

Two Paradigms on Study Slab Continuous Casting Process with Mold Electromagnetic Stirring

Zuosheng Lei^{1*}, Bin Li¹, Yueming Zhou², Xing Wu³, Yunbo Zhong¹, Zhongming Ren¹

1. State Key Laboratory of Advanced Special Steel & Shanghai Key Laboratory of Advanced Ferro-metallurgy & School of Materials Science and Engineering, Shanghai University, Shanghai 200072, China
2. Baosteel Central Research Institute, 200072, Shanghai, China.
3. School of Computer Engineering and Science, Shanghai University, 200072, Shanghai, China.

* Corresponding author: lei_zsh@staff.shu.edu.cn

Abstract: Electromagnetic stirring (EMS) is an efficient technology to control the flow structure in slab continuous casting mold. But there is still an important opened problem to be answered firstly, that is, what kind of flow structure is our goal by using electromagnetic stirring in order to get good casting products, and how to optimize the flow fields in slab continuous casting mold with EMS? Two kinds of research paradigms are proposed in this study. One is based on causal relationship between the flow field and its effects on the mold flux entrapment and solidification process. Two parameters, named Mold Flux Entrapment Index and Velocity Uniform Index were proposed in order to evaluate the flow field in the mold. Based on these two indexes, optimization stirring parameters were proposed under different casting situation. The other research paradigm is machine learning big data model based on correlation analysis of nearly all the input parameters of casting machine and slab quality as an output parameter. Data acquisition from the continuous casting machine, data mining by machine learning algorithms and online automatic control parameters output are three main aspects in the second research frame.

Key words: Slab Continuous Casting, Flow Control, Electromagnetic Stirring, Big Data Machine Learning.

Introduction

Fluid flow in the mold is very important to product quality in the steel slab continuous casting [1]. Electromagnetic stirring [2] is one typical technologies in which Lorentz force can be generated in the up zone of liquid steel to controlling the flow field in the mold and has being widely applied in the industrial process. Mathematical modeling and physical modeling using low melt point metal have been developed to understand the fluid flow phenomena with electromagnetic field. But up to now, most of the work can only tell us *what it is* about the flow field in the mold rather than *what should be*. There is still an important open problem to be answered firstly, that is, what kind of flow structure is our best choice to get the best casting products when we use electromagnetic technologies? How to evaluate the flow field with the imposing of electromagnetic field in the mold is a key problem. In this study, two research paradigms in order to resolve the above-mentioned problems are proposed and examined. One is based on causal relationship between the flow field and its effects on the mold flux entrapment and solidification process, and the other is machine learning big data model based on correlation analysis of nearly all the input parameters of casting machine and slab quality as an output parameter. Some preliminary results are introduced here.

Mathematical model based on causal relationship

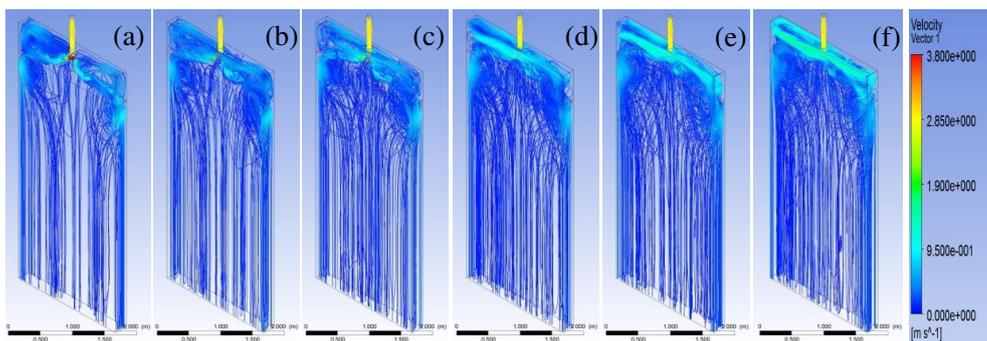


Fig.1 Calculate flow field in the mold with different EMS current
(a) 0A, (b) 300A, (c) 400A, (d) 500A, (e) 600A, (f) 700A

A mathematical model coupled with magnetic fields and flow fields is established to numerical simulate the flow field in the industrial mold under different EMS parameters and continuous casting conditions. This model has been validated by contrast to a physical modelling applying low melt point metal [2]. Fig. 1 shows some typical calculated

results when the casting speed, the section of the mold the SEN submerge depth, and the exit port angle are 1.4m/min, 2150mm×230mm, 170mm, and 15°downward, respectively.

It can be seen from Fig.1 that the flow field without EMS is a typical double-roll structure, and a horizontal circulation in the upper part of mold appears with EMS, and the velocity increases with the increasing EMS current. But the problem is which EMS current is the best one in order to improve the slab quality? Two Indexes are proposed in order to evaluate the flow field in the mold.

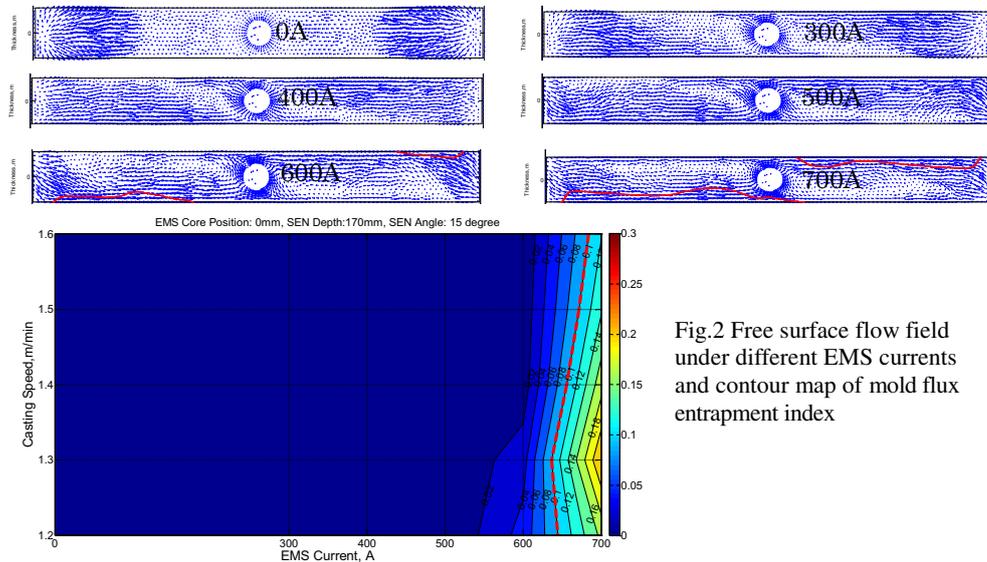


Fig.2 Free surface flow field under different EMS currents and contour map of mold flux entrapment index

In slab continuous casting process, the free surface is very important to control the velocity of the liquid metal flow under the mold flux. If the velocity of this area is too high, the possibility of mold flux entrapment might increase. In order to evaluate this effect quantitatively, a new index, named Mold Flux Entrapment Index (MFEI), is introduced and it is defined as the surface $S_{v>v_c}$ in free surface in the mold where the steel velocity is greater than the critical mold flux entrapment velocity v_c to the total surface of free surface S_{total} . The MFEI can be calculated as

$$MFEI = \frac{S_{v>v_c}}{S_{total}} \times 100\% \quad (1)$$

Where v_c can be obtained by eq.

$$v_c^2 \geq \frac{2(\rho_1 + \rho_2)}{\rho_1 \rho_2} [\gamma(\rho_1 - \rho_2)]^{1/2} \quad (2)$$

Where ρ_1 and ρ_2 are the density of liquid steel and mold flux, and γ is the surface tension between liquid steel and mold flux. Eq. (2) is the Kelvin-Helmholtz instability criterion between two immiscible liquid. It suggests that once the velocity difference of liquid steel and mold flux is greater than the critical velocity, the possibility of mold flux entrapment will increase. The critical velocity can be determined by experiments in facts, but here hypothesis was took that the critical velocity is 0.8m/s.

Fig.2 shows the free surface flow field and contour map of mold flux entrapment index under different EMS currents and casting speed. From the map, the region right to the red line is relatively dangerous from the viewpoint of mold flux entrapment. So the maximum EMS current can be selected under different casting speed.

As we know that the growth speed of initial solidifying shell is decided by two aspects. One is the cooling density from the water-cooled copper mold, and the other is the impact of the hot liquid steel flow in front of the initial shell. In order to prevent the crack formation caused by thermal stress, it is very important to keep the shell growing uniformly. It is the flow velocity in front of the initial solidifying shell that determine the convection heat transfer between the interface of the shell and liquid steel, so the uniform of the velocity in front of this interface is applied to evaluate the impact of flow field on initial shell growth.

Due to the help of EMS Lorentz force, a horizontal circulation will form in the stirring zone, and it will affect the flow structure of the low part in the mold. An index named, Velocity Uniform Index (VUI), is introduced followed reference [2]. To give a quantitative valuation of the effect of flow field on solidification on every level, The VUI is defined as:

$$VUI = \frac{\oint_{\Gamma} |V(x)| dx}{\max(|V(x)|) \oint_{\Gamma} dx} \times 100\% \tag{3}$$

Where Γ is a closed curve 20 mm away from the inner mold wall, see in the Fig.3, and V_x is the absolute velocity of every point on Γ . It is obvious that VUI has a value between 0 and 1. This value greater the better the flow field is. Fig.3 shows the VUI of different levels in the mold when the EMS currents are different. It can be seen that the VUI increases with the EMS current, but decreases a little in the deep part of the mold.

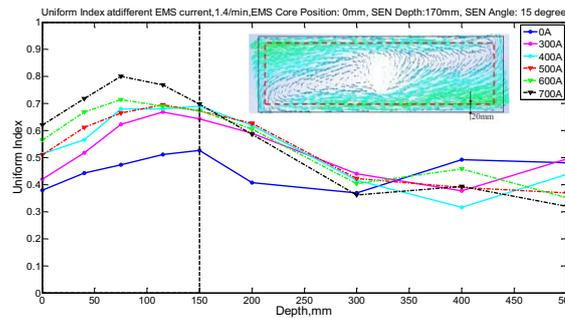


Fig.3 VUI under different EMS currents

By comprehensive evaluation of these two indexes an optimized EMS current can be achieved under a given continuous casting condition. There are still other aspects have not be took into consideration so far, for example, the gas bubble and inclusiong transport behavior in the mold, the stress of solidified shell, and so on.

Big data model based on correlation analysis by machine learning

The study roadmap discribe above is a typical analytical research method in which every detailed mechanism should be clarified before the best operation parameters can be determined. But in fact, it is not only difficult but also time cost and sometimes impossible to studied thoroughly in such a complex continuous casting system with so many input parameters.

With the development of computer technology nowadays, it is possible to deal with massive large data or big data from the industrial process. By artificial intelligence algorithm developed recently the correlation between input parameters and output parameter of an industrial system can be obtained. Continuous casting process, as a complex system, is very suitable for big data analysis in order to find the best opeartion parameters.

The whole research sketch map are showed in Fig.4. There are mainly three parts in this process, data acquisition, data mining and prediction & real-time controlling. So far, we have developed an off-line system including the first two sections. The real-time control sections will be applied after the machine learning system be fully trained and examined.

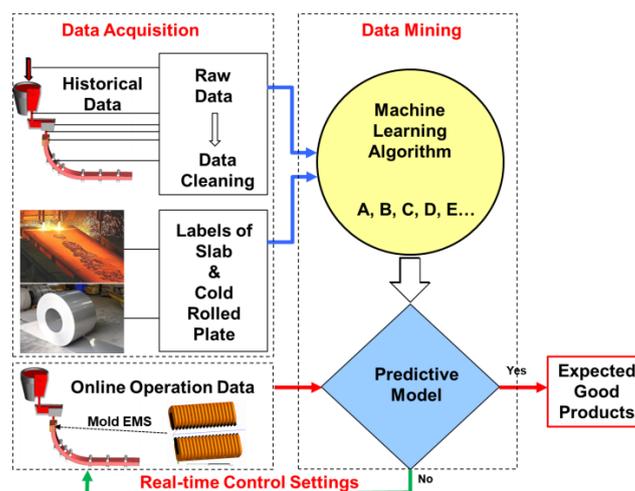


Fig. 4 Sketch map of big data model for continuous casting process

-Data acquisition. Nearly most of the casting operation parameters are collected every one second. These parameters are casting speed, EMS currents and frequency, cooling water flow rate of mold, argon injection flow rate, submerge entry nozzle depth, temperature of the mold copper plate, free surface fluctuation, mold flux addition rate, and so on. The quality of slab and cold rolled plate are labeled corresponding to the operation parameters. All the data must be cleaned and have a good time stamp.

-Data mining. The data collected from the continuous casting machine is divided into two parts. 75% of the data including both the operation parameters and labeled products quality is used as training set and the others 25% data is used as test data. The training set data were input into machine learning software package including more than ten kinds of supervised learning algorithm, then every algorithm can give a predict simulation of the test set data. The algorithm with the highest prediction accuracy is the winner be choosed to obtain *the model* of the whole continuous casting system, including the EMS technology. The forecast accuracy can reached 99.5%. Learning from history can predict the future, then the model can be used to predict the product quality when online process parameters were input in it.

So far, the historical production data more than one year duration of No.2 continuous casting machine of Baosteel Zhanjiang works have been collected and stored for the machine learning. Also, the big data model can tell us which parameters affect the slab quality most. For example, from high to low according to weight, surface fluctuation, casting slab width, EMS currents, casting speed and temperature of mold copper plate are the first five important parameters. This give us a possible solution in order to improve the slab quality by taking the most important parameters into account first.

- Intelligent real-time controlling. Based on the big data model, it is possible to realize a totally intelligent control of continuous casting process. When the model give a negative prediction it can intelligently find a parameters settings in the multi-dimension phase space to change the outputs. So far we have not realize this section, it need more profound study under the sincere cooperation of both metallurgical field and computer technology field.

Conclusions

In this study, two kinds of research paradigms are proposed in order to optimize the slab continuous casting process with EMS controlling the flow field in the mold. One is based on causal relationship between the flow field and its effects on the mold flux entrapment and solidification process. The other is machine learning big data model based on correlation analysis of nearly all the input parameters of casting machine and slab quality.

The first research method can give us some mechanism explain on some particular aspect, but can not give a comprehensive understanding of the whole process. The later reserch method did not give causal explain on every single problem, but can give an online prediction on the product quality.

Different research paradigms provide different thinking method. This two method should rely on each other and explain each other mutually in order to optimize the whole process.

Acknowledgment

This project financially supported by National Science Foundation of China (NO. 51274137) and Shanghai Economic and Information Committee (No.CXY-2016-015).

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