computing, image recognition, digital twin, etc., in the "AI + APC intelligent control, AI algorithms + machine vision, working condition identification, model quality prediction, digital twin visualization" technology, can form the AI ability matrix, real-time perception, diagnosis and quality prediction of the cement production dynamics It can realize real-time perception, diagnosis and quality prediction of cement production dynamics, empowering cement intelligent production, energy saving and carbon reduction, and improving quality and efficiency. These AI technologies and methods provide new possibilities and directions for the future development of the cement industry. Hoping that these technologies will make greater contributions to the green and intelligent development of the cement industry in future practical applications.

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