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Review

Research Progress of Intelligent Ore Blending Model

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Abstract: The iron and steel industry has made an important contribution to China's economic development, and sinter accounts for 70–80% of the blast furnace feed charge. However, the average grade of domestic iron ore is low, and imported iron ore is easily affected by transportation and price. The intelligent ore blending model with an intelligent algorithm as the core is studied. It has a decisive influence on the development of China's steel industry. This paper first analyzes the current situation of iron ore resources, the theory of sintering ore blending, and the difficulties faced by sintering ore blending. Then, the research status of the neural network algorithms, genetic algorithms, and particle swarm optimization algorithms in the intelligent ore blending model is analyzed. On the basis of the neural network algorithm, genetic algorithm and particle swarm algorithm, linear programming method, stepwise regression analysis method, and partial differential equation are adopted. It can optimize the algorithm and make the model achieve better results, but it is difficult to adapt to the current complex situation of sintering ore blending. From the sintering mechanism, sintering foundation characteristics, liquid phase formation capacity of the sinter, and the influencing factors of sinter quality were studied, it can carry out intelligent ore blending more accurately and efficiently. Finally, the research of intelligent sintering ore blending model has been prospected. On the basis of sintering mechanism research, combined with an improved intelligent algorithm. An intelligent ore blending model with raw material parameters, equipment parameters, and operating parameters as input and physical and metallurgical properties of the sinter as output is proposed.

Keywords: intelligent algorithm; sintering foundation characteristics; liquid phase formation capacity of sinter; influencing factors of sinter quality

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1. Introduction

The world's iron ore resources are dominated by large-scale, high-grade, and low-cost open-pit mining, with an average grade of 46.7%. Although the overall grade of iron ore is high, the grade of iron ore varies greatly. Among them, the grade of iron ore from the United States, China, Ukraine, Brazil, Australia, Russia, and India is 33.3%, 34.5%, 35.4%, 44.1%, 48%, 56%, and 61.8% [1], as shown in Figure 1. Although China has abundant iron ore reserves, its iron ore resources are mainly small-scale, low-grade, and high-cost underground mining, with the average grade of iron ore being 34.5%. Moreover, most iron ore is lean ore, and it usually takes 2.5 to 4 tons of iron ore to produce 1 ton of iron products [2,3]. Therefore, China's iron ore production cannot meet the large consumption of iron ore powder resources in China, so it needs to import a large amount of iron ore from Australia and Brazil. Although Australia and Brazil have high iron ore grades, the two countries have large land areas, and iron mines are relatively scattered, resulting in differences in the composition of iron ore in different countries and places due to the differences in geological conditions [4,5]. China imports dozens of foreign iron ore powder. In addition, due to the impact of transportation, price, and other aspects, iron, and steel enterprises need to replace new ore powder from time to time in sintering production.

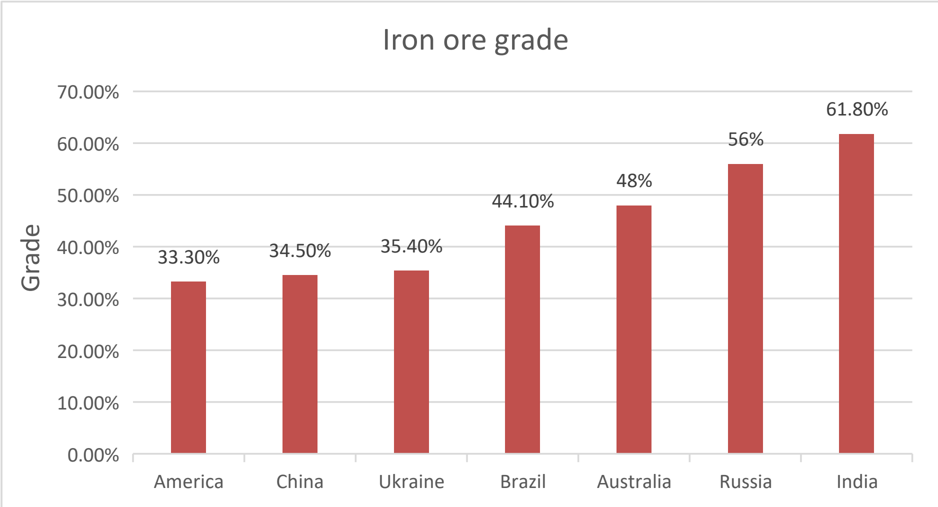

Figure 1. High and low iron ore grades by country.

In actual production, the sinter batching is usually adjusted manually according to the experience of engineers, and it is difficult to master the rules in this method. According to the experience of ore blending, the optimal quality of sintered ore is often not obtained, resulting in waste of raw materials and environmental pollution. In addition, it takes a long time to replace the new ore powder with a sintering cup experiment, and a complete set of sintering cup experiments takes about ten hours, which is time-consuming and laborious. Therefore, the control of raw material parameters, equipment parameters and operation parameters, the development of optimal sintering ore allocation, and the study of intelligent ore allocation models are tasks that need to be accomplished urgently in the steel manufacturing industry. Therefore, it is an urgent task to study intelligent ore blending models in the iron and steel manufacturing industry. Sintering foundation characteristics, liquid phase formation capacity of the sinter and the influencing factors of sinter quality were studied. Combined with an intelligent algorithm, it can carry out an intelligent ore blending more accurately and efficiently.

2. Intelligent Ore Distribution Theory

Sinter production is a mixture of raw materials containing iron, melts, fuels, and returned ore, which is mixed and watered for the first time and granulated and watered for the second time [6]. After pelletizing, a uniform fabric is placed on top of the sintering trolley, which is then fired and sintered, resulting in a finished sintered ore. Among them, the iron-bearing raw materials are various iron ore powder and block ore, the flux includes dolomite powder and limestone powder, the fuel is coke, and the return ore is sinter less than 5 mm [7], as shown in Figure 2.

The evaluation indicators of sinter quality are the physical properties and metallurgical properties of the sinter [8,9], and the quality of the sinter is generally evaluated by these two properties. The two indicators that have the greatest influence on the physical properties of sintered ore are the drum index and the yield [10]. The four indicators that have the greatest influence on the metallurgical properties are the low-temperature reduction pulverization index RDI, the reduction index RI, the load softening temperature $T_{10\%}$, and the load softening temperature $T_{40\%}$ [11]. All these indices can be obtained experimentally and used as output indices in the intelligent ore allocation model to evaluate the quality of sintered ore.

Figure 2. Sintering Metallogenesis process of iron ore powder.

Factors affecting the quality of sinter ore are influenced by parameters such as operating parameters and equipment parameters, in addition to raw material parameters [12]. In order to obtain a good quality sinter ore, it is necessary to adjust the relationship between the various parameters and the effect on the physical and metallurgical properties of the sinter [13]. However, this is not a simple linear relationship, and traditional ore allocation methods are complex and time-consuming to operate and difficult to solve complex ore allocation problems [14]. Therefore, the introduction of intelligent algorithms to study the ore allocation model will enable companies to change the sintering raw materials and equipment without changing them. The intelligent ore allocation model changes the raw material parameters ratios and adjusts the operating and equipment parameters [15].

3. Research Status of Intelligent Ore Blending Model Based on Intelligent Algorithm

Traditional sintering ingredients mainly rely on manual experience, including theoretical calculation methods summarized according to sintering experience, the use of Excel function for the ore blending algorithm, and the optimization goal of the lowest-cost linear programming method [16]. The traditional ore blending method has the advantages of fast calculation speed, simplicity and convenience, but it is only suitable for the case of fewer ore species, and the accuracy depends on manual experience [17].

At present, most steelmakers rely mainly on imported iron ore, which has an unstable composition. In order to solve the problems of multiple ore species, nonlinear, multiple parameters, and large scale in sintering ingredients, the application of an intelligent algorithm is more efficient and accurate [18,19]. In the intelligent ore blending model, an intelligent algorithm is the key link of the model. Intelligent algorithms such as genetic algorithm, neural network algorithm, and particle swarm optimization algorithm can solve some problems of ingredients by themselves, but it is difficult to get the optimal solution. A better optimal solution can be obtained using a combined algorithm [20]. Therefore, this paper analyzes and studies the application of neural network algorithm, particle swarm optimization algorithm, genetic algorithm, and their improved algorithms in intelligent ore blending models.

3.1. Research on Intelligent Ore Blending Model Based on Neural Network Algorithm

Neural network algorithm is a commonly used algorithm in intelligent ore blending models. As shown in Figure 3, Neural network algorithm have the advantages of self-organization, self-adaptability, self-learning, nonlinear approximation capability, stable performance, and wide application and are often used as algorithms for intelligent ore allocation [21,22]. However, it also has disadvantages such as slow operation speed, not easy to reach a global optimum, and difficulty in determining network parameters and training parameters [23,24].

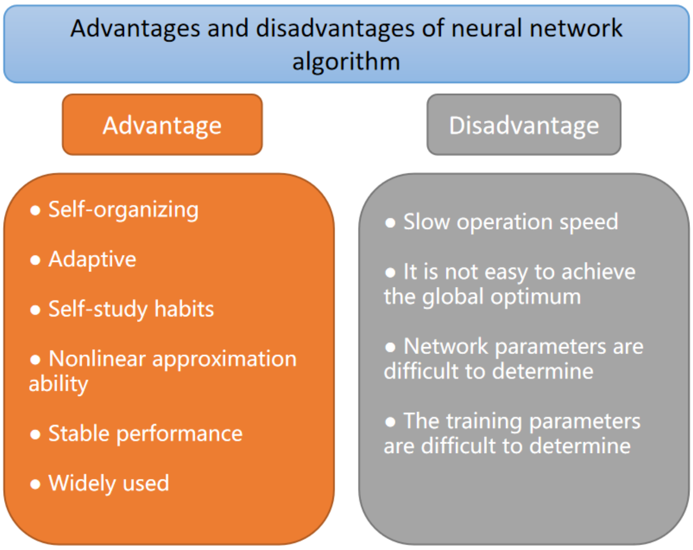

Figure 3. Comparison of advantages and disadvantages of neural network algorithms.

In recent years, scholars at home and abroad have extensively studied the application of neural network algorithm in ore blending models. For example, in 1999, Jiansheng Feng et al. [25] established an intelligent ore blending model based on a neural network algorithm to solve the problems of Baosteel using a variety of imported iron ore and changing raw materials. The prediction rate of sinter quality reaches 85%, which plays a good guiding role in sinter batching. In 2003, Yuntao Li et al. [26] focused on the complexity of sintering ingredients and the defects of neural networks, such as not being easy to reach the global optimal and slow operation speed. A genetic algorithm is used to optimize the parameters of the neural network, and a dynamic learning method is adopted to add momentum terms in the learning process. Experiments show that the prediction effect of the improved synthetic neural network model is much better than that of the simple neural network algorithm. Wei Wang et al. [27] considered sintering ingredients from both economic and technical aspects in 2006. An intelligent ore blending model composed of a linear programming model and a neural network model was established, which saved 5.71 yuan per ton of sinter. In 2011, Youming Hu [28] studied how to obtain an ingredient scheme with good economic performance and qualified quality because of the shortage of iron ore resources. The neural network model, genetic algorithm model, theoretical calculation model, and expert system are combined. The intelligent ore blending model is established, and good results are achieved in Lian Steel, making the prediction accuracy of sinter quality reaches more than 85%. Xiaohui Fan et al. [29] focused on the complex and delayed problems of sinter quality prediction in 2012. Firstly, the main factors are determined by stepwise regression analysis, and then the prediction model is established by a neural network. The prediction accuracy of the fuel ratio model is 93.33%, which can provide guidance for actual production. Dingsen Zhang [30] applied the improved multi-objective genetic algorithm, neural network algorithm, and Technique for Order Preference by Similarity to an Ideal Solution method in 2017. According to the requirements of mixed ore, optimize the batching of iron ore. The results show that the optimization effect of a non-dominated sorting genetic algorithm with an elite strategy is stronger than that of a non-dominated sorting genetic algorithm. In actual production, it has brought considerable economic benefits for the enterprise. In 2022, Yifan Li et al. [31] adopted a genetic algorithm to optimize the cyclic neural network for the problem of delayed sinter detection results. A GA-RNN Genetic Algorithm-Recurrent Neural Networks) quality prediction model with raw material composition as input parameters and physical and metallurgical properties of sinter as output was established. The average prediction error of RDI and RI was 0.92% and 0.95%, respectively. It can predict sinter quality and save costs for enterprises.

Through the analysis of related work, it can be found that the neural network algorithm can be combined with genetic algorithm and linear programming method to solve the shortcomings of neural network algorithm, such as slow operation speed, difficulty achieving global optimum, and difficulty in determining the network parameters and training parameters. The intelligent ore blending model based on a neural network combination algorithm has a certain guiding role for the actual production.

3.2. Research on Intelligent Ore Blending Model Based on Genetic Algorithm

Genetic algorithm is often used in intelligent ore blending models. As shown in Figure 4, the genetic algorithm has the advantages of robustness, group search, global optimization, and scalability, so it is widely used in intelligent ore blending models [32,33]. However, the genetic algorithm also has some shortcomings, such as easy to fall into a local minimum, slow convergence speed, premature convergence, low efficiency, and irregular and inaccurate coding [34,35].

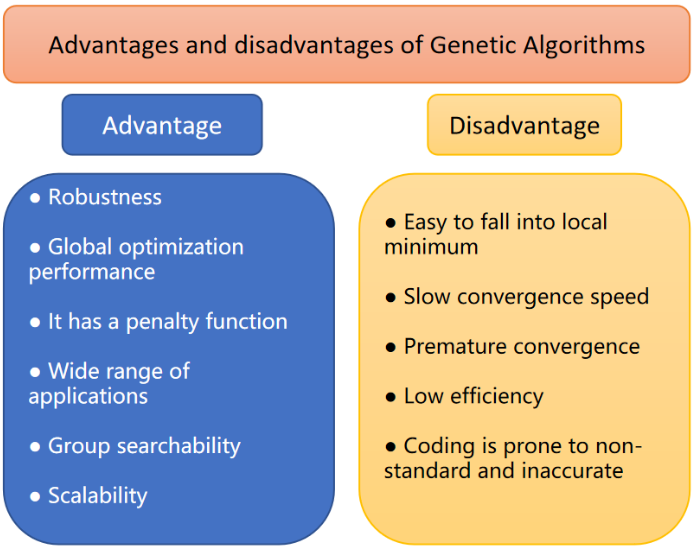

Figure 4. Comparison of advantages and disadvantages of genetic algorithm.

In recent years, extensive research has been carried out by domestic and international scholars using genetic algorithms in ore dosing models. For example, Niloy K. Nath et al. [36] 2005 evaluated the optimum coking rate for two-layer sintering in a sintering batching model to obtain the ideal melting fraction and heat distribution to obtain the optimum sintered ore quality. Xuewei Lv et al. [37] in 2007, aiming at the sintering batch problem of Chonggang, The intelligent ore blending model was established by stepwise regression analysis and genetic algorithm. On the basis of meeting all the indicators, the raw material cost of sinter is reduced by 14.7 per ton. Zhao Yang et al. [38] combined generalized regression neural network and genetic algorithm in 2011 in view of the complex variability of sintering ingredients. The experimental results show that the model has more convenient operation, higher accuracy and reliability and can provide theoretical support for the research of intelligent ore blending model. Giri et al. [39] established a mathematical model of mass and energy balance based on the gas phase and solid phase with partial differential equations in 2012. Using a genetic algorithm to optimize the process parameters, the establishment of the model can be used as a tool to predict the sintering speed and temperature. Tiebin Wu et al. [40] proposed a constrained optimization problem based on an adaptive penalty function and an improved genetic algorithm for the proportioning problem in sintered ingredients in 2017, and their experimental results showed that the proposed constrained genetic algorithm is effective and feasible. Dandan Wang et al. [41] 2018 proposed a combination of genetic algorithm and fireworks algorithm to optimize the support vector machine parameters and train using production data to finally obtain the optimal prediction model for BTP (Burning Through Point), and the test results showed that the model has a high accuracy with an average relative error of 0.0778%, which can meet the actual production requirements. Guangyue Liu et al. [42] proposed a probabilistic optimization algorithm combining quantum parallel computing and genetic algorithm in 2019. The quantum parallel genetic algorithm model can measure the assimilation and fluidity of iron ore powder and predict the metallurgical properties of sinter. The quality of the sinter can be further improved by reducing some unnecessary sinter cup experiments.

The above scholars have studied the application of genetic algorithms in sintering ore blending problems. Through the research, it can be found that in order to solve the shortcomings of genetic algorithms, such as easy to fall into the local minimum, slow convergence, premature convergence, low efficiency, and easy to appear non-standard and inaccurate in coding. In the ore blending model, scholars use stepwise regression analysis method, partial differential equation, and fireworks algorithm to combine with genetic algorithm. A combination algorithm based on a genetic algorithm is established and applied to the ore blending model with good results.

3.3. Research on Intelligent Ore Blending Model Based on Particle Swarm Optimization Algorithm

Particle swarm optimization is a commonly used algorithm in intelligent ore blending models. As shown in Figure 5, particle swarm optimization has the following advantages: fast convergence speed, simple principle, easy to find the optimal global solution, and strong universality and leaping [43,44]. Therefore, it is often used in the algorithm of intelligent ore blending model. However, it also has the following disadvantages, which are difficult in setting parameters, ease in falling into local optimal, and sometimes troublesome network weight coding and genetic operator selection [45,46].

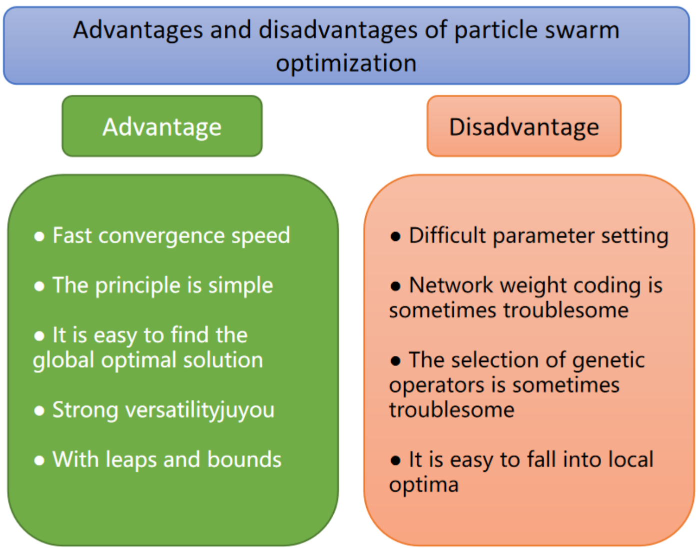

Figure 5. Comparison of advantages and disadvantages of particle swarm optimization.

In recent years, particle swarms optimization has been widely used in the ore blending model. For example, Zhi Li et al. [47] used particle swarms optimization algorithm to conduct computational modeling on sintering batch optimization in 2005. Mix iron ores with different chemical compositions. According to the established intelligent ore blending model, the chemical composition of the mixture can meet the requirements of sintering. In 2008, Min Wu et al. [48] focused on the optimization of sintering ingredients and the precocious convergence characteristics of the particle swarms optimization algorithm. The conjugate gradient method with constraints is combined with the particle swarm algorithm to exploit the local search capability of the conjugate gradient method and the global search capability of the particle swarm algorithm to find the best. The experimental results show that the model can optimize the ingredients, reduce the production cost, reduce the harmful ingredients and increase the useful ingredients in the mixture. Hui Zhao et al. [49], in 2012, to improve the universality and adaptability of sintering ingredients, proposed a modified particle swarms optimization algorithm with an adjustment function derived from the Cauchy distribution function is proposed. The experimental results show that the improved particle swarms optimization has the advantages of high precision, high efficiency, and strong optimization ability and can effectively reduce the sintering cost. Min Wu et al. [50] in 2018 aimed at the problem that coke was more complex than the model in the sintering process. In order to reduce coal consumption, a sintering stage optimization method combining particle swarms optimization and back propagation neural network algorithm was proposed. The temperature distribution in the combustion zone of different sintering endpoints is accurately simulated, and the mass of the original mixture can be simulated and calculated, which provides a basis for the judgment of the sintering state. It can analyze the energy flow in the sintering process and calculate the theoretical value of the coke ratio, which is conducive to reducing the carbon dioxide emission in the sintering process. Velmurugan et al. [51] analyzed the microhardness and density of the sintered products in 2019. Particle swarms optimization, integrated artificial neural network algorithm, and genetic algorithm were used to optimize the process parameters in order to obtain better mechanical properties. The experimental results show that the model can improve the quality of the sinter by increasing the microhardness and density of sintering products. In 2020, Kumano A et al. [52] aimed at minimizing the cost of ore. In order to overcome the complexity problem, the linear programming method and particle swarms optimization algorithm are combined. The model can produce a solution in 2 min, reducing material costs by 1%. Xiaokai Quan et al. [53] targeted the problem of air leakage detection in the sintering process in 2022. The current methods used by enterprises have delayed detection results and high inspection costs. Based on this, the particle swarms optimization algorithm is used to optimize the initial parameters of the backpropagation neural network. Compared with the traditional method, this model can shorten the detection process and time. The error is controlled within 5%, which enables enterprises to deal with air leakage in time and improve the quality of the sinter.

The application of the particle swarm algorithm in the sintering allocation problem is summarised above. Through the study, it can be found that to solve the difficulties in setting the parameters of particle swarm algorithm, easily fall into local optimum, network weight encoding and genetic operator selection difficulties, scholars have used conjugate gradient method, neural network algorithm and linear programming method in combination with particle swarm algorithm, using the combination of particle swarm algorithm and genetic algorithm, and applied in the ore allocation model to achieve better results.

These improved algorithm models have made some achievements in sintering ore blending, but it is difficult to adapt to the current complex situation of sintering ore blending, so the model needs to be further optimized and improved. The above studies are based on the algorithm as the core, only for raw material parameters, ratio, cost optimization, ore blending model. The influences of factors affecting the sintering foundation characteristics, the liquid phase formation capacity of the sinter, and the influencing factors of sinter quality were not considered. Therefore, the above factors need to be studied as the theoretical basis of the intelligent ore blending model to provide guidance for the intelligent ore blending model.

4. Research on Intelligent Ore Blending Model Based on Sintering Mechanism

4.1. Optimization of Ore Blending Based on Sintering Foundation Characteristics

As iron ore powder imported from abroad is constantly changing, the sinter performance is unstable, and the sintering cup experiment takes a long time. It is an important method to optimize ore blending to study the sintering foundation characteristics [54]. Shengli Wu et al. measured the high-temperature characteristics of 10 kinds of iron ore from China, Brazil, and Australia. A new concept of complementary ore blending based on high-temperature characteristics is proposed. The optimization scheme of ore blending is designed and a good sintering index is obtained [55]. Yunqiang Xie et al. adopted the micro-sintering method. The basic characteristics of 8 kinds of iron ore powder commonly used in an iron and steel enterprise were studied. Based on the basic characteristics of iron ore powder, the ratio of iron ore powder was optimized. Improved the sinter drum strength and sinter index. It provides the basis for sintering ore blending in enterprises [56]. Jianchao Li et al. studied the basic characteristics of five commonly used mineral powders in Hangang, and the basic characteristics of mixed ore were studied. The optimal ore blending scheme for these five kinds of ore powder is obtained [57]. Qiang Ren et al. conducted experiments on the basic characteristics of the sintering of A and B mineral powders at different proportions in steel mills. Considering the price of A and B mineral powder, Two optimal ore blending schemes of iron ore powder were formulated [58]. Kai Zhao et al. tested the basic characteristics of seven iron ore powders in Xinggang. According to the test results, the ore blending scheme was optimized. The grade of the sinter is improved [59]. Shengli Wu et al. tested the high-temperature characteristics of iron ore powder from Brazil, China, and Australia. The mixed ore composed of 30–45% Brazilian ore + 25–50% Australian ore + 20–30% Chinese concentrate has a good sintering effect [60]. Tielei Tian et al. studied the basic sintering characteristics of six iron ore powders. On this basis, the experiment of sintering optimization ore blending was carried out [61]. Tian Shuo conducted experiments on the basic properties of Brazilian card powder and Yangdi mineral powders and found that the best overall performance was achieved when the ratio of Brazilian card powder to Yangdi mineral powders was 3:7 [62]. Chaoquan Yao et al. conducted experiments on the basic characteristics of sintering of seven kinds of iron ore powder in Tiangang. According to the results, five groups of optimized ore blending schemes are proposed. The comprehensive indexes of sintering were increased [63]. Chengsong Liu et al. conducted experiments on the basic characteristics of six kinds of iron ore powders in China. According to the test results, ore blending was carried out and verified by the sintering cup experiment. The results show that the yield and quality indexes of the optimized ore blending scheme are higher than those of the benchmark scheme [64]. By studying the characteristics of iron ore powder foundation and optimizing the original ore blending scheme, optimized ore blending can be achieved. It will give full play to the advantages of iron ore powder foundation characteristics and provide technical support for the optimization of ore blending.

4.2. Study on Liquid Phase Formation Capacity of Sinter

The liquid phase formation capacity of the sinter was studied. Guocheng Zhang et al. studied the formation performance of MgO in the sinter liquid phase. The results showed that with the increase of MgO content, Liquid phase production was reduced when the MgO quality score increased from 1.6% to 1.9%. The development of acicular and lamellar calcium ferrite was limited, and the content of the dendrite calcium ferrite phase increased [65]. Xianzhen Wang et al. studied the influence of ZnO on the liquid phase formation ability of sinter. ZnO addition can promote the formation of the sinter liquid phase. When the mass fraction of ZnO increases from 0 to 4%, the morphology of composite calcium ferrite gradually changes from massive to strip and needle [66]. Liu Xiaojie et al. pointed out that the content of acicular calcium ferrite increased with the increase of PMC 0.044 mm fine powder. As the Tambazimbi mineral powder increases, acicular calcium ferrite changes from a uniform distribution to a concentrated uniform. As the Baka mineral powder increases, the content of calcium ferrite first decreases and then increases [67]. Xuheng Chen et al. studied the influence of sintering temperature on the ore facies of sinter. As the temperature goes up, the contents of calcium ferrite and hematite in sinter decrease gradually, while the contents of silicate and magnetite increase gradually [68]. Tao Deng et al. studied the influence of liquid phase formation and distribution under different mass fractions of MgO and Al_2O_3. Through the sinter cup experiment and Factsage software, When the mass fraction of Al_2O_3 in the sinter is 3.0%, the mass fraction of MgO is 2.0%. The mineral phase, liquid phase, and mineral composition reach the optimum sintering and smelting standard [69]. Lina Liu et al. studied the ore phase structure and metallurgical properties of Sijiaying iron ore powder sinter. With the increase of alkalinity, the contents of magnetite, hematite and vitreous decrease gradually. Calcium ferrite increased, reducing and low temperature reducing pulverization performance improved, and drum strength increased [70]. Qie Yana et al. studied the influence of TiO_2 content on the mineral phase structure of sinter. The results showed that with the increase of TiO_2 content, the bond phase strength decreased, calcium ferrite decreased, and the glass phase increased [71]. Zhimin Li et al. studied sinter facies of Chenggang with different MgO contents. With the increase of MgO content, the cohesive phase of the sinter decreases, and the metal phase increases. The structure gradually changed from a dissolution structure to a granular structure [72]. The above research is carried out to study the influencing factors of sinter liquid phase formation capacity. It can comprehensively analyze the factors affecting the liquid phase formation ability of iron ore powder and guide the model of sintering ore blending from the mechanism.

4.3. Study on Influencing Factors of Sinter Quality

Through the study of the factors affecting the quality of sinter, it has a vital role in the proportion of sinter production and the quality of sinter. By studying the effect of TiO_2 content on the quality of sintered ore, Liu Zhouli et al. demonstrated that with the increase of TiO_2 content, the drum strength and sintered ore yield decreased, and the low-temperature reduction pulverization index became worse [73]. Fengming Wang et al. studied the influence of SiO_2 on the quality of sinter. With the increase of SiO_2 content, The compressive strength becomes better, and the reducibility becomes worse [74]. Jianfeng Lang et al. studied the influence of MgO on sinter quality. The research results indicate that when the alkalinity is 1.8, the addition of MgO makes the reduction property of the sinter worse, and the resistance to low-temperature reduction degradation and softening property of sinter improves [75]. Xuesong Li studied the influence of quick lime on sinter quality. It is pointed out that with the increase of quicklime content, the drum index of the sinter increases first, then becomes stable, and then decreases, and the low-temperature reduction degradation index of the sinter increases gradually [76]. Zhengjie Wang et al. studied the effect of SiO_2 and CaO on the quality of sintered minerals. When the content of SiO_2 is 4.8%, the quality index of sintered mineral increases first and then decreases with the increase of alkalinity. When the content of SiO_2 is 4–6.8%, and the content of CaO is in the range of 9.6%, the drum strength has little change [77]. Xingjian Wang et al. studied the influence of Al_2O_3 mass fraction and different alkalinity on the reduction behavior of sinter. It is pointed out that for the sinter samples used in the experiment. When the mass fraction of Al_2O_3 increases from 1% to 4%, the reduction increases first and then decreases. When the alkalinity increased from 1.8 to 2.4, the reduction rate showed an increasing trend [78]. Umadevi et al. aimed at the effect of MgO addition amount on the quality of low and high silicon sinter. Studies have shown that the amount of MgO added varies from 1.4% to 3.2%. The reducibility of the two sinters decreases with the increase of MgO addition [79]. Lina Liu et al. studied the influence of different carbon content on the ore facies of Sijiaying iron concentrate sinter. When the Sijiaying iron concentrate powder ratio is 50–90%, with the increase of carbon content, the drum index increases first and then decreases. When the ratio is 100%, with the increase of carbon content, the drum index is increased, the low-temperature reduction degradation index is improved, and the reduction degree is slightly decreased [80]. The above research on the factors affecting the quality of sintering products can optimize the sintering ingredients so as to better guide the sintering ore blending model.

5. Prospect of Intelligent Ore Blending Model

The combination algorithm based on neural network algorithm, genetic algorithm, and particle swarm optimization algorithm has achieved good results in the intelligent ore blending model. However, generally, a small number of factors affecting sinter quality have been studied, and few scholars have comprehensively studied the input parameters and output parameters. It is not comprehensively considered that the raw material parameters, equipment parameters, and operation parameters are taken as input parameters, and the physical and metallurgical properties of sinter are taken as output parameters. The above studies are all intelligent ore blending models with algorithm as the core research, and consider the optimization process of sinter ore blending based on data. The basic characteristics of iron ore powder, sintering mechanism, liquid phase generation ability, and other factors are not considered. If the data has large fluctuations, it may affect the results and have instability.

To solve these problems, Based on the study of the basic characteristics of iron ore powder, sintering mechanism, liquid phase generation ability, and other factors, the algorithm in the intelligent ore blending model will be deeply and extensively studied. The raw material parameters, equipment parameters, and operation parameters will be taken as input parameters, and the physical and metallurgical properties of sinter will be taken as output parameters. The advantages and disadvantages of a single algorithm will be analyzed for different input and output parameters and data volume. According to the advantages and disadvantages of various algorithms, a better combination algorithm will be found. Through the establishment of this model, it is expected to provide guidance for the enterprise sintering production, more accurate and more efficient intelligent ore blending. It will be able to match the labor intensity of ore engineers and experimenters to produce high-grade sinter, improve economic efficiency for enterprises, save raw materials, and also contribute to national energy conservation and emission reduction.

6. Conclusions

This paper analyzes the iron ore resources at home and abroad, studies the sinter ore blending theory and the current ore blending situation, and expounds on the research progress of an intelligent ore blending model with an intelligent algorithm as the core. The application of neural network algorithm, genetic algorithm, and particle swarm optimization algorithm in the intelligent ore blending model is analyzed. According to its advantages and disadvantages, the application and actual effect of the combination algorithm in the intelligent ore blending model is studied. Research and analysis show that the combined intelligent algorithm is more suitable for the intelligent ore blending model. Finally, the research prospect of an intelligent sintering ore blending model is given. It is suggested to further study the combined intelligent algorithm, which is more suitable for the intelligent ore blending model. By studying the characteristics of iron ore powder foundation and optimizing the original ore blending scheme, optimized ore blending can be realized. The influencing factors of the liquid phase generation ability of sinter are studied. It can comprehensively analyze the factors affecting the liquid phase generation ability of iron ore powder and guide the model of sintering ore blending from the mechanism. The research on the factors affecting the quality of the sinter can optimize the sintering ingredients so as to better guide the sintering ore blending model. It is proposed that the algorithm in the intelligent ore blending model should be deeply and extensively studied on the basis of the basic characteristics of iron ore powder, sintering ore-forming mechanism, liquid phase generation ability, and other factors. An intelligent ore blending model with raw material parameters, equipment parameters, and operation parameters as input parameters and physical and metallurgical properties of sinter as output parameters will be established. In order to improve the accuracy, universality, and stability of the intelligent ore blending model.

Author Contributions: Y.L. is responsible for the idea of the paper, the method in the paper and the writing of the original paper. B.W. and Z.Z. are responsible for the theoretical research and writing of the paper. Y.B. is responsible for sorting out and analyzing the algorithms involved in the paper. A.Y. is responsible for the chart making and part of the paper writing. All authors have read and agreed to the published version of the manuscript.

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