Data-Driven Design: A New Paradigm and Application Exploration for Aluminium Reduction Cell Design

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Abstract

With the transformation and upgrading of the aluminum smelter industry, traditional design methods can no longer meet the complexity and efficiency requirements of modern engineering projects. This paper proposes a data-driven design paradigm for aluminum reduction cells, integrating 3D Building Information Modelling (BIM) technology, intelligent optimization platforms, and machine-learning algorithms to achieve full digital management of the design process. This paradigm significantly improves design accuracy and efficiency, providing precise material quantity estimation and multi-physics simulation support during the planning phase. It offers strong support for investment decisions and engineering optimization. Furthermore, this paper explores the potential application of big data computing power in the development and planning of high amperage cells, providing new insights for future intelligent design and large-scale optimization. Through practical project verification, this method has shortened the design cycle by 40 %, reduced design changes by 25 %, and demonstrated significant advantages in cost reduction, providing a new solution for the intelligent transformation of the aluminum smelter industry.

Keywords: Data-driven design, Aluminum reduction cell design, 3D BIM technology, Intelligent optimization platform; Machine-learning.

1. Introduction

1.1 Industry Background

As an energy-intensive industry, the aluminum smelter industry is facing severe energy efficiency challenges. In recent years, although the energy consumption level of the global aluminum smelter industry has declined, there is still much room for energy saving. According to the statistics of the International Aluminum Association, there are obvious differences in the energy consumption level of the aluminum smelter industry in different countries and regions. The average energy consumption of some countries with advanced aluminum smelter technology has dropped to 12.8 kWh/kg Al level, but the average energy consumption of aluminum smelters in many countries is still above 13.5 kWh/kg Al, indicating that there is still potential to further reduce energy consumption through technological innovation and management optimization. Therefore, improving the energy efficiency level of the aluminum smelter industry has become an urgent need for the transformation and upgrading of the industry.

1.2 Limitations of Traditional Design Methods

The traditional cell design mainly uses the design-bid-build (DBB) mode, which faces many limitations in complex projects. First of all, the high rate of design change is a prominent problem. Due to the incomplete consideration of project requirements and site conditions in the early design stage, design changes frequently occur during the construction phase, which increases the project cost and construction period. According to statistics, the rate of change of the cell design project under the traditional design mode is as high as 30 %. Secondly, the long design cycle is also an important factor restricting the development of the industry. It usually takes 6–8 months from project initiation to design completion, which is difficult to meet the requirements of rapid progress of modern engineering projects.

1.3 Technology Opportunities

With the rapid development of information technology, data-driven and BIM technologies are gradually rising in the field of industrial design. BIM technology realizes information integration and sharing in the design, construction and operation and maintenance stages by establishing a three-dimensional digital model [1]. In the field of metallurgy, BIM technology has been applied to the design optimization of iron and steel plants and has achieved remarkable results. At the same time, the technology of intelligent optimization platform is also increasingly mature. Machine learning algorithms have been preliminarily applied in the optimization of electrolytic cell parameters. Through the establishment of mathematical models, the current efficiency, electrode distance and other key parameters of the electrolytic cell are optimized, and the design accuracy is improved.

1.4 Research Objectives

Although BIM technology has been widely applied in the field of construction [1], its integration in cell design still faces two major challenges:

1) the lack of specialized parametric modeling tools;
2) The magnetic field criterion is not suitable for the characteristics of high-current cells [2].

This study aims to propose a ‘data-BIM-algorithm’ trinity design paradigm to address the shortcomings of inaccurate material estimation and inability to conduct simulation analysis in traditional designs. Through the integration of data-driven technology, BIM technology and intelligent optimization algorithms, the full-process digital management of aluminum-reduction-cell design is realized, the design accuracy and efficiency are improved, and a new solution is provided for the intelligent transformation of aluminum reduction industry.

2. Method

2.1 Technical Framework Diagram

The intelligent design system of aluminum reduction cell on cloud developed by this project is mainly based on open-source software Python. Its technical framework includes data layer, modeling layer and analysis layer as shown in Figure 1. The data layer is responsible for receiving and preprocessing data. Through the scheme planning software module implemented with Python, the designer can quickly determine the scheme of the cell by only determining the key parameters and pass it to the core module Pot3D. The modeling layer is divided into two levels. The first level is the core module Pot3D, which is responsible for data comparison, revision and conversion, and outputs the data format and script code that can be recognized by the 3D modeling software; The second level is the traditional commercial 3D modeling software, such as ANSYS SCDM® Solidworks, etc., which automatically generates the 3D scheme model by running the script output by Pot3D. In the analysis layer, simulation software such as ANSYS Workbench® and COMSOL® are used for pre-analysis and calculation to evaluate the feasibility of the scheme.

After evaluation, the use of the "Cloud-Based Aluminum Electrolytic Cell Intelligent Design System"-Pot3D has significant advantages compared to traditional design methods. See Table 1 for details.

Table 1. Comparison between Pot3D and traditional design method.

	Traditional CAD design	Pot3D system
Modeling mode	Hand drawn drawing + Secondary development modeling	Parameterized script automatic generation
Data interface	Closed API	Open-source Python standardized scripts
Design cycle (500 kA pot）	8 months	4.5 months

2.1.1 Data Layer

The data layer is used to receive and preprocess data. This project uses Python to develop a scheme-planning software module that allows designers to define the key parameters of the cell. Defining a cell scheme (excluding the busbars) requires about 100 data values. Different from other design software, this interface contains the default values for most data. The designer can quickly determine a cell scheme by only determining about 20 data values such as the cell's amperage, anode and cathode sizes, anode and cathode numbers, cavity depth (others use the default values), and then transfer the data to the core module Pot3D. The core function of this layer can be simply summarized as "scheme digitization". The data flow in the Figure 1 follows a sequential relationship from top to bottom. Horizontal item have a parallel relationship and can be used simultaneously or separately for multiple purposes.

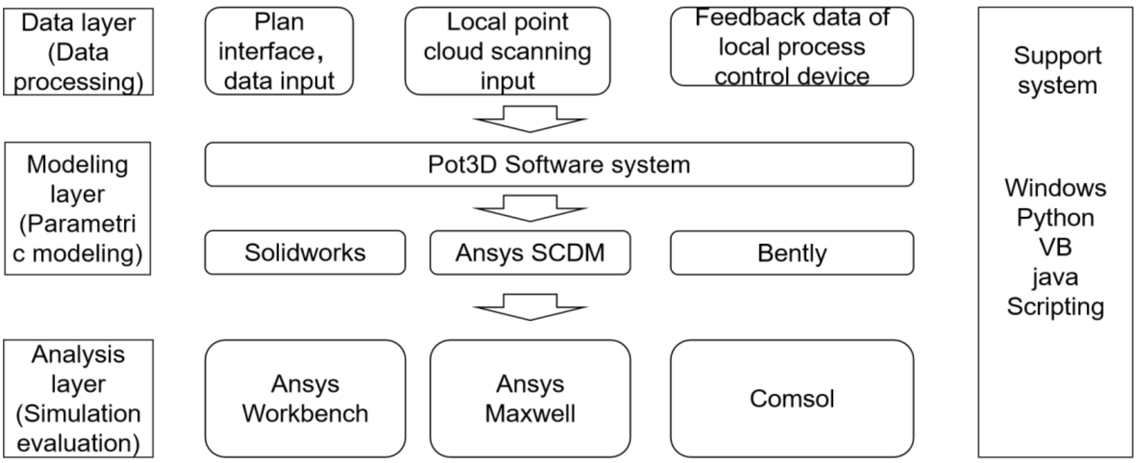


Figure 1. Technical framework of intelligent design system for a cell on cloud developed by the project.

2.1.2 Modeling Layer

As shown in Figure 1, the modeling layer is divided into two levels.

1) The first level is the core module Pot3D, which compares and revises the scheme data and feedback data sent from the data layer. After confirmation, it is converted into the data format output that can be recognized by the subsequent 3D modeling software according to the set algorithm. At the same time, a small piece of script code for directing the operation of relevant modeling software is produced.

2) The second level is the traditional commercial 3D modeling software. At present, the project has developed the interfaces of several common engineering design software, such as ANSYS SCDM® , Solidworks®, Bently®, AutoCAD® and so on (other CAD

software can also be added if necessary). There is no need for secondary development of these CAD software. As long as the Pot3D output script is run, it will automatically produce three-dimensional scheme models according to the output data. It should be noted that the model of this scheme is relatively rough and does not have details such as welds, bolts and holes. It can only be used for schematic scheme, statistics of main materials (required by budget) and simulation evaluation. All models have been checked for collision and interference. If they do not meet the conditions, they need to be re adjusted and re generated at the data layer.

2.1.3 Analysis Layer

The three-dimensional scheme model (or model data required by ANSYS® mapdl or some self-made calculation software) with interference/collision removed and output from the modeling layer can be input into ANSYS Maxwell® (electromagnetic field), ANSYS Workbench® (heat, fluid, structure), or COMSOL® (coupled field) for simulation analysis to evaluate the feasibility of the scheme.

2.2 Key Technology

2.2.1 BIM Deep Application

The application of BIM Technology in the field of cell design is not yet in-depth, but its characteristics of three-dimensional visualization, parametric modeling and full life cycle data integration are urgently needed for cell design. 3D visualization can fundamentally change the limitations of traditional 2D design, improve design efficiency and reduce engineering risks. Parametric modeling is the core advantage of industrial BIM, which is suitable for the cell design with small changes in form but different capacities and sizes. The full life cycle data integration is conducive to the preservation and retrieval of scheme data tables and 3D models at any time.

3D visualization: the 3D visualization of industrial BIM has significant advantages in complex industrial fields such as aluminum reduction cells, which can fundamentally change the limitations of traditional 2D design, improve design efficiency and reduce engineering risks. For example, a cell busbar scheme can quickly generate its spatial three-dimensional model through industrial BIM for designers to check whether it meets the design requirements, and determine whether there are collision, interference and other phenomena by software to detect errors in advance, which are difficult for traditional two-dimensional plane design. In our cloud based intelligent cell design system, a 3D model can be quickly generated as shown in Figure 2. Designers only need to conceive their schemes and provide formatted scheme tables.

Parametric modeling: parametric modeling is the core advantage of industrial BIM. Although the capacity and size of the cells are different, the overall shapes are similar, which is suitable for parametric modeling. However, considering the complexity of the electrolytic cell, this project does not adopt the simple scaling mode that takes the size scaling method to meet the requirements of the specific scheme after establishing a basic model. For the different schemes, the parameter values (such as cathode spacing, guide rod size) are mathematically scaled in the background of the software. The output is a new scheme data sheet used in three-dimensional cell models by SCDM®, SolidWorks® and other CAD software as shown in Figure 3.

Life cycle data integration: The scheme data sheet and 3D model of the project are easy to save and can be accessed at any time during the whole life cycle of the project.

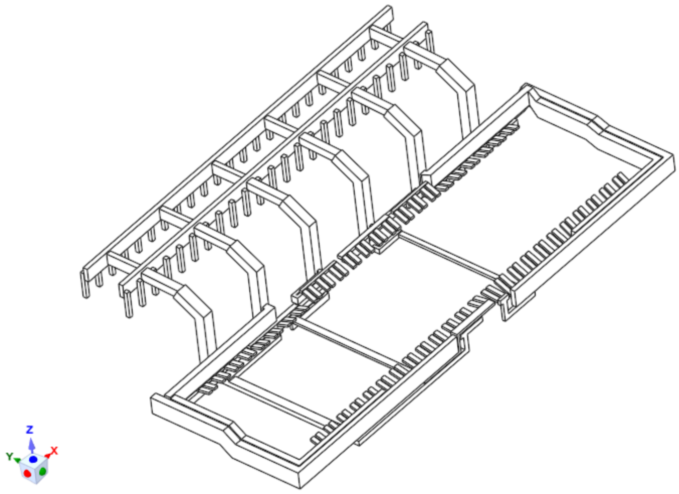


Figure 2. Three-dimensional busbar scheme.

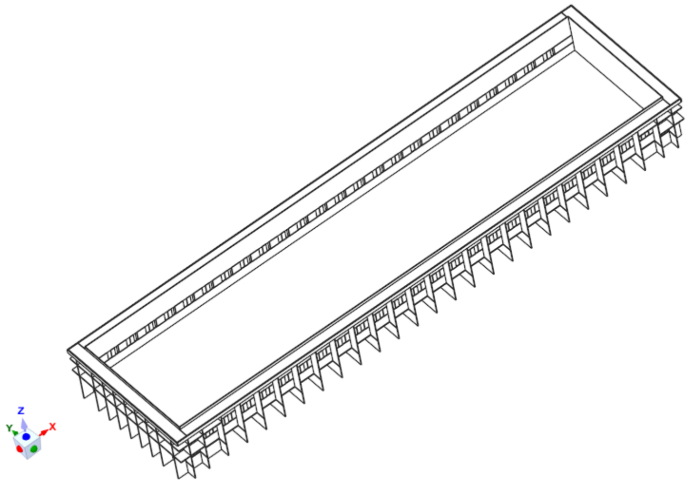


Figure 3. Shell model of the cell generated by system parameterization (simplified).

2.2.2 Optimization Algorithm

Optimizing the electromagnetic performance of busbar configuration is the core challenge in the design of aluminum electrolytic cells. This study proposes an optimization framework based on the analysis of magnetic field distribution characteristics, which includes three stages: sample screening, regression modeling, and parameter correction. The magnetic field evaluation and optimization process: A) Fits magnetic field data through spatial coordinate transformation, B) uses least squares regression to evaluate the sensitivity of busbar geometric parameters, and C) constructs a multi-objective optimization model based on NSGA-II algorithm to seek the optimal solution.

A) Sample selection and magnetic field feature extraction

Select a historical scheme similar to the capacity and structure of the target electrolytic cell (such as 500 kA double anode configuration) from the case base, and extract the geometric parameters of the busbars and the vertical magnetic field distribution data in the center of the molten aluminum layer. Through spatial coordinate transformation, the discrete magnetic field data is fitted to the following polynomial form [3, 4], Equation (1):

$$B_z(x, y) = C_0 + C_x X + C_y Y + C_{xy} XY \quad (1)$$

where:

C_0	Constant term, reflecting the arithmetic mean value of the magnetic field, G
C_x and C_y	Characterizing magnetic field gradient, G
C_{xy}	Describes the nonlinear coupling effect, G
X, Y	Dimensionless numbers after normalization, ∈ [-1;1]

The optimization objective is constrained to $-5\ G \leq C_0 \leq 5\ G$ and $-10\ G \leq C_x \leq 10\ G$ [3–5] to control the stability of electrode distance and fluctuation of molten aluminum. C_0 is average values, and C_x is the overall gradient value in x direction. This is different from the commonly used criteria in China. At present, China generally takes $|B_z|_{avg} \leq 5\ G$ "the average of the absolute values of the four-quadrant vertical magnetic field" as the evaluation standard of the stability of the vertical magnetic field. But this is actually caused by misreading the early Sele criterion [5, 6]. In fact, in Sele's own article, it refers to the arithmetic mean C_0, i.e., in Equation (1), and the argument that the gradient in the X direction of the vertical magnetic field (i.e., C_x.) proposed by Urata [3] in recent years is equally important, has also been recognized.

B) Regression analysis and sensitivity assessment

The least square method is used to regress the sample magnetic field data, to calculate the coefficient matrix $[C_0, C_x, C_y, C_{xy}]$, and to evaluate the sensitivity of the geometric parameters of the busbars (such as the inclination of the guide rod and the length of the compensation busbar) to each coefficient through variance analysis. Defining sensitivity indicators, Equation (2):

$$S_i = \frac{\partial C_i}{\partial P_j} \cdot \frac{P_j}{C_i} \quad (2)$$

where: P_j is the j-th busbar parameter. Sensitivity ranking provides priority guidance for manual intervention or automatic optimization.

C) Multi-objective collaborative optimization

The multi-objective optimization model is built based on NSGA-II algorithm [2], and the objective function is, Equation (3):

$$min(w_1 \cdot \frac{|I_N - I_C|}{I_N} + w_2 \cdot \frac{|\Delta B_N - \Delta B_C|}{\Delta B_N}) \quad (3)$$
$$s.t. \quad -5\ G < C_0 < 5\ G, \quad -10\ G < C_x < 10\ G, \quad Tmax < 70\ ℃$$

where

I_N	new investment
I_C	actual investment of the sample in the library
ΔB_N	Deviation between the magnetic field of the new scheme and the standard value
ΔB_C	Deviation between the magnetic field of the scheme and the standard value in the sample library
w_1	weight of economic component, %
w_2	weight of electromagnetic component, %

In the backend software of this project, an optimization algorithm combining case library and target optimization was adopted for the configuration of aluminum electrolytic cell busbars. Our company's long-term accumulation of busbar case library covers 57 global electrolytic cell solutions (300–600 kA), including some typical designs of international aluminum giants, ensuring algorithm generalization ability. Based on this case library, with electromagnetic characteristics, economic characteristics, and engineering characteristics as the objectives, the model has set the total weight and construct a multi-objective optimization algorithm to seek the optimal solution. The electromagnetic characteristics, economic characteristics, and engineering characteristics here are shown in Table 2.

Table 2. Target characteristics of busbar design.

Item	Index
Electromagnetic characteristics	Stability criterion, magnetic field specification, current deviation (≤ 5 %)
Economic characteristics	Busbar mass (tonnes), welding and bolt quantity, energy consumption (busbar voltage drop)
Engineering characteristics	Maximum temperature rise (°C), total length of busbars

Criteria for determining the target scheme:

$$S = w_1 \cdot \frac{|I_N - I_C|}{I_N} + w_2 \cdot \frac{|\Delta B_N - \Delta B_C|}{\Delta B_N} + w_3 \cdot \frac{M_C}{M_N} \tag{4}$$

where:

I_N new investment
I_C actual investment of the sample in the library
ΔB_N Deviation between the magnetic field of the new scheme and the standard value
ΔB_C Deviation between the magnetic field of the scheme and the standard value in the sample library
M_N Calculated quantities of the new busbar scheme
M_C Ccalculated quantities of the standard scheme
w_1 weight of economic component, % (generally 30 %)
w_2 weight of electromagnetic component, % (generally 50 %)
w_3 weight of engineering features component, % (generally 20 %)

For the multi-objective optimization problem of busbar scheme selection, the non-dominated sorting genetic algorithm II (NSGA-II) is used to solve it, which is an algorithm specially used to solve the optimization problems with multiple conflicting objectives (such as the balance of electromagnetic performance, economy and engineering constraints in the design of cell busbar). Its core idea is to simulate natural selection through genetic algorithm, and to search a Pareto optimal solution set efficiently by combining non dominated sorting and congestion comparison. The population size is set to 100, with 500 iterations, a crossover probability of 0.9, and a mutation probability of 0.1, determined on the sensitivity analysis [2]. The algorithm is integrated into the Pot3D module of the cell design system on the cloud.

3. Case Verification

3.1 Case 1: Busbar Scheme of a 500 kA Cell

Taking a 500 kA cell of our company as an example, this paper introduces the application of "cloud aluminum reduction cell intelligent design system" in engineering design. The process consists in selecting a 500 kA cell busbar scheme with similar basic conditions from the base case (see Figure 4), and pointing out the problem of too high magnetic field in the original scheme after evaluation by intelligent optimization algorithm, and adjusting it. The adjusted scheme meets the requirements of program judgment, and its rationality is verified by simulation analysis.

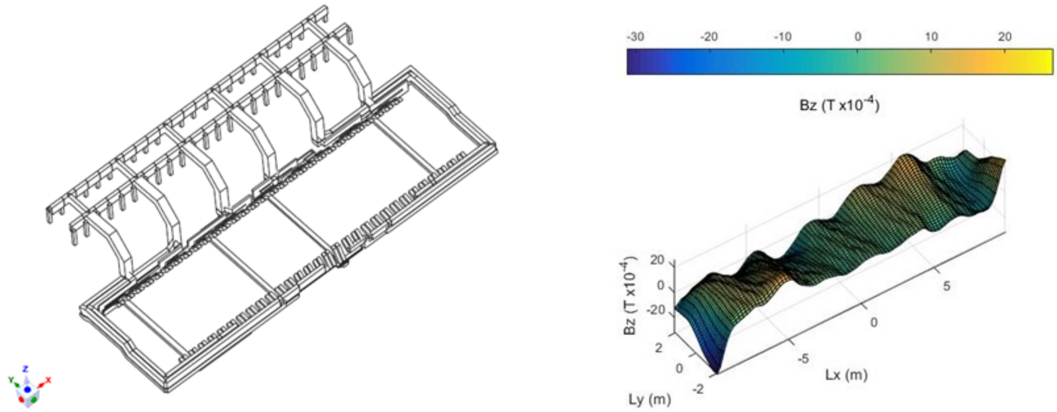


Figure 4. Busbar diagram of similar scheme in sample library (external compensation busbar is not shown) and vertical magnetic field distribution.

A) After the evaluation of the intelligent optimization algorithm, it is pointed out that the disadvantage of the scheme in Figure 4 is that the modulus of the arithmetic mean value of the magnetic field is large ($C_0 = -5.591$G), which is no longer within the C_0 reasonable range. Therefore, the algorithm instruction is returned for modification. After analysis, C_0 is mainly caused by the busbars horizontally arranged around and at the bottom of the cell. Specifically, in this case, the local busbars are too concentrated, resulting in excessive magnetic field. After dispersing them and offsetting each other as much as possible, the magnetic field meets the requirements. After several adjustments, the following scheme given in Figure 5 is adopted to meet the determination requirements of the program. ($C_0 = 2.687$ G) as shown in Table 3.

Table 3. Comparison of a 500 kA cell busbar scheme before and after modification.

	C_0	C_x	C_y	C_{xy}
Original scheme (G)	-5.5907	3.5013	-0.5522	0.2699
Improved scheme (G)	2.6870	3.8643	-0.5239	3.9428

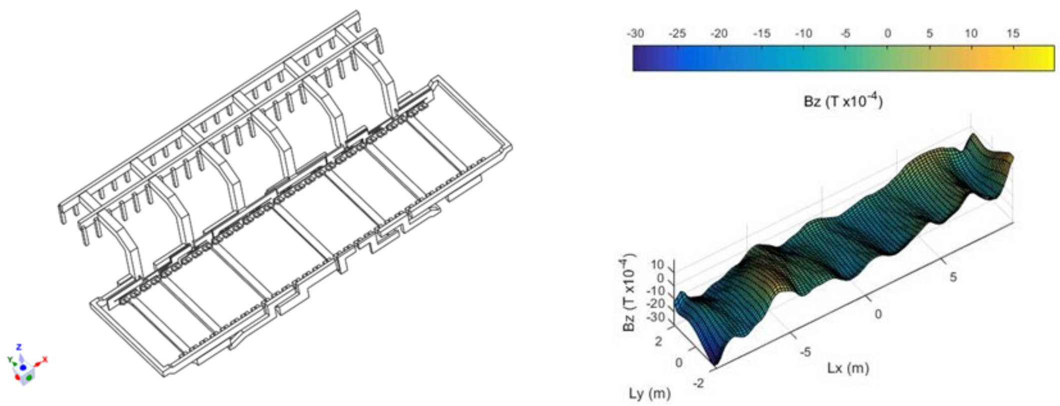


Figure 5. Schematic diagram of improved scheme busbars, meeting algorithm requirements (external compensation busbar is not shown), and vertical magnetic field distribution.

B) Previously, busbar designs can only be simulated and analysed once the detailed design was completed. Nowadays, as long as basic design of the busbar scheme exists, ANSYS and COMSOL can conduct simulation analysis on such design (default values are used for undetermined parameters) and determine whether it meets or not performance criteria.

C) After forming the three-dimensional scheme, because the three-dimensional model has been formed, although some details such as solder joints and screws are still missing, the volume of the main materials is known, and the mass of the main materials (tonnes) can be obtained by multiplying the volume by the density. The investment in engineering of the cell accounts for about 40–50 % of the total investment. In this way, the total investment of each scheme can be seen at a glance. The investor can accurately estimate the project cost before the project operation, so that he can make accurate decisions.

D) The actual magnetic field measurement results after the project completion given in Figure 6 confirm the efficiency of the method.

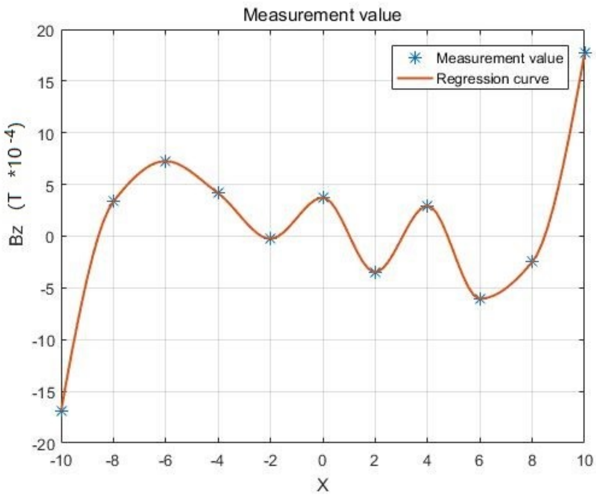
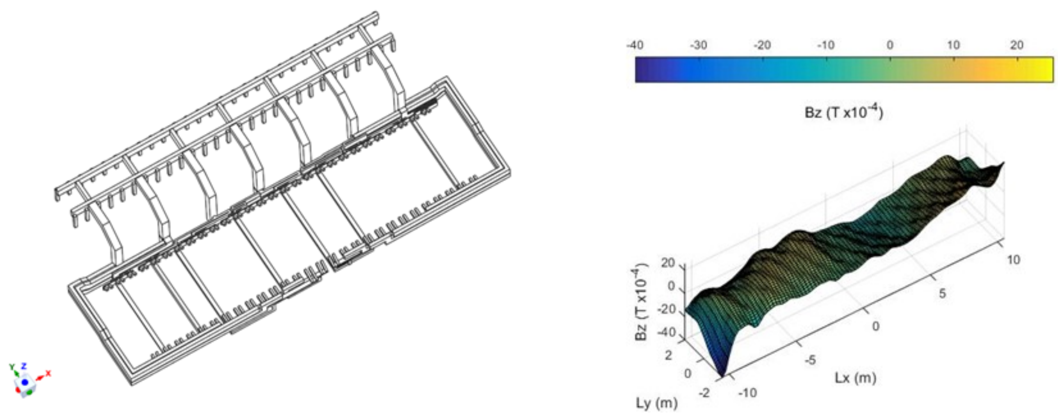


Figure 6. Measured values of vertical magnetic field in the improved 500 kA cell.

3.2 Case 2: Analysis of Busbar Scheme of a 530 kA Cell

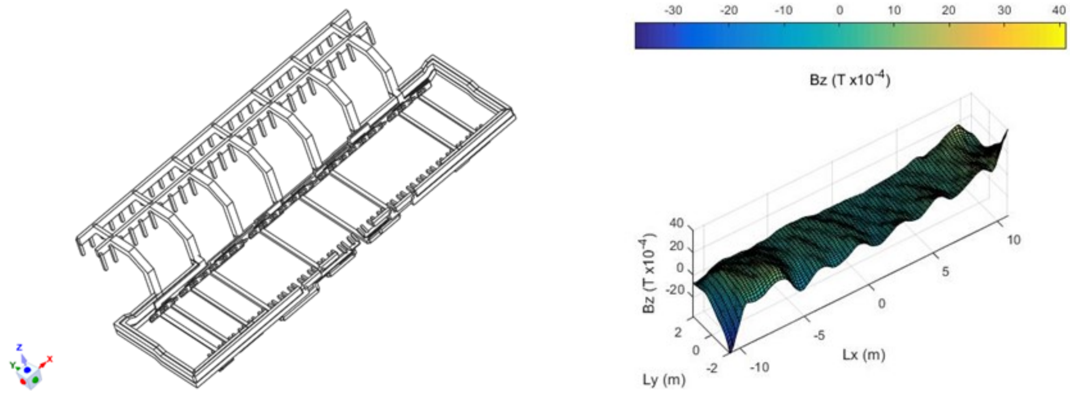
The structure and magnetic field of the original scheme are shown in Figure 7.



(a) (b)

Figure 7. Initial 530 kA electrolytic cell busbar design scheme (a) and vertical magnetic field distribution (b).

Through calculation and analysis, C_0=B_{z0} $= 1.187\ G$, C_x=*14 G*, C_x is mainly caused by the adjacent cell, and the busbar around and at the bottom of the cell. The value is positive, indicating that the compensation for the adjacent cell is excessive. It is necessary to reduce the busbar current at the duct end, and properly adjust and disperse the busbar at the bottom of the cell to reduce the local magnetic field, and then reduce the gradient of the vertical magnetic field B_z in the X direction. The improved scheme and graphics are given in Figure 8.



(a) (b)

Figure 8. Improved 530kA cell busbar design scheme (a) and vertical magnetic field distribution (b).

As shown in Table 4, a fter the improvement,$\boldsymbol{C_0}$ is increased, but it is still within the feasible range, while $\boldsymbol{C_x}$ is reduced to 3.616 G, with obvious improvement.

Table 4. Comparison of a 530 kA cell busbar scheme before and after improvement.

	C_0	C_x	C_y	C_{xy}
Original scheme (G)	1.1876	14.7452	-2.3851	-1.9668
Improved scheme(G)	3.1505	3.6136	-0.7531	-2.9607

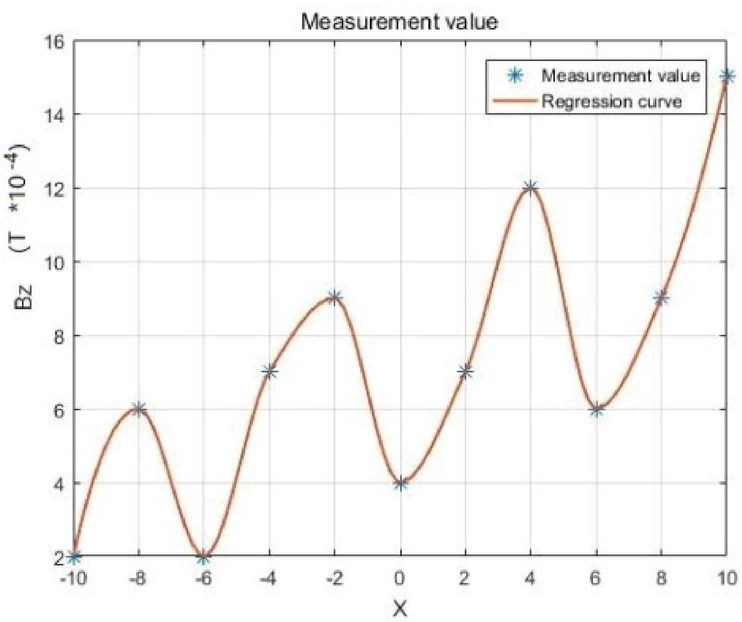


Figure 9. Measured values of vertical magnetic field in the improved 530 kA cell.

Figure 9 shows the measured vertical magnetic field distribution of the electrolytic cell during actual production, which effectively reflects the characteristics of the improved scheme.

4. Discussion

4.1 Project Innovations

Tool innovation: the first special BIM system for the cell, which realizes the whole chain automation from parameter input to multi-physical-field simulation;

Theoretical innovation: propose C_0, C_x multi parameter criteria to solve the blind spot of magnetic field design of high current cells. Especially the C_x introduction has solved the problem of inadequate vertical magnetic field criteria for modern high amperage cells.

Algorithm innovation: NSGA-II optimization framework driven by case base, balancing electromagnetic/economic/engineering objectives.

4.2 Scope and Limitations of the System

At present, the system can only be used for technology suppliers with a large case base, and the scheme relies heavily on the accuracy of simulation operation, which takes a long time. Single optimization takes 6 hours (Intel Xeon 16 cores) and further parallelization is required; The coverage rate of the case library for cell types above 630 kA is only 4 %.

4.3 Improvement Direction

The future research can further enhance the machine-learning algorithm to automatically optimize the reduction cell shell, lining and busbar scheme.

5. Conclusions

In this paper, a new data-driven design paradigm of aluminum reduction cell is proposed. Through the integration of 3D BIM technology, intelligent optimization platform and machine learning algorithms, the whole process digital management of the design is realized. This method significantly improves the design accuracy and efficiency, and shows the advantages in shortening the design cycle, reducing design changes and reducing costs through the actual project verification. This study breaks through the pure theoretical analysis of previous work [5] and achieves the engineering implementation of criteria for the first time. The research results of this project provide new solutions for the intelligent transformation of the aluminum smelter industry and offer new ideas for future research.

6. Acknowledgment

On the 4th anniversary of the passing of my teacher, Mr. YAO Shihuan, I wish to commemorate his memory through this article.

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