

Machine learning-enabled composition optimization and industrial production of heat-treatment-free high-strength ductile iron

Bingtao Tang

Qilu University of Technology

Zhiwei Zhang

Qilu University of Technology

Wenyu Liu

Qilu University of Technology

Jian Ye

Linqing Jinguang Machinery Manufacturing co, LTD

Jinguo Jiao

Linqing Jinguang Machinery Manufacturing co, LTD

Maozhen Zhang

Linqing Jinguang Machinery Manufacturing co, LTD

Suxin Zhai

Linqing Jinguang Machinery Manufacturing co, LTD

Depeng Shen

`depengshen@qlu.edu.cn`

Qilu University of Technology

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Abstract

Achieving high strength and adequate ductility in as-cast ductile iron without heat treatment remains a major challenge. In this work, a machine learning-assisted alloy design strategy integrating orthogonal experiments and ensemble learning was developed to establish composition-property relationships for composition optimization. Based on the optimized design and advanced casting technologies, including fully automatic cored-wire feeding spheroidization process, and triple inoculation, a heat-treatment-free high-strength ductile iron was successfully developed. The optimized alloy achieved a tensile strength of 974 MPa, a yield strength of 613 MPa, and an elongation of 6.2% in the as-cast state. Eliminating conventional heat treatment substantially reduces manufacturing time, energy consumption, and production cost while maintaining excellent mechanical performance. This work demonstrates the effectiveness of data-driven alloy design for developing high-performance ductile irons and provides a practical pathway toward sustainable and intelligent cast iron manufacturing.

Introduction

Ductile iron is one of the most widely used cast ferrous materials owing to its low production cost, excellent castability, and high specific strength. The presence of spheroidal graphite significantly alleviates the stress concentration associated with flake graphite, thereby reducing its detrimental cutting effect on the metallic matrix and enabling an attractive combination of strength, ductility, and toughness ^[1]. Under optimized microstructural conditions, the specific strength of ductile iron can approach that of medium-carbon steel, while its density is less than 60% of steel, making it particularly attractive for lightweight structural applications ^[2]. As a result, ductile iron has been extensively employed in conventional automobiles, construction machinery, pipelines, agricultural equipment, and other engineering components. Owing to its flexible microstructural design, the mechanical performance of ductile iron can be tailored over a wide range through appropriate control of graphite morphology and matrix constitution ^[3, 4].

Despite these advantages, developing as-cast ductile iron with simultaneously high strength and adequate ductility remains a significant challenge. Conventional high-strength ductile irons generally rely on post-casting heat treatment, such as normalizing, quenching and tempering, or austempering, to obtain the desired microstructure and mechanical properties. Although these processes effectively improve strength, they inevitably increase production time, energy consumption, manufacturing cost, and process complexity, while also introducing additional variations in product quality. Therefore, achieving the target microstructure and mechanical properties directly in the as-cast condition, without subsequent heat treatment, has become an important objective for both academic research and industrial production. The mechanical properties of ductile iron are primarily governed by graphite characteristics and matrix microstructure ^[5]. A highly spheroidized graphite morphology minimizes stress concentration, whereas a fine and homogeneous pearlitic matrix provides effective strengthening while maintaining reasonable ductility. Consequently, alloy design has become one of the most effective approaches for regulating microstructural evolution during solidification and subsequent cooling. Carbon

and silicon are the primary graphitizing elements that determine graphite morphology, nodule count, and solidification behavior^[6]. Copper, chromium, and manganese are widely employed to promote pearlite formation, refine the interlamellar spacing^[7–9], it can also increase the strength and hardness, and improve the toughness of as-cast ductile iron^[10–12]. However, excessive additions of these alloying elements may increase carbide formation, elemental segregation, chill tendency, or brittleness, thereby deteriorating ductility and toughness^[13, 14]. Nickel and molybdenum are also effective strengthening elements that improve hardenability, thermal stability, and impact resistance^[15–20]. Nevertheless, their relatively high cost limits their application in conventional ductile irons, and their strengthening effects depend strongly on interactions with other alloying elements. Therefore, developing a rational compositional design strategy that simultaneously balances multiple alloying elements remains a key challenge for producing high-performance as-cast ductile iron.

To date, alloy composition optimization for ductile iron has been predominantly based on empirical knowledge, isolated alloying experiments, and repeated trial-and-error approaches. Because the relationships between multiple alloying elements, microstructural evolution, and mechanical properties are highly nonlinear and strongly coupled, conventional experimental optimization is both time-consuming and inefficient. Recent advances in machine learning have provided powerful tools for accelerating materials discovery and alloy design by establishing quantitative composition-property relationships from experimental data. Machine learning techniques have been successfully applied to the prediction of phase evolution, microstructure, and mechanical properties in various metallic materials, offering higher efficiency and predictive capability than traditional statistical methods. Ward et al. successfully applied random forest models for materials property prediction, showing that ensemble learning algorithms possess strong capabilities in handling complex materials datasets and evaluating feature contributions^[21]. Schmidt et al. further summarized the advantages of machine learning algorithms, such as random forest and gradient boosting, in materials informatics, highlighting their excellent nonlinear fitting capability and robustness for limited datasets^[22]. Hariharan et al. employed a high-speed 3D printing approach coupled with machine learning to accelerate the development of novel alloys for additive manufacturing, using in-situ alloying of high-strength steel with pure Al and flexible energy input adjustments to establish process-structure-property (PSP) relationships^[23]. Moreover, Wen et al. demonstrated that introducing elemental interaction descriptors can improve the ability of machine learning models to capture synergistic effects among alloying elements, indicating the importance of feature engineering in complex alloy design^[24]. However, the application of machine learning to the compositional optimization of heat-treatment-free high-strength ductile iron remains limited, and systematic studies integrating data-driven alloy design with industrial casting processes are still scarce.

In this work, a machine learning-assisted alloy design strategy was proposed to optimize the chemical composition of as-cast ductile iron. Based on orthogonal experimental data, ensemble learning models were established to predict mechanical properties and combined with a differential evolution algorithm for composition optimization. Guided by the optimized design, a heat-treatment-free high-strength ductile iron was successfully developed using fully automatic cored-wire feeding spheroidization

process, and triple inoculation. The optimized alloy exhibited an excellent combination of strength and ductility in the as-cast state.

Experimental methods

A data-driven alloy design strategy combined with experimental validation was employed to develop high-performance as-cast ductile iron. The overall experimental procedure consisted of alloy composition design, casting process optimization, microstructural characterization, mechanical property evaluation, and machine learning-assisted composition optimization, as illustrated in Fig. 1.

High-quality steel scrap, Q10 pig iron, and recycled iron were used as the primary raw materials and melted in a medium-frequency induction furnace. During melting, 3.5 wt.% recarburizer, 0.8 wt.% ferrosilicon, appropriate amounts of ferromanganese and ferrochrome, and silicon carbide for melt modification were added. Electrolytic copper (0.6 wt.%) was introduced as the main alloying addition. The tapping temperature of molten iron was controlled at 1540 ± 20 °C. A fully automatic cored-wire feeding spheroidization process combined with MES-based data acquisition and process control was applied. A 13 mm diameter spheroidizing cored wire containing 15 - 18 wt.% Mg, 1.5 - 2.5 wt.% RE, ≤ 0.3 wt.% Ti, and 44-46 wt.% Si was employed, with a spheroidizer addition of approximately 0.6 wt.%. Triple inoculation process was adopted, in-ladle inoculation using 0.8 wt.% FeSi inoculant, in-stream inoculation using 0.2 wt.% Si-Ba-Ca inoculant, and in-mold inoculation using 0.2 wt.% Si-Bi inoculant. The Bi-containing inoculant was introduced to promote stable eutectic solidification and reduce chilling tendency^[24]. The molten iron temperature before pouring was maintained at 1500 - 1540 °C, and the initial pouring temperature was controlled at 1380 - 1420 °C. The pouring time was limited to less than 12 min, and the final mold pouring temperature was maintained at 1320-1340 °C. The chemical compositions of the prepared alloys were measured by optical emission spectroscopy. Metallographic specimens were prepared using conventional grinding and polishing procedures. The samples were mounted in thermosetting resin, sequentially ground using SiC abrasive papers from 400 to 5000 grit, and polished with diamond suspension to obtain a mirror-like surface. For microstructural observation, the polished samples were etched with 4% nital solution (4 vol.% nitric acid in ethanol). Optical microscopy and scanning electron microscopy (SEM) were employed to characterize the graphite morphology and matrix microstructure. Quantitative analyses of graphite nodularity, graphite size, pearlite fraction, and eutectic cell number were performed according to standard metallographic evaluation methods. The mechanical properties were evaluated by tensile testing using a WDW-200E universal testing machine at a constant strain rate of 0.001 s^{-1} . Three specimens were tested for each condition to ensure the reliability of the experimental results. Ultimate tensile strength, yield strength, elongation, and hardness were measured to assess the comprehensive mechanical performance of the developed ductile iron.

A machine learning-assisted alloy optimization framework was established to accelerate the composition design of high-performance ductile iron. The experimental dataset was constructed from orthogonal experiments and additional composition-property data. Python (version 3.10) combined with

the Scikit-learn library was used for data preprocessing, model development, and performance evaluation. The contents of Si, Mn, Cu, Cr, and Ni+Mo were selected as input variables, while tensile strength, yield strength, and elongation were defined as output targets. Data preprocessing was performed using Z-score normalization and the interquartile range (IQR) method. Elemental interaction terms were introduced through feature engineering to capture nonlinear relationships between alloy composition and mechanical properties. Random forest (RF) and gradient boosting regression (GBR) algorithms were employed to construct composition - property prediction models, with the dataset divided into training and testing sets at an 8:2 ratio. Feature importance analysis was conducted to evaluate the influence of alloying elements, and the optimized prediction model was further combined with a differential evolution (DE) algorithm to determine the optimal alloy composition considering strength - ductility balance and casting requirements.

3.1 Orthogonal Experimental Design

Several common factors significantly affecting ductile cast iron properties were experimentally screened. An orthogonal experimental design was adopted, and the overall results are summarized as follows:

Table 1. Orthogonal experimental design with four factors and three levels.

	Cu (%) Factor 1	Si (%) Factor 2	Cr (%) Factor 3	Mn (%) Factor 4
Test 1	Cu:0.226%	Si: 2.248%	Cr: 0.136%	Mn: 0.183%
Test 2	Cu:0.214%	Si: 2.457%	Cr: 0.257%	Mn: 0.427%
Test 3	Cu:0.247%	Si: 2.838%	Cr: 0.338%	Mn: 0.654%
Test 4	Cu: 0.476%	Si: 2.263%	Cr: 0.244%	Mn: 0.672%
Test 5	Cu: 0.452%	Si: 2.536%	Cr: 0.362%	Mn: 0.159%
Test 6	Cu: 0.438%	Si: 2.824%	Cr: 0.151%	Mn: 0.435%
Test 7	Cu: 0.739%	Si: 2.732%	Cr: 0.369%	Mn: 0.416%
Test 8	Cu: 0.801%	Si: 2.564%	Cr: 0.172%	Mn: 0.708%
Test 9	Cu: 0.765%	Si: 2.831%	Cr: 0.235%	Mn: 0.195%
Level 1	Cu:0.15-0.3%	Si: 2.2-2.3%	Cr: 0.1-0.2%	Mn: 0.1-0.25%
Level 2	Cu: 0.3-0.6%	Si: 2.4-2.6%	Cr: 0.2-0.3%	Mn: 0.25-0.5%
Level 3	Cu: 0.6-0.9%	Si: 2.7-2.9%	Cr: 0.3-0.4%	Mn: 0.5-0.75%

Table 2. Orthogonal experimental analysis.

	Cu (%) F1	Si (%) F2	Cr (%) F3	Mn (%) F4	UTS (MPa)	Elongation (%)
1	0.23%	2.25%	0.15%	0.18%	775	4.5
2	0.23%	2.50%	0.25%	0.38%	812	4.8
3	0.23%	2.80%	0.35%	0.63%	765	5.7
4	0.45%	2.25%	0.25%	0.63%	838	4.1
5	0.45%	2.50%	0.35%	0.18%	822	5.3
6	0.45%	2.80%	0.15%	0.38%	697	6.8
7	0.75%	2.25%	0.35%	0.38%	874	4.6
8	0.75%	2.50%	0.15%	0.63%	883	5.2
9	0.75%	2.80%	0.25%	0.18%	875	6.4
K1	2352	2487	2355	2472	UTS	
K2	2357	2517	2525	2383		
K3	2632	2337	2461	2486		
k1	784.0	829.0	785.0	824.0		
k2	785.7	839.0	841.7	794.3		
k3	877.3	779.0	820.3	828.7		
Range R	93.3	60.0	56.7	34.3		
Rank	A>B>C>D					
Opt. lvl	A3	B2	C2	D3		
Opt. comb.	A3B2C2D3					
K1	15.0	13.2	16.5	16.2	Elong.	
K2	16.2	15.3	15.3	16.2		
K3	16.2	18.9	15.6	15.0		
k1	5.00	4.40	5.50	5.40		
k2	5.40	5.10	5.10	5.40		
k3	5.40	6.30	5.20	5.00		
Range R	0.44	1.73	0.27	0.70		
Rank	B>D>A>C					

Opt. lvl	A3	B3	C1	D2
Opt. comb.	B3D2A3C1			

As shown in Figs. 2(a) and (b), Cu exhibits the most pronounced effect on the ultimate tensile strength (UTS) of the as-cast high-strength ductile iron, followed by Si and Cr, whereas Mn has only a marginal influence. The dominant contribution of Cu is mainly attributed to its strong pearlite-promoting capability and solid-solution strengthening effect, which effectively enhances the load-bearing capacity of the matrix. Recent studies have further demonstrated that appropriate Cu addition can refine the pearlitic microstructure, suppress discontinuous cementite formation, and improve both tensile strength and fracture resistance of pearlitic ductile irons ^[25]. Regarding elongation, Si is identified as the most influential alloying element, followed by Mn, whereas Cu and Cr exhibit comparatively weaker effects. The significant influence of Si originates from its graphitization-promoting ability and its suppression of carbide formation, which improve matrix continuity and deformation compatibility. Previous investigations have also reported that silicon content and pearlite fraction jointly govern the strength-ductility balance of ductile iron, highlighting the necessity of optimizing Si within a suitable compositional range ^[26].

The comprehensive influence of the alloying elements is summarized in Figs. 2(c) and (d), confirming that Cu is the dominant alloying element controlling the overall mechanical performance of the as-cast alloy. Therefore, Cu was selected as the primary alloying element for composition optimization, while Si and Cr were regarded as secondary strengthening elements. By contrast, Mn exhibited the lowest sensitivity within the investigated composition range. Considering the combined requirements of strength and ductility together with the orthogonal factor-level analysis, the A3B2C2D2 combination was selected because it provided the closest approximation to the optimum performance with a balanced mechanical-property profile. Accordingly, the preliminary optimized composition ranges were determined to be 0.6-0.9 wt.% Cu, 2.4-2.6 wt.% Si, 0.2-0.3 wt.% Cr, and 0.25-0.5 wt.% Mn, which were subsequently adopted for further experimental verification and machine-learning-assisted composition optimization.

Previous studies have demonstrated that Ni and Mo, as typical microalloying elements, effectively enhance the microstructural stability of pearlite, improve hardenability, and strengthen the ferritic/pearlitic matrix, thereby enhancing the strength and service performance of ductile iron. Consequently, they are widely employed in high-performance ductile irons. Nevertheless, the relatively high cost of Ni and Mo limits their extensive application, making the strengthening efficiency achieved at low addition levels and their synergistic interactions with the primary alloying elements of greater practical significance ^[27]. As shown in Fig. 3, the simultaneous addition of Ni and Mo in the range of 0-0.7 wt.% resulted in continuous increases in both the ultimate tensile strength and yield strength (YS). This improvement can be attributed to the enhanced stability of the pearlitic matrix and the increased resistance to dislocation motion arising from solid-solution strengthening and microstructural refinement. Previous investigations have reported that Ni promotes pearlite formation, refines the interlamellar spacing, and consequently increases the tensile and yield strengths of ductile iron, although excessive additions inevitably reduce ductility. In contrast, elongation exhibited a nearly linear

decreasing trend with increasing Ni and Mo content. Specifically, every 0.1 wt.% increase in the combined Ni and Mo addition reduced the elongation by approximately 0.26%, corresponding to a relative decrease of about 4.2%. When the total addition exceeded 0.2 wt.%, the elongation approached the engineering requirement of 5%, indicating that the strengthening effect was accompanied by a noticeable deterioration in plastic deformation capability. This strength-ductility trade-off is consistent with the increased pearlite fraction and matrix hardening induced by Ni and Mo additions, which suppress plastic deformation and accelerate crack initiation during tensile loading.

Considering the contradictory influences of Ni and Mo on strength and ductility, as well as their relatively high alloying cost, further optimization based solely on conventional trial-and-error experiments would be inefficient. Therefore, a machine-learning-assisted optimization strategy was adopted in the present work to quantitatively evaluate the synergistic effects among Ni, Mo, Cu, Si, Cr, and Mn under low-alloying conditions. This approach enables the identification of an optimal compositional window that maximizes strengthening efficiency while minimizing the deterioration in ductility and alloying cost.

Table 3. Mechanical properties at different Ni+Mo contents.

Tensile Strength (MPa)	Yield Strength (MPa)	Elongation (%)	Si (%)	Mn (%)	Cu (%)	Cr (%)	Ni (%)	Mo (%)	Ni+Mo (%)
965	626	4.6	2.443	0.355	0.752	0.283	0.370	0.320	0.690
945	612	5.0	2.536	0.348	0.711	0.247	0.350	0.221	0.571
940	616	5.1	2.427	0.333	0.660	0.251	0.347	0.200	0.547
948	613	5.0	2.429	0.377	0.765	0.245	0.333	0.191	0.524
933	588	5.6	2.541	0.329	0.684	0.259	0.180	0.129	0.309
925	580	5.4	2.636	0.349	0.704	0.263	0.142	0.132	0.274
909	580	5.5	2.641	0.352	0.651	0.228	0.092	0.078	0.170
895	565	6.1	2.583	0.324	0.691	0.254	0.071	0.062	0.133

3.2 Machine Learning

It should be noted that orthogonal experiments and traditional alloy design methods are primarily used to analyze single-factor influence patterns, and they still have limitations when dealing with the complex interactions among multiple alloying elements. For instance, Cu, Si, Cr, Mn, Ni, and Mo may jointly affect the final properties by altering graphite nucleation, the matrix phase proportions, and the precipitation behavior of secondary phases. Therefore, it is difficult to obtain the globally optimal composition combination solely through a limited number of experiments. Based on this,a prediction model was established between alloy composition and mechanical properties (tensile strength, yield strength, and elongation) using machine learning methods and an ensemble learning strategy. The overall workflow consisted of data preprocessing, feature engineering, model construction, interpretability analysis, and

composition optimization. First, the Z-score and interquartile range (IQR) methods were employed for outlier detection to improve the reliability of model training. The contents of Si, Mn, Cu, Cr, and Ni+Mo were selected as input variables. Extended features were constructed by introducing elemental interaction terms, the squared term of Ni+Mo, and element coupling terms to enhance the model's capability to capture complex alloying effects. Random forest (RF) and gradient boosting regression (GBR) algorithms were used to establish mechanical property prediction models. The dataset was divided into training and testing sets at a ratio of 8:2 and subjected to standardization. Feature importance analysis was performed to reveal the contribution patterns of different alloying elements to mechanical properties. Finally, the optimized prediction model was integrated with the differential evolution algorithm to achieve data-driven alloy design optimization.

Based on orthogonal experimental analysis and machine learning predictions of the optimal elemental alloying ratio, the final optimized target composition was determined by considering the balance among key mechanical properties, including tensile strength, yield strength, and elongation. The optimization also accounted for the matrix microstructure, graphite nodule diameter, nodularity, hardness, impact toughness, and practical service performance. The optimized composition was determined as follows: 3.5-3.8% carbon, 2.4-2.7% silicon, 0.6-0.8% copper, 0.2-0.3% chromium, and 0.3-0.6% manganese, with other alloying elements added in appropriate amounts.

Table 4. Target chemical composition of as-cast high-performance ductile iron.

Element	C	Si	Cu	Cr	Mn	P	S	Ni+Mo
Content / %	3.5~3.8	2.4~2.7	0.6~0.8	0.2~0.3	0.3~0.6	≤0.05	≤0.025	≤0.1

3.3 Mechanical Properties and Microstructure

Smaller graphite nodule size and higher graphite grade lead to better mechanical properties [28]. As illustrated in Fig. 5(a-d), under the conventional inoculation process, the graphite size was grade 6. After triple inoculation, the graphite nodules were refined to grade 7. The triple inoculation significantly increased the number of graphite nodules and the nucleation rate. The number of eutectic cells increased from 80-100 in the conventional process to 180-230. As a result, more graphite particles formed per unit area, with a more uniform distribution.

The formation of spheroidal graphite includes nucleation and growth. Nucleation depends on the large number of crystallization nuclei generated by melting, spheroidizing, and inoculation treatments. The final graphite morphology is determined by process conditions. Spheroidizing treatment promotes a spheroidal graphite distribution and reduces the cutting effect on the matrix. Fully automatic spheroidizing cored-wire treatment was adopted, and nodularity increased from 80-90% to 90-95%. The nodularity grade improved from grades 2-3 to grades 1-2

The microstructure of the specimen prepared after composition optimization is shown in Figs. 5(e-h), the metallographic structure consisted mainly of pearlite and graphite, with bull's-eye ferrite. The pearlite

lamellar spacing was refined. After alloying, a fine pearlitic structure formed, with lamellar spacing refined to 300-500 nm. In local regions, the spacing was even finer and the lamellae were shorter. This resulted mainly from the synergistic effect of multiple alloying elements. During eutectic transformation, Cu promotes graphitization, suppresses or eliminates cementite formation, improves graphite morphology, increases graphite roundness, and raises the number of graphite nodules. During eutectoid transformation, Cu promotes pearlite nucleation and growth. It refines pearlite interlamellar spacing and improves the microstructural and property uniformity across large-section ductile iron. At low Mo contents, Mo strengthens and refines pearlite, reduces the amount of ferrite, and causes only a weak chill tendency. The combined use of Mo and Cu is more favorable for pearlite refinement and for strengthening ferrite within pearlite^[29]. When 0.2-0.5% Cr is added and ductile iron is produced in-stream inoculation, the matrix is pearlitic. The pearlite lamellar spacing is small, only 0.5 μm . This occurs because Si particles added in-stream inoculation enter the molten iron and melt. Silicon is a graphitizing element. During liquid-state crystallization, Si dissolves into austenite. On the one hand, it rejects more Cr into the melt, thereby increasing the Cr/C ratio of the residual liquid. On the other hand, it also rejects more C into the residual liquid, forming carbon-rich zones near primary austenite. A larger number of carbon-rich zones increases the probability of carbide nucleation and reduces carbide size. During the eutectic stage, carbide nucleation and growth also reject Si. This affects the carbide growth rate. As a result, pearlite interlamellar spacing decreases, grains are refined, and material strength increases.

The mechanical properties of the specimens optimized by machine learning are shown in Fig. 6, all of which are superior to those of the original specimens. They fully met the property requirements of the QT800-5 to QT950-6 series. The prepared specimens reached a maximum tensile strength of 974 MPa, a yield strength of 613 MPa, an elongation of 6.4%, a nodularity of 95%, and a graphite size grade of 7. The hardness values were all higher than 230 HB. All performance indicators met the expected targets and reached a leading domestic level.

Table 5. Mechanical properties and metallographic characterization.

No.	UTS (N/mm2)	YS (N/mm2)	Elong. (%)	Hardness (HB)	Graphite size
1	926	593	6.7	259	7
2	974	613	6.4	273	7
3	948	627	6.5	264	7
4	956	606	6.3	268	7

Conclusions

(1) Based on orthogonal experimental data, this study established predictive models between alloy composition and mechanical properties using machine learning methods and ensemble learning strategies. The optimal target composition for high-performance as-cast ductile cast iron was determined as follows: carbon content of 3.5-3.8%, silicon content of 2.4-2.7%, copper content of 0.6-0.8%, chromium content of 0.2-0.3%, manganese content of 0.3-0.6%, and nickel plus molybdenum content $\leq 0.2\%$. Without adding precious metal alloying elements, this composition achieved an excellent balance between high strength and high ductility.

(2) A series of novel high-strength as-cast ductile cast irons were successfully developed. The materials fully satisfied the performance requirements of QT800-5 to QT950-6 grades. The prepared specimens achieved a tensile strength of 974 MPa, yield strength of 613 MPa, elongation of 6.2%, nodularity of 95%, and graphite size grade of 7. All performance indicators met the expected targets.

(3) During the production of high-performance as-cast ductile cast iron, a new process combining fully automated nodularization cored-wire treatment and triple inoculation was adopted. The triple inoculation technology increased the number of eutectic cells from 80-100 to 180-200 and improved the graphite size grade from Grade 6 to Grade 7. The nodularization cored-wire treatment increased nodularity from 80-90% to 90-95% and reduced the defect rate from 2-3% to below 1%.

Declarations

Ethical Statement

Not applicable. This study did not involve human participants, their data, or biological specimens.

Declaration of competing interest

The authors declare that they have no conflicts of financial interest or personal relationships that could have influenced the work presented in this article. Informed consent was obtained from all individual participants included in the study.

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Data availability

Data will be made available on request.

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Figures

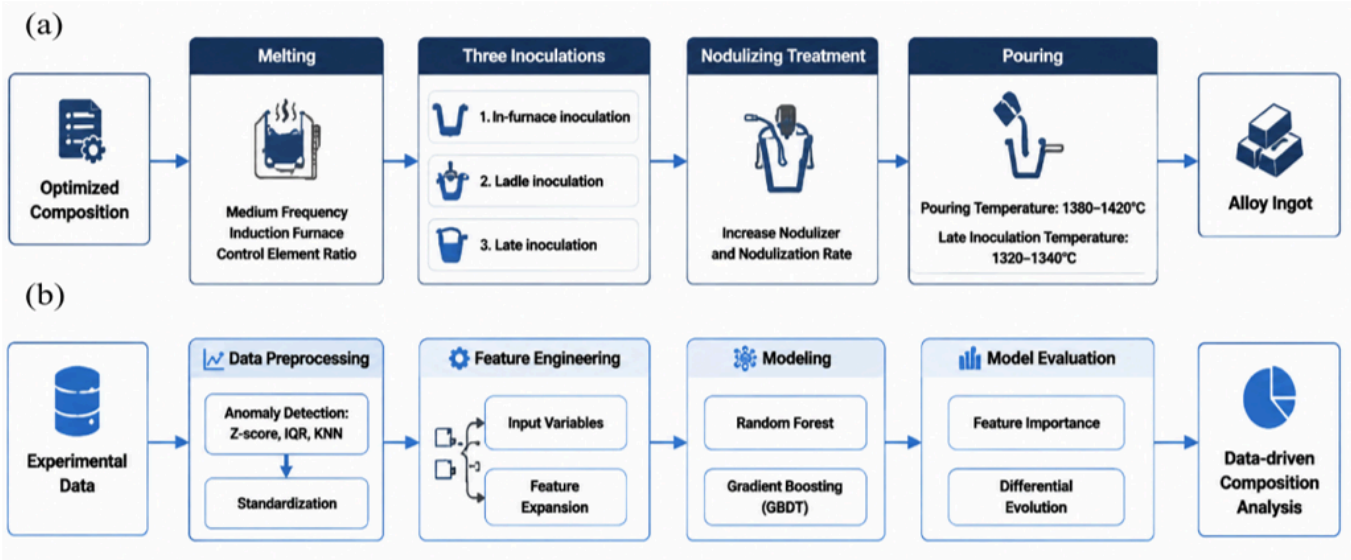


Figure 1

(a) Casting process flowchart, (b) Machine learning flowchart.

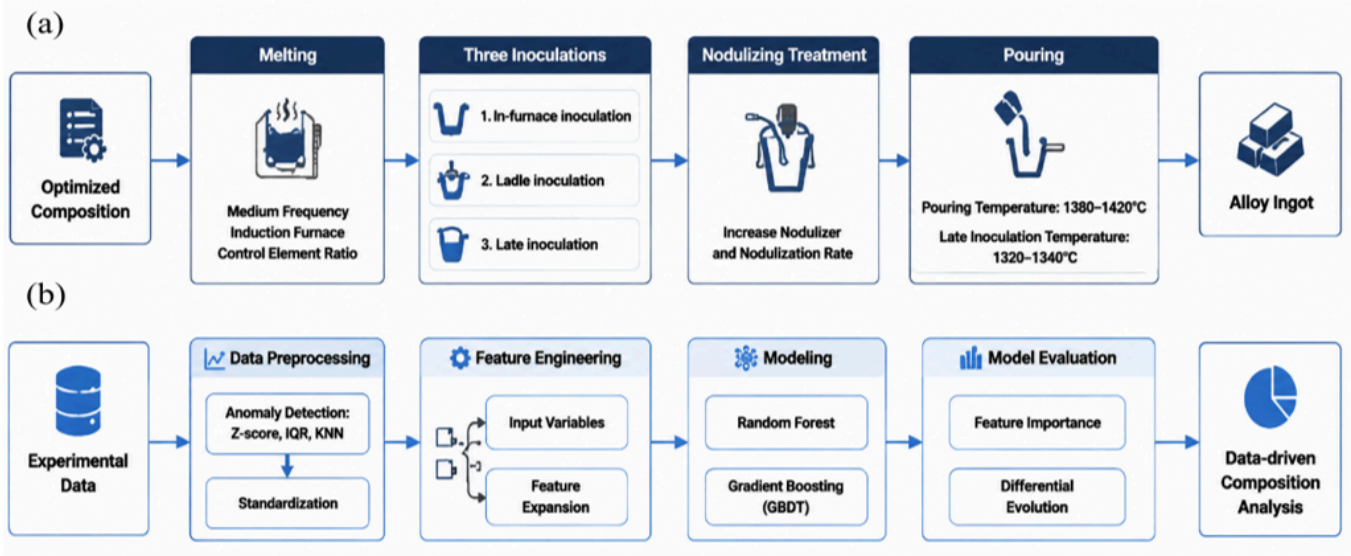


Figure 1

(a) Casting process flowchart, (b) Machine learning flowchart.

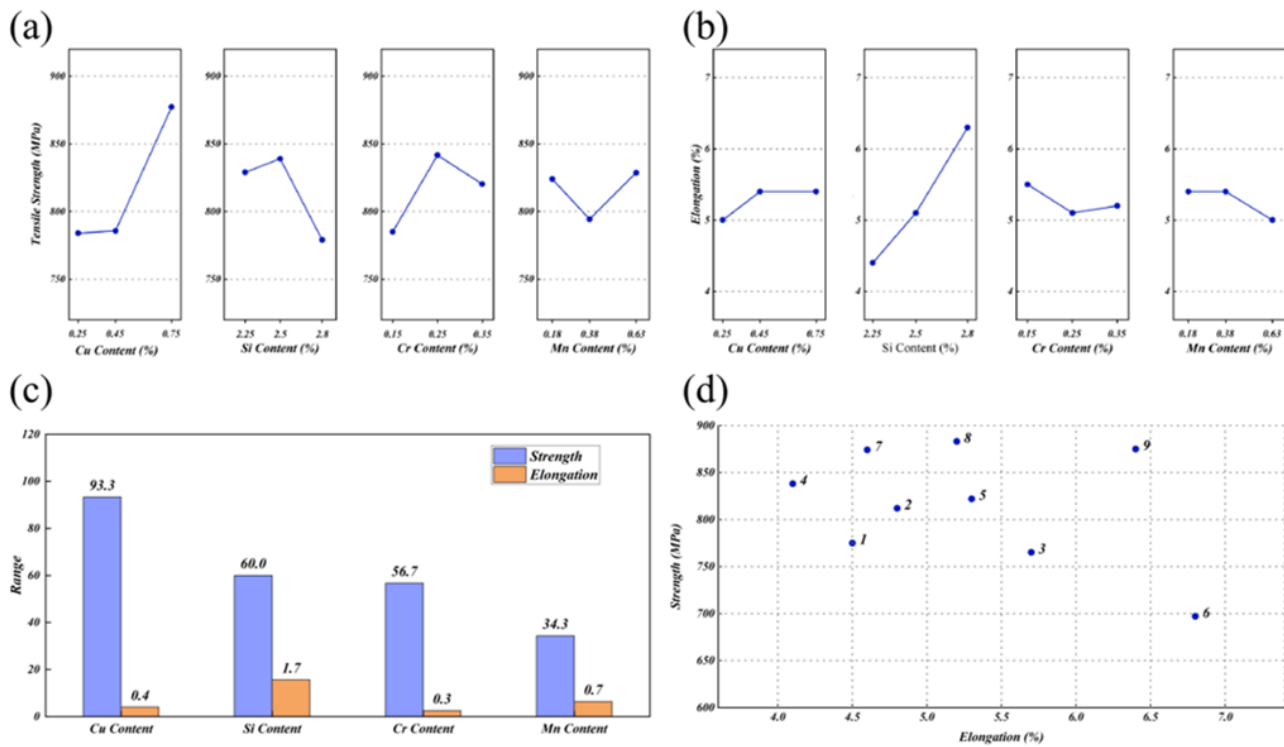


Figure 2

(a) Main effect plots of individual alloying elements on tensile strength; (b) main effect plots of individual alloying elements on elongation; (c) range analysis; (d) Scatter plot of tensile strength versus elongation for each test group.

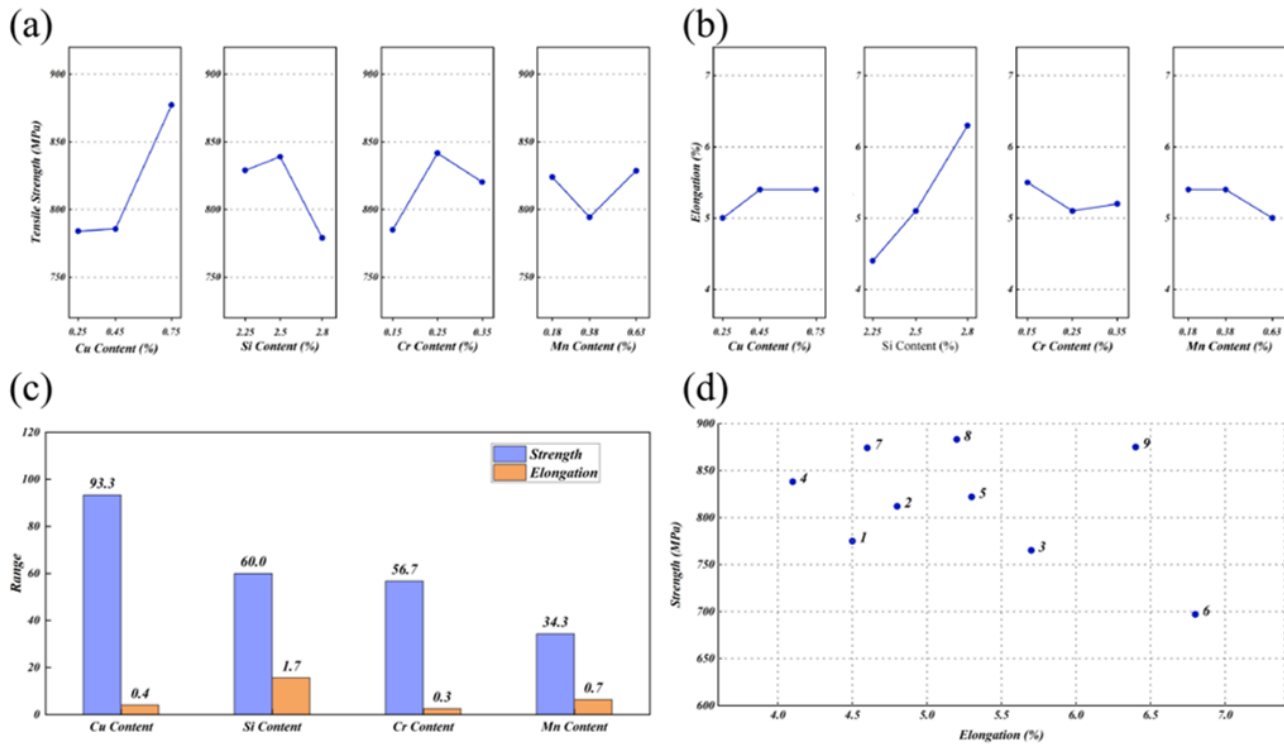


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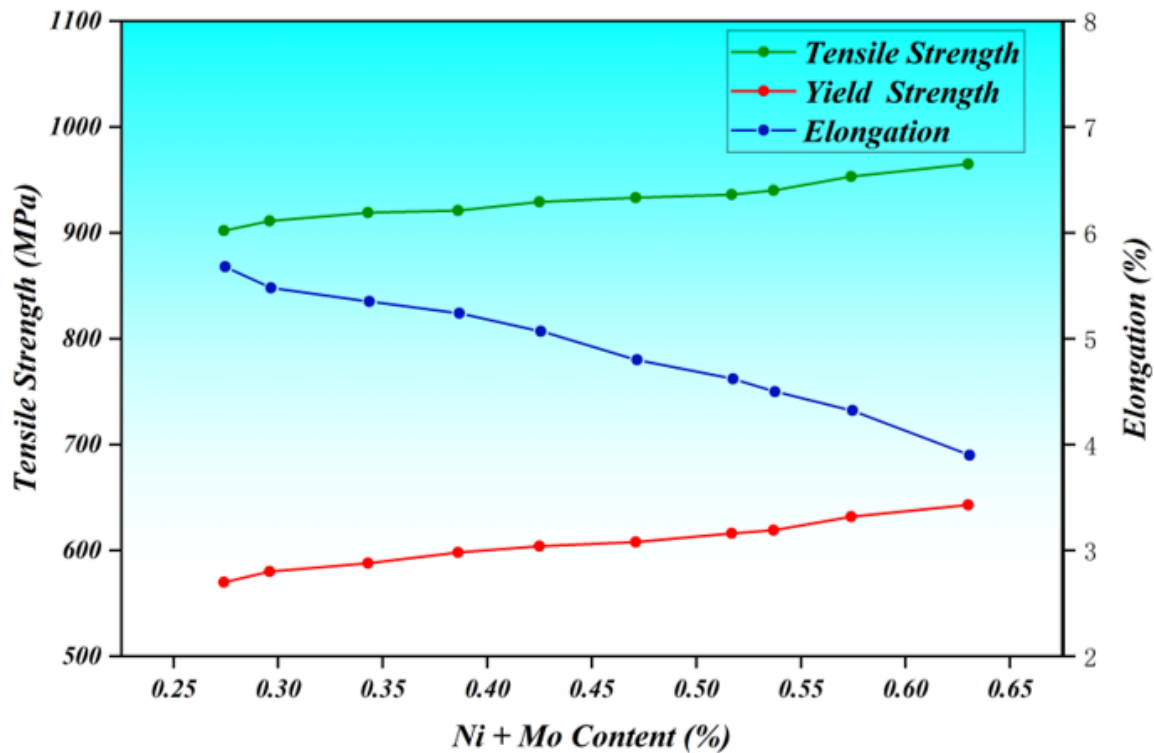


Figure 3

Effect of total Ni+Mo content on mechanical properties.

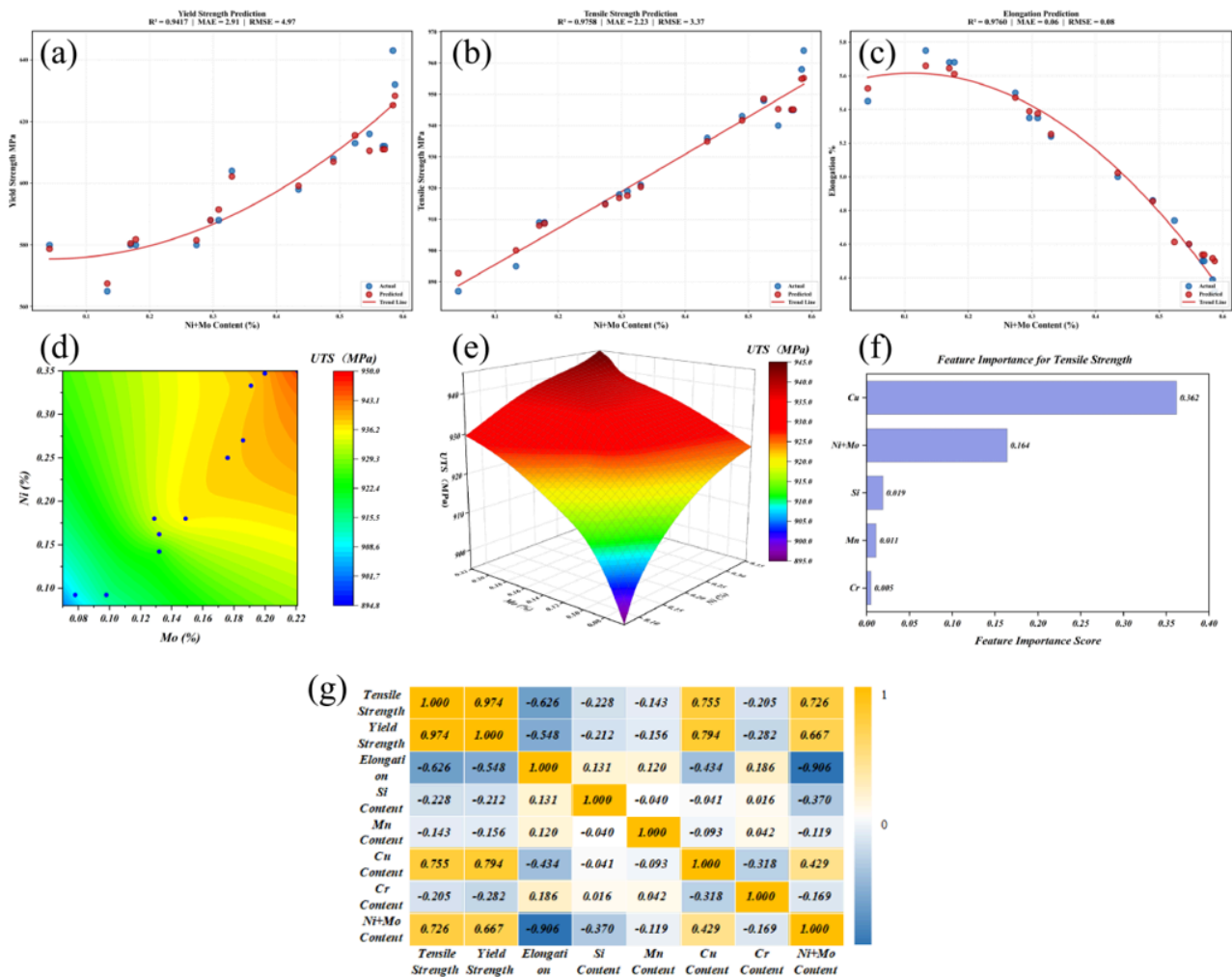


Figure 4

(a-c) Effect of Ni+Mo content on mechanical properties; (d) (e) effect of Ni+Mo interaction on tensile strength (two-dimensional heat map and three-dimensional response surface); (f) feature importance of Ni+Mo based on the random forest model; (g) correlation heat map between mechanical properties and alloying element contents.

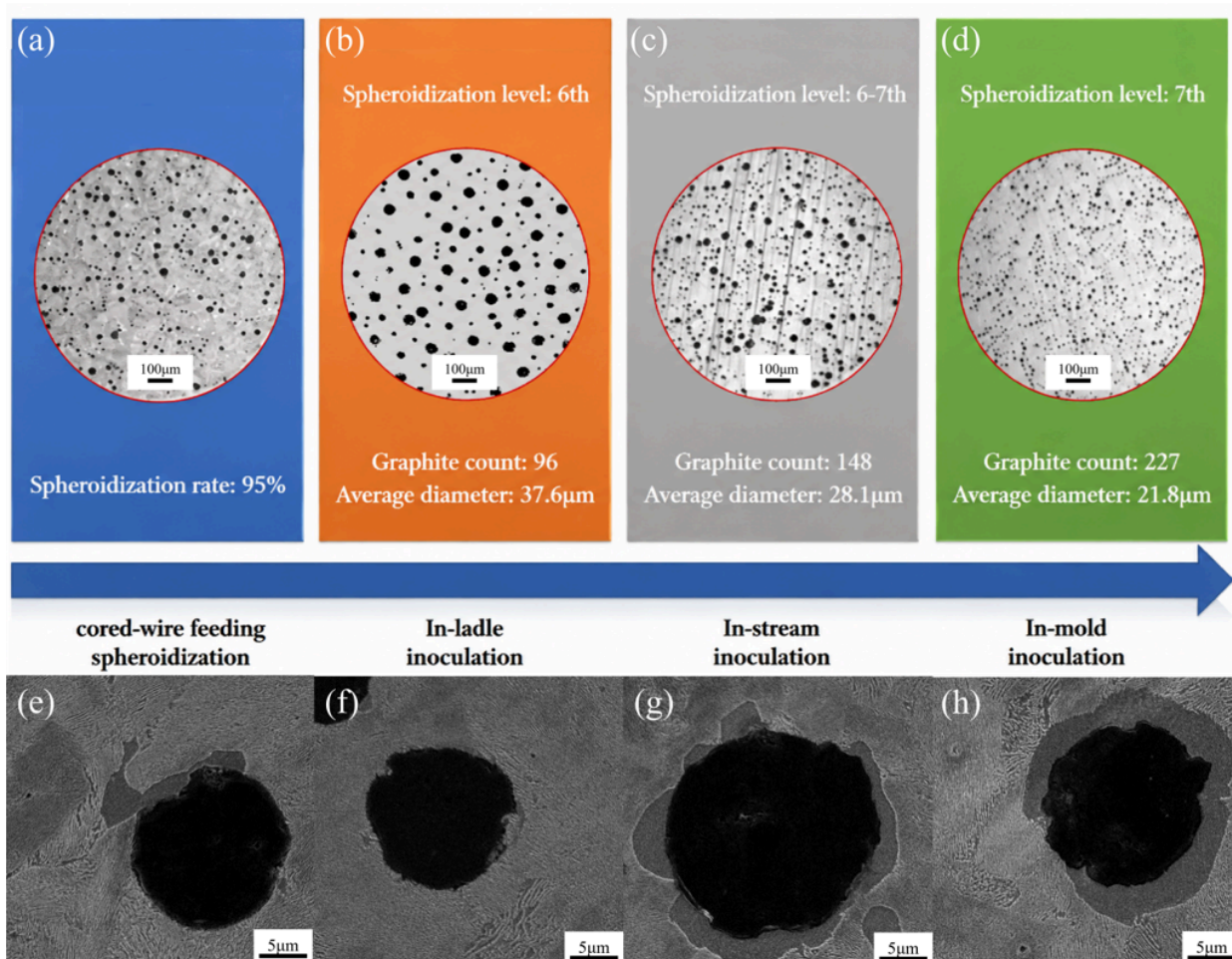


Figure 5

Metallographs of spheroidal graphite in ductile iron (a) Nodularity of 95% obtained by cored-wire feeding spheroidization; (b) Graphite size grade 6 (In-ladle inoculation); (c) graphite size grade 6-7 (In-stream inoculation); (d) graphite size grade 7 (In-mold inoculation); Microstructures of ductile iron (e) Specimen 1; (f) specimen 2; (g) specimen 3; (h) specimen 4.

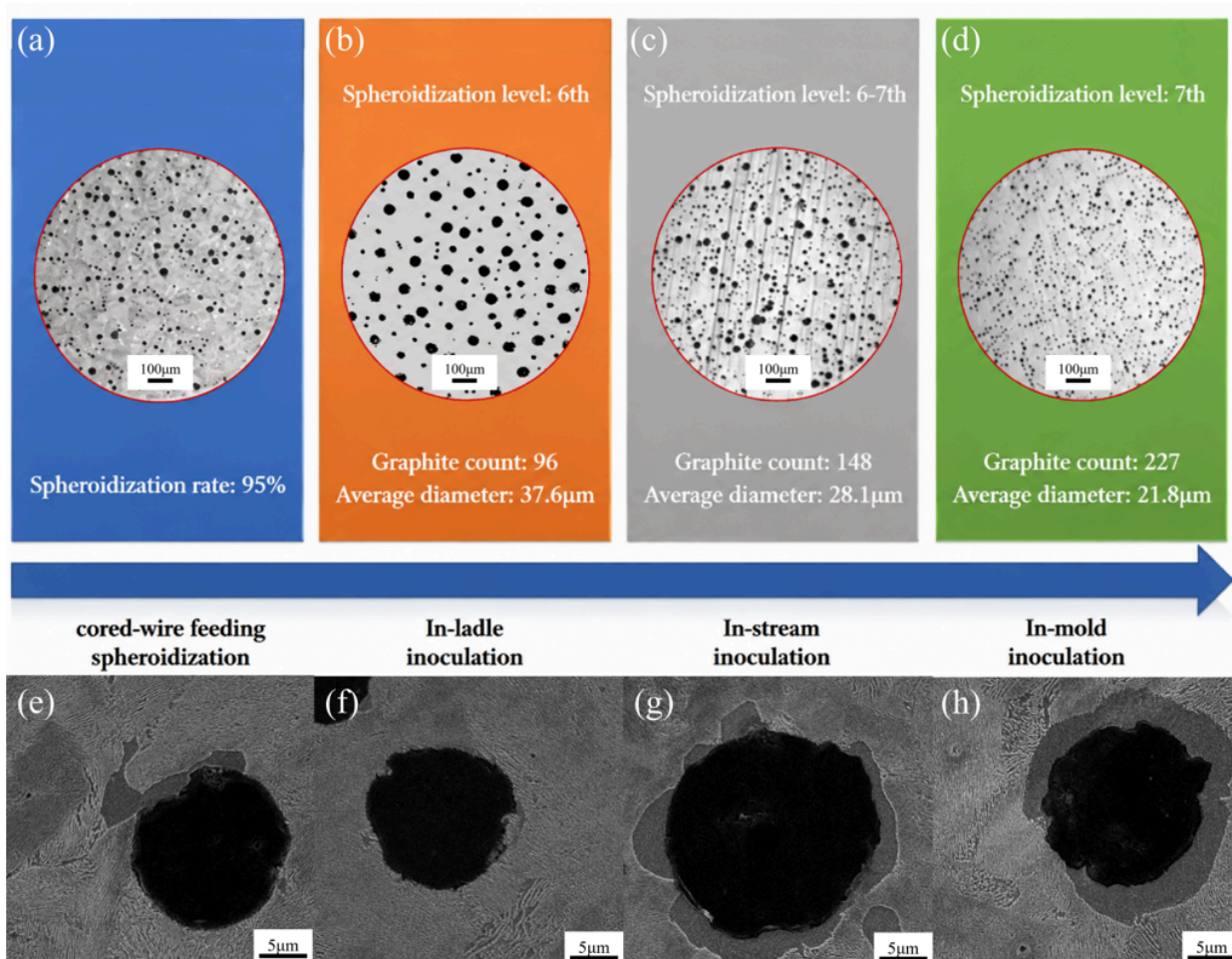


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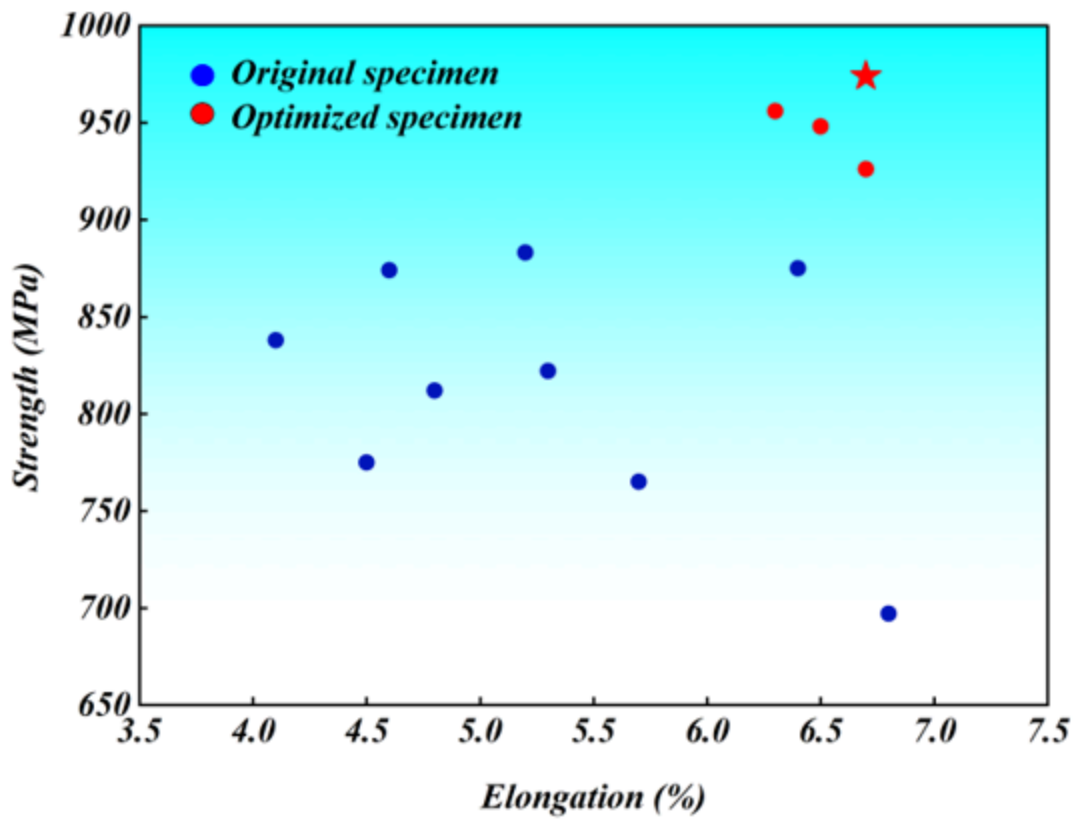


Figure 6

Mechanical Properties.

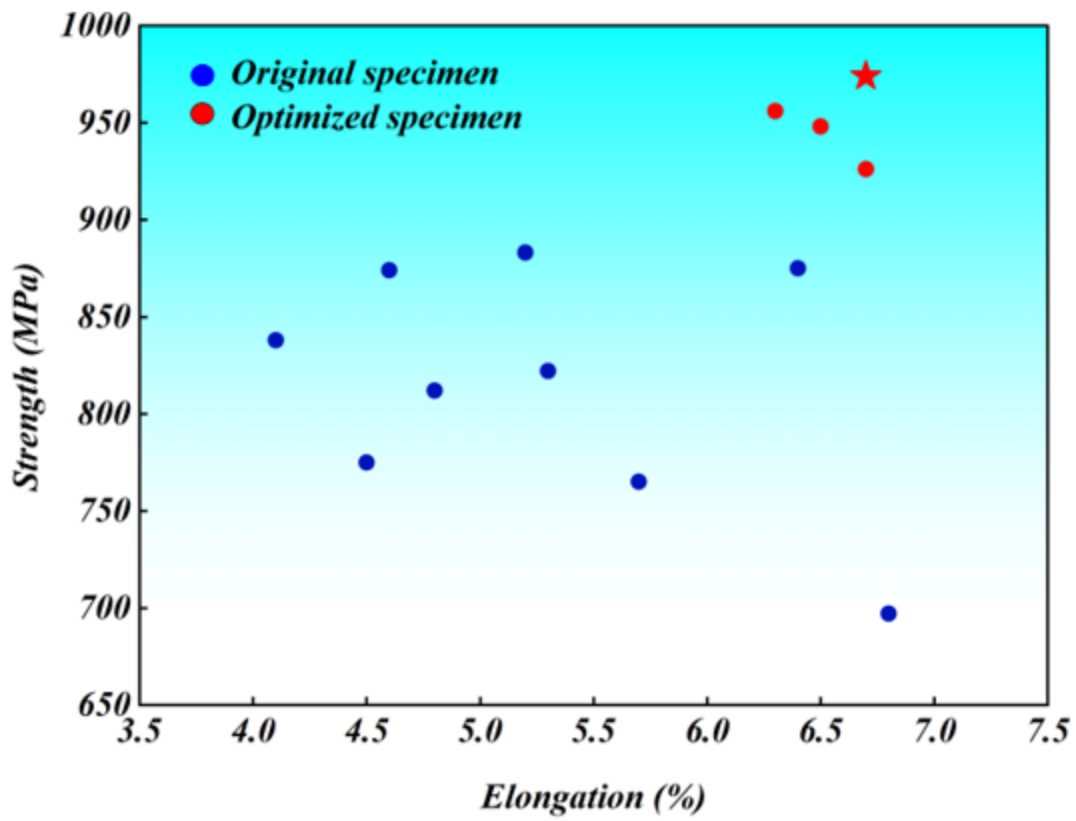


Figure 6

Mechanical Properties.