Application of Dynamic Optimization and Carbon Efficiency Synergy Driven by QFD-TOC Model in Low-Carbon Aluminium Electrolysis

Kangsong Luo[1], Wei Tang[2], Rui Lu[3] and Yan Wang[4]
1, 3. Engineers
2. Associate Senior Engineer
4. Assistant Engineer
Guangxi Hualei New Materials, Pingguo, China
Corresponding author: 1160079571@qq.com
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Abstract

To address bottlenecks in the low-carbon transformation of the aluminium electrolysis industry, including the rough process optimization, lagging carbon efficiency management, and difficulty in multi-objective dynamic synergy, this paper innovatively proposes a QFD-TOC dual-drive dynamic optimization method. For the first time, the Quality Function Deployment (QFD) is deeply integrated with the Theory Of Constraints (TOC) to establish a low-carbon process optimization system that links "policy demand - process constraints- real-time regulation". By using QFD to hierarchically analyse the dual-carbon policies, cost-reduction needs of enterprises, and technical characteristics of the process (e.g., cell temperature, anode effect coefficient), carbon efficiency conflict points in aluminium electrolysis production are precisely identified. Combined with TOC, a dynamic constraint boundary adaptive model is developed to achieve real-time multi-objective synergy optimization of "carbon – energy - efficiency". This study overcomes the core difficulties of slow dynamic response and poor multi-objective coordination in aluminium electrolysis low-carbon optimization, offering a systematic solution that integrates theoretical innovation with practical implementation. This solution is of significant practical importance for advancing the green upgrade of the aluminium industry.

Keywords: QFD-TOC model, Low-carbon aluminium electrolysis process, Dynamic optimization, Carbon efficiency synergy.

1. Introduction

The aluminium electrolysis industry, being a high-energy consumption and high-carbon emission sector, is undergoing a critical period of green low-carbon transformation. Currently, the industry faces core challenges such as rough process optimization, lagging carbon efficiency management, and difficulty in multi-objective dynamic synergy. There is an urgent need to develop a systematic method for low-carbon process optimization. This paper innovatively proposes a QFD-TOC dual-drive dynamic optimization model that deeply integrates Quality Function Deployment (QFD) with the Theory of Constraints (TOC) [1]. The goal is to establish a low-carbon process optimization system that links "policy demand - process constraints - real-time regulation." By using QFD to hierarchically analyse dual-carbon policies, enterprise cost-reduction needs, and technical characteristics (such as cell temperature and anode effect coefficient), carbon efficiency conflict points in aluminium electrolysis production are precisely identified. Combining TOC, a dynamic constraint boundary adaptive model is established to achieve real-time multi-objective synergy optimization for "carbon – energy - efficiency." This study successfully addresses the core issues of slow dynamic response and poor multi-objective synergy in low-carbon optimization in aluminium electrolysis. It provides a systematic solution that combines theoretical innovation with practical application, offering significant real-world value for advancing the green transformation of the aluminium industry.

2. Background and Current Situation

As a vital basic material industry in China, aluminium electrolysis has seen rapid development in recent years. According to the latest statistics, the carbon emissions from China's aluminium electrolysis industry are approximately 420 million tonnes per year, accounting for 77 % of the carbon emissions in the non-ferrous metals industry and 5 % of the country's total carbon emissions. The electricity consumption is 502.2 TWh, accounting for 6.7 % of the national total. The aluminium electrolysis accounts for 78 % of the total carbon emissions in aluminium industry, making it the main battlefield for pollution reduction and carbon emissions reduction. In July 2024, the National Development and Reform Commission (NDRC) and other departments jointly issued the *Special Action Plan for Energy Conservation and Carbon Reduction in the Aluminium Electrolysis Industry* [2, 3], which clearly states that by the end of 2025, the production capacity of the aluminium electrolysis industry that meets or exceeds the energy efficiency benchmark level should reach 30 %. Capacities below the energy efficiency baseline should undergo technological transformation or be eliminated, while the utilization rate of renewable energy in the industry should reach more than 25 %, and the output of recycled aluminium should reach 11.5 million tonnes. By implementing energy conservation and carbon reduction modifications, the aluminium electrolysis industry is expected to save about 2.5 million tonnes of standard coal and reduce CO_2 emissions by approximately 6.5 million tonnes from 2024 to 2025 [4, 5].

However, the low-carbon transformation of the aluminium electrolysis industry still faces numerous bottlenecks. Firstly, process optimization is often rudimentary, with existing process parameter adjustments mainly based on empirical judgment, lacking systematic analysis and optimization. Secondly, carbon efficiency management is lagging, as the industry has yet to establish scientific, systematic methods for carbon efficiency evaluation and management. Lastly, achieving multi-objective dynamic synergy is challenging, as aluminium electrolysis production involves multiple objectives such as carbon emissions, energy consumption, and production efficiency, with complex conflicts between these goals, making dynamic synergy optimization difficult. Additionally, the aluminium industry is not only a high-energy-consuming sector, but also approximately 87 % of China's electrolytic aluminium is powered by thermal power. The structural contradiction in energy use is the biggest challenge in achieving the aluminium industry's “dual carbon” goals. The global average carbon emission per tonne of aluminium from electricity consumption is 10.4 tonnes, while in China it is 12.8 tonnes. The aluminium electrolysis accounts for 78 % of the carbon emissions in aluminium industrial chain.

3. Challenges and Areas for Improvement

The core challenges faced by the aluminium electrolysis industry in its low-carbon transformation include the following:

(1) Traditional aluminium electrolysis process parameter adjustments are often based on empirical judgment, lacking systematic analysis and optimization. There are complex interactions and conflicts between process parameters such as bath temperature, current density, and molecular ratio. These adjustments require multi-objective balancing, but existing methods struggle to achieve comprehensive, dynamic parameter optimization.

(2) In aluminium electrolysis production, carbon emissions mainly come from electricity consumption, basic reaction for making aluminium and PFCs (e.g., CF_4, C_2F_6) generated by anode effects. CF_4 has global warming potential (GWP) of 7 380, and CF_6 has a GWP of 12 400 (according to IPCC 6th Assessment Report [6]), much higher than CO_2's GWP of 1. However, the industry has yet to establish a scientific, systematic method for carbon efficiency evaluation and management, making it difficult to accurately measure and effectively control carbon emissions.

(3) Difficulty in multi-objective dynamic synergy. Aluminium electrolysis production involves multiple objectives, including carbon emissions, energy consumption, and production efficiency, with complex conflicts between them. For example, increasing current density can boost output but also raises energy consumption; lowering cell temperature can reduce thermal energy loss but may increase operational costs; using renewable electricity can reduce carbon emissions but comes with higher power supply costs. Achieving dynamic synergy optimization between these goals is a critical challenge in the low-carbon transformation of aluminium industry.

4. Current State of Research and Technological Development

In response to the challenge of optimizing low-carbon aluminium electrolysis processes, researchers both domestically and internationally have conducted extensive studies, primarily focused on the following areas:

In terms of low-carbon electrolysis technologies, molten salt electrolysis and ionic liquid electrolysis are key research directions. Molten salt electrolysis uses molten salts as electrolytes to reduce energy consumption during the electrolysis process and simultaneously decrease fluoride emissions. Ionic liquids, as a new type of electrolyte, offer advantages such as low volatility, excellent thermal stability, high conductivity, and environmental friendliness. The adoption of ionic liquid electrolysis can significantly reduce energy use and pollutant emissions during aluminium production.

In terms of energy-saving and emission-reduction technologies, waste heat recovery and intelligent control systems have received widespread attention. Implementing waste heat recovery allows full utilization of the heat generated during aluminium electrolysis to preheat raw materials or produce steam, thereby lowering energy consumption. Intelligent control systems monitor and optimize the reduction process in real-time, reducing unnecessary energy losses and improving energy efficiency. For example, the green low-carbon deep energy-saving aluminium electrolysis system developed by Shenyang Aluminium and Magnesium Engineering & Research Institute (SAMI) reduced direct current consumption by 700–900 kWh/t Al (5 % lower than the international advanced level), extended the service life of electrolysis cells by about 1 000 days, reduced production fluctuation by 80 %, and brought fluoride emissions down to less than 0.5 g/m^3, only one-sixth of the national standard value [7, 8].

In terms of process parameter optimization, multi-objective optimization algorithms have been widely adopted. NSGA-II (Non-dominated Sorting Genetic Algorithm), as an efficient multi-objective optimization algorithm, has been successfully applied to aluminium electrolysis process optimization. For instance, one research team improved the NSGA-II algorithm and, using production data from an aluminium smelter in Guizhou, constructed a multi-objective optimization model targeting maximum current efficiency and minimum energy consumption per tonne of aluminium. Results showed that the optimal NSGA-II algorithm achieved a current efficiency of 95.66 % and energy consumption of 12 425 kWh/t Al; compared to the traditional NSGA-II, current efficiency improved by 0.31 % and energy consumption dropped by 22.11 kWh/t Al, achieving energy-saving and cost-reducing benefits [9].

In addition, digital twin and IoT technologies are gaining increasing attention in aluminium electrolysis process optimization. For example, Zunyi Aluminium Co., Ltd., in collaboration with Huawei, developed a “Dynamic Optimization and Prediction Model for Complex Aluminium Electrolysis Systems”, which uses IoT sensors to collect real-time operational data from electrolysis cells. Combined with AI algorithms, it predicts optimal parameter combinations to precisely regulate the molecular ratio, aluminium fluoride addition, and aluminium tapping volume.

However, most existing studies focus on optimizing single technologies or parameters and lack a systematic method that integrates Quality Function Deployment (QFD) with the Theory Of Constraints (TOC), making it difficult to solve the problem of multi-objective dynamic synergy in the low-carbon transformation of aluminium electrolysis. This study addresses this gap by proposing a QFD-TOC dual-drive dynamic optimization model, providing new theoretical and methodological support for low-carbon process optimization in aluminium electrolysis industry.

5. Experimental or Modelling Plan

The QFD-TOC dual-drive dynamic optimization model deeply integrates the demand translation capability of Quality Function Deployment (QFD) with the bottleneck identification methods of the Theory of Constraints (TOC), creating a closed-loop optimization system from macro-level policy demands to micro-level process regulation. Through QFD, external dual-carbon policy requirements and internal corporate needs for cost reduction and efficiency improvement are systematically translated into specific process characteristics and parameter optimization objectives. TOC is then applied to identify critical bottlenecks that constrain overall system performance in meeting these demands. Finally, based on a deep understanding of these bottlenecks, a dynamic constraint boundary adaptive model is established. Through sensing, control, and algorithmic technologies, real-time and synergistic optimization of key process parameters is achieved, as shown in Figure 1.

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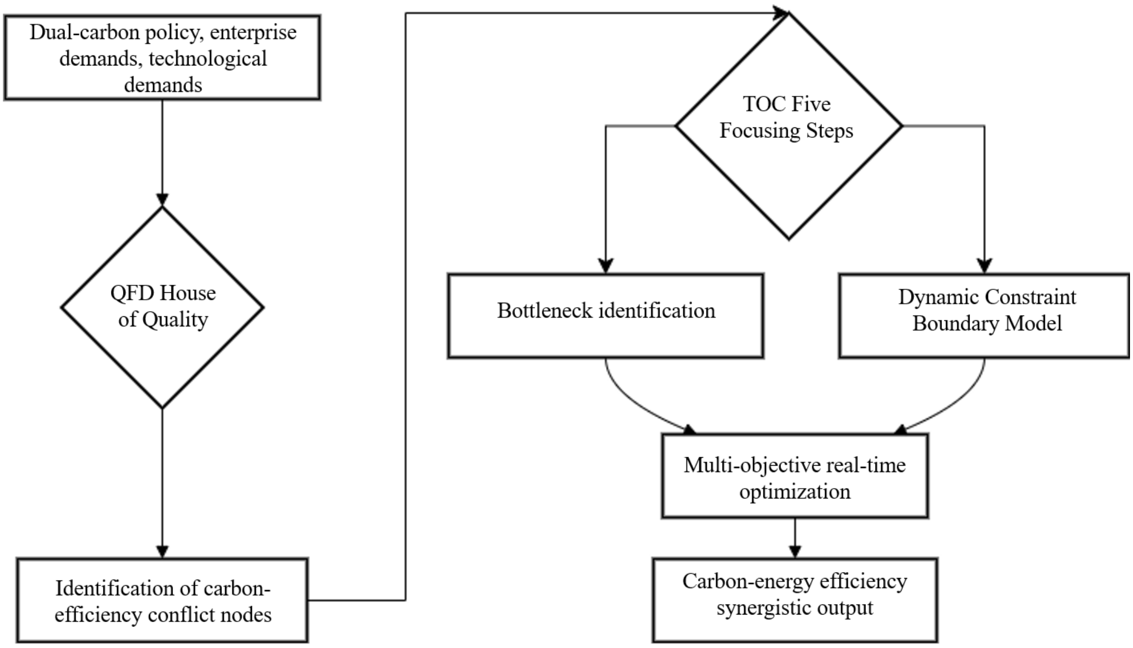
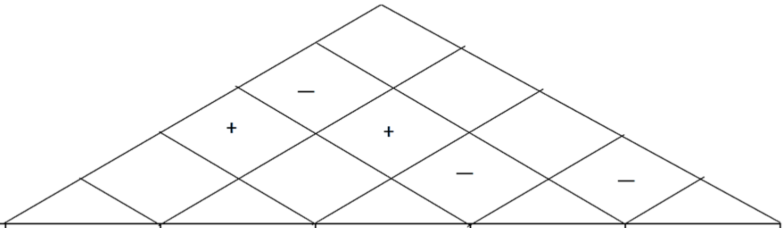


Figure 1. Framework of QFD-TOC dual-drive model.

6. Work Description, Results, and Discussion

6.1 Construction of QFD House of Quality and Identification of Carbon Efficiency Conflict Points

QFD (Quality Function Deployment) is a systematic method for translating Customer Requirements (CRs) into Engineering Characteristics (ECs). The QFD House of Quality for low-carbon process optimization in aluminium electrolysis (see Figure 2) integrates dual-carbon policies, enterprise cost-reduction demands, and technical characteristics into a cohesive system. The House of Quality includes: customer requirements such as policy, enterprise, and technical demands; key process parameters of aluminium electrolysis; and the matrix quantifying the relationship strength (1–9 scale) between customer requirements and technical characteristics. Additionally, by evaluating technical characteristics, the importance of technical requirements is determined, and the correlations among different customer requirements (positive, negative, or neutral) are analysed to guide subsequent optimization.



Customer requirements i \ Technical characteristics j		Importance (Ki)	Cell Temperature	Current density	Molecular ratio	Anode effect coefficient	Proportion of green electricity
Policy requirements	Reduction of carbono emissions	5	7	3	2	9	9
Enterprise requirements	Cost control	2	1	7	2	3	7
	Capacity efficiency	4	7	6	5	7	1
Techonological requirements	Process stability	3	5	5	9	5	3
Importance of technical characteristics S_j			80	68	61	94	72

Figure 2. QFD house of quality for low-carbon aluminium electrolysis process optimization.

In the QFD House of Quality, the equation S_j for calculating the total importance of technical characteristics is as follows, Equation (1):

$$\boldsymbol{S_j = \sum_i^n \omega_i \cdot R_{ij}} \tag{1}$$

where:

$\boldsymbol{S_j}$ Total importance of technical characteristic **j**

$\boldsymbol{\omega_i}$ Weight of customer requirement **i**

$\boldsymbol{R_{ij}}$ Relationship strength between requirement **i** and technical characteristic **j** (1–9 scale).

This equation quantifies the importance of each technical characteristic in meeting overall low-carbon and efficiency demands. By calculating and ranking the $\boldsymbol{S_j}$ values, the key technical characteristics that contribute most to the objectives and require priority optimization can be identified.

As shown in Figure 2, policy demands such as lowering carbon emissions (e.g., maintaining low cell temperature to reduce heat loss) may conflict with enterprise demands for increasing current density to boost production, which could lead to higher cell temperatures or intensified anode effects – thus forming conflicts. Identifying these carbon efficiency conflict points in aluminium production is crucial. Furthermore, quantitative analysis determines the severity and prioritization of these conflict points, see Table 1.

Table 1. Severity and priority of conflict points.

Technical Characteristic	Total Importance	Optimization Direction Recommendation
Anode Effect Frequency	94	Focus on reducing anode effects (e.g., optimizing the electrolysis process) while balancing carbon emissions and production efficiency goals.
Cell Temperature	80	Control within a reasonable range to improve production efficiency while avoiding risks to process stability.
Proportion of Green Electricity	72	Increase green electricity usage to reduce carbon emissions, but assess its impact on production efficiency (current rating is only 1).
Current Density	68	Raising current density reduces cost, but attention must be paid to its potential negative impact on carbon emissions (rated 3).
Molar Ratio	61	Optimizing molar ratio is key to process stability but has relatively low contribution to other demands (e.g., cost control).

Identifying these conflict points provides clear directions for subsequent process parameter optimization. For example, to address the conflict between current density and anode effect, measures must be taken to suppress anode effects while increasing current density, such as optimizing the magnetic field design of the electrolysis cell or operating under low molecular ratios.

6.2 TOC Bottleneck Identification and Dynamic Constraint Model Establishment

6.2.1 Application of the TOC Five-Focusing Steps in Aluminium Electrolysis Processes

The Theory of Constraints (TOC), proposed by management scientist E. Goldratt, is based on the core idea that the overall performance of any complex system is constrained by a few key bottlenecks. By systematically identifying, managing, and breaking through these bottlenecks, the overall system efficiency can be maximized. Unlike traditional optimization methods, TOC emphasizes "focused management" rather than "comprehensive balance," concentrating on the most critical limiting factor of the objective function. In low-carbon aluminium electrolysis process optimization, TOC theory (see Figure 3) is deeply integrated with the above QFD analysis results to construct a systematic bottleneck identification framework.

Through the application of the TOC five-focusing steps, we identified the core bottleneck in the aluminium electrolysis process – the anode effect. The anode effect not only increases carbon emissions (the GWP of CF_4 and C_2F_6 is far higher than CO_2), but also raises energy consumption and compromises cell stability.

In the optimization process, targeted warning and control strategies were designed to address the anode effect as the core bottleneck. By applying deep learning to historical data, an Anode Effect Warning Index (**AEWI**) was established as per Equation (2).

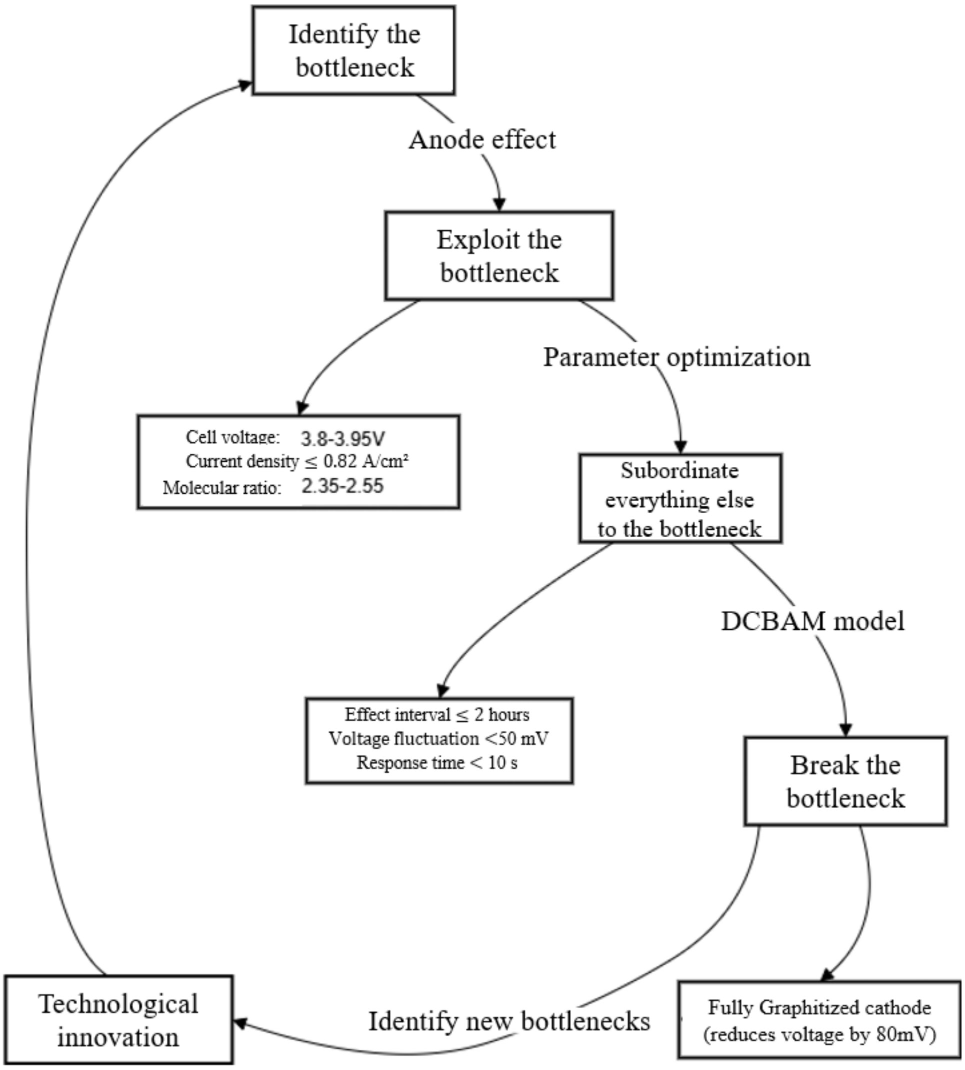


Figure 3. Process of TOC five-focusing steps in low-carbon aluminium electrolysis process optimization.

$$AEWI = \omega_1 \cdot \frac{V-V_b}{V_m-V_b} + \omega_2 \cdot \frac{R-R_b}{R_m-R_b} + \omega_3 \cdot \frac{F-F_b}{F_m-F_b} \quad (2)$$

where:

V, R, F Real-time values of voltage, resistance, and excess fluoride concentration
V_b, R_b, F_b Baseline values
Vm, Rm, Fm Historical maximum values
ω_1=0.5, ω_2=0.3, ω_3=0.2 Weighting coefficients.

When the **AEWI** exceeds the preset threshold (0.75), the system automatically triggers anode effect prevention measures, including adjusting current density, feeding strategy, and crust-breaking frequency. In practical application, this strategy reduced the occurrence of anode effects.

6.2.2 Construction of a Dynamic Constraint Boundary Adaptive Model

In a continuous production process like aluminium electrolysis, process parameters and external conditions (such as power supply and raw material quality) are subject to dynamic fluctuations.

To address such uncertainties, a dynamic constraint boundary adaptive model was proposed in this study. The core idea of this model is that operational constraints of key process parameters (e.g., allowable fluctuation range of cell temperature, upper limit of anode effect occurrence) should not remain fixed, but instead be adaptively adjusted in response to real-time production conditions and external factors, Equation (3):

$$B(t) = B_0 + \alpha \cdot \Delta P(t) + \beta \cdot \Delta T(t) + \gamma \cdot \Delta E(t) \tag{3}$$

where:

$B(t)$	Dynamic constraint boundary value at time t
B_0	Baseline constraint value (recommended value under standard conditions)
$\Delta P(t)$	Real-time fluctuation of key process parameters
$\Delta T(t)$	Real-time quantification value of external disturbance factors
$\Delta E(t)$	Real-time feedback signal of overall system energy or carbon efficiency performance
α, β, γ	Adaptive adjustment coefficients 0.15, 0.08, 0.12.

Considering the characteristics of low-carbon aluminium electrolysis processes, the model was further extended to a multi-objective optimization form, Equation (4):

$$minF(x) = \left[f_c(x), f_{en}(x), f_{ef}(x)\right]^T \tag{4}$$

Constraint conditions:

$$g_i(x,t) \leq B_i(t), i = 1,2,\ldots,m$$

$$h_i(x,t) = 0, i = 1,2,\ldots,n$$

where:

x	Process parameter vector (including cell temperature, current density, and molecular ratio)
f_c, f_{en}, f_{ef}	Objective functions for carbon emissions, energy consumption, and production efficiency
g_i	Inequality constraint function
h_i	Equality constraint function
$B_i(t)$	Dynamic boundary value of the No. i constraint.

6.3 Implementation and Effect Analysis of Multi-Objective Real-Time Collaborative Optimization

Using a 500 kA electrolytic cell of a smelter as the case, based on the carbon-efficiency conflict nodes identified by QFD (Table 1) and the bottleneck (anode effect) locked by TOC, real-time monitoring data were collected, including cell voltage (±0.01 V accuracy), cell temperature (±2 °C accuracy), anode effect frequency, and renewable electricity share. According to Equation 3, with B_0 as the baseline values (cell temperature 950 °C, anode effect frequency ≤ 0.05 AE/cell·day), adaptive coefficients were determined through historical data analysis (α = 0.6, β = 0.25, γ = 0.15). An improved NSGA-III algorithm was used to solve the multi-objective function, Equation (5):

$$minF(x) = \left[f_c(x), f_{en}(x), f_{ef}(x)\right]^T \tag{5}$$

Constraint condition: $g_i(x,t) \leq B_i(t), i = 1,2,\ldots,m$; $h_i(x,t) = 0, i = 1,2,\ldots,n$ dynamic boundary adjustment.

Based on the reference operating conditions: cell temperature 960 ±10 °C, molar ratio 2.3, anode effect frequency of 0.08 EA/cell·day, specific DC power consumption 12 800 kWh/t Al, current efficiency 93.5 %, and carbon intensity 12.8 t CO_2/t Al (thermal power accounts for 87 %). The results of the optimization are given in Table 2.

Table 2. Comparison of optimization strategies (based on 6-month production averages).

Indicator	Baseline Strategy	Single-Objective Optimization (Energy Reduction Only)	QFD-TOC Multi-Objective Optimization
Cell temperature (°C)	960	945	952
Anode effect frequency (times per cell per day)	0.08	0.1	0.03
DC power consumption (kWh/t Al)	12 800	12 200	12 400
Current Efficiency (%)	93.5	92.8	94.2
Carbon emissions (t CO_2/t Al)	12.8	12.5	12.3
CF_4 emissions (kg/t Al)	1.2	1.5	0.45

Before applying the QFD-TOC model, the baseline DC power consumption for the 500 kA electrolytic cell was 12 800 kWh/t Al. Through systematic optimization using the QFD-TOC model, especially the precise control of cell temperature (a key technical characteristic identified by QFD) and effective suppression of anode effects (the core bottleneck identified by TOC), production statistics showed a significant reduction in specific comprehensive energy consumption. After optimization, energy consumption dropped to 12 400 kWh/t Al. This represents an approximate 400 kWh/t Al reduction in energy consumption, a decrease of about 3.13 %. The model guides smelters to precisely control bath temperature within a targeted low-temperature range (e.g., 950 ±10 °C), while strictly maintaining the anode effect frequency at a low level (e.g. ≤ 0.05 AE/cell·day). These measures effectively reduce heat loss and ineffective power consumption, translating into direct economic benefits and indirect carbon reduction outcomes. Smelters should focus on energy-related technical characteristics with high importance identified by QFD and on bottlenecks determined by TOC for targeted optimization.

Improving current efficiency directly means producing more aluminium with the same energy input, or using less energy to produce the same amount of aluminium, making it a key factor in cost reduction and efficiency improvement. Smelters should leverage the QFD-TOC model to prioritize optimization of process parameters affecting electrolyte uniformity, cavity stability (e.g., magnetohydrodynamic stability), and material balance, while strictly controlling disturbances like anode effects.

The QFD-TOC model, through TOC bottleneck management and advanced early warning strategies such as AEWI, can reduce the occurrence of anode effects by at least 37.5 % (from 0.08 to 0.05 AE/cell·day) or more, significantly cutting PFCs (strong greenhouse gases) emissions, by an estimated 50 % or higher.

7. Conclusions

This study proposes a QFD-TOC dual-drive dynamic optimization model that effectively addresses challenges in the low-carbon transformation of aluminium electrolysis, such as rough process optimization, lagging carbon-efficiency management, and difficulties in multi-objective dynamic coordination. By constructing a QFD House of Quality, we accurately identified carbon-efficiency conflict nodes in aluminium production and proposed targeted optimization strategies. Through the application of TOC, we developed a dynamic constraint boundary adaptive model, enabling real-time multi-objective coordination across carbon, energy, and efficiency dimensions. The QFD-TOC model is not merely a single-point technical improvement; it establishes a complete optimization loop from macro-level policy requirements (translated via QFD) to micro-level process bottlenecks (broken through with TOC), and ultimately to dynamic, real-time process regulating. This effectively tackles core issues in traditional aluminium electrolysis process optimization, such as inefficiency, carbon management delays, and the challenge of dynamically balancing carbon, energy, and efficiency goals.

Results show that the QFD-TOC model can significantly reduce carbon emissions and energy consumption in aluminium electrolysis while improving production and energy efficiency. The model demonstrated notable optimization effects at key conflict points, such as current density vs. anode effect and bath temperature vs. energy consumption. Moreover, it can adapt to dynamic conditions like fluctuations in green electricity supply, enabling adaptive adjustment of process parameters. By precisely identifying and optimizing energy-efficiency-related technical characteristics through QFD, and managing energy consumption bottlenecks (such as ineffective power use caused by anode effects) through TOC, the model can achieve an average energy consumption reduction of about 3 % per unit product (simulation data, roughly 350–400 kWh/t Al), along with a 1.5–2 % increase in current efficiency. The QFD-TOC model provides a scientific, systematic, and highly actionable methodological framework and technical implementation path for the low-carbon transition of the aluminium electrolysis industry, and potentially other high-energy-consuming process industries.

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