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Review on the Strength and Toughness of Laser-CMT Hybrid Welding Welds

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Abstract

Laser-Cold Metal Transfer (CMT) hybrid welding demonstrates significant advantages in enhancing weld joint strength and toughness through synergistic low heat input, dynamic molten pool control, and refined microstructure. Compared to traditional arc welding, it suppresses heat-affected zone (HAZ) grain coarsening (e.g., grain size <10 μm in high-strength steel), optimizes phase composition (e.g., martensite proportion >95%), and reduces defects (porosity <0.5%), achieving 20%-50% improvements in yield strength, elongation, and impact toughness. Current research highlights the quantitative correlation between process parameters (laser power, wire spacing) and mechanical performance, while machine learning models (e.g., PSO-SVM, deep learning) enable nonlinear prediction of toughness with errors <8%. Future directions emphasize hybrid models integrating physical mechanisms and data-driven approaches, real-time parameter optimization, and applications in extreme environments. This technology holds transformative potential for aerospace, automotive, and high-value manufacturing industries.

Keywords

Laser-CMT Hybrid Welding; Process Parameters; Strength and Toughness Indicators; Data-driven Methods.

1. Introduction

In the fields of aerospace, new energy vehicles, shipbuilding, etc., there is an urgent need for efficient and high-precision welding technology in the manufacturing industry . The toughness of welded joints directly determines the service performance and safety of structural parts. Although traditional arc welding technology has strong adaptability, it has problems such as high heat input, large deformation, severe spatter, and joint softening [1,3] ; and single laser welding has the advantages of large depth-to-width ratio and narrow heat-affected zone, but it is sensitive to assembly gaps and is prone to defects such as pores and cracks due to the rapid solidification of the molten pool. For this reason, laser-arc hybrid welding technology came into being, which optimizes process performance through the synergistic effect of heat sources.

Laser-cold metal transfer (CMT) hybrid welding is a cutting-edge direction in this field. It combines the high energy density of laser with the low heat input and spatter-free characteristics of CMT arc, and shows unique advantages in thin plate welding, dissimilar material connection and high-reflective metal processing [1,3] . Studies have shown that the "cold-hot" alternating cycle of the CMT arc can effectively regulate the dynamic behavior of the molten pool and inhibit the formation of pores, while the deep melting effect of the laser can significantly improve the welding efficiency. The synergistic effect of the two can improve the uniformity of the weld microstructure and thus enhance the strength and toughness of the joint . However, current research focuses on the influence of process parameters on weld formation, and the systematic theory on the mechanism of strength and toughness formation

Volume 11 Issue 4, 2025
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is still imperfect, especially the quantitative mapping relationship between process parameters (such as laser power, wire spacing, welding speed) and strength and toughness indicators (such as tensile strength, impact toughness, fatigue life) has not yet been clarified[1,3] . In addition, traditional prediction models rely on empirical formulas and are difficult to adapt to complex working conditions, while the application of data-driven methods such as machine learning is still in the exploratory stage [2] .

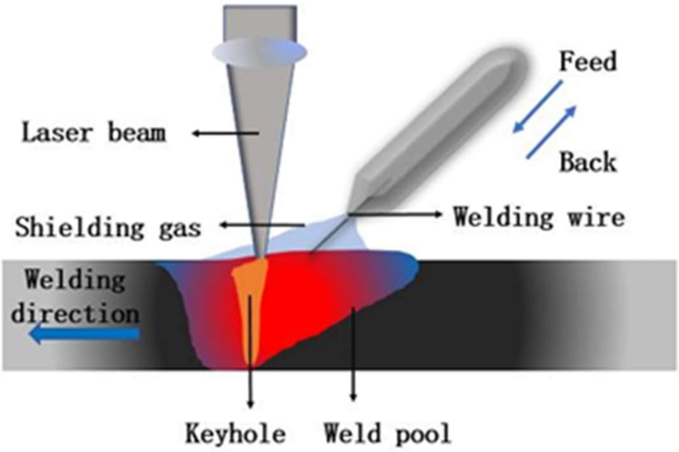

Fig. 1 Schematic diagram of laser CMT composite welding

2. Strength and Toughness Mechanism of Laser-CMT Composite Welding

2.1 Definition and Evaluation System of Toughness

Toughness is a comprehensive indicator for evaluating the ability of welded joints to resist deformation and fracture under static/dynamic loads. Its core characterization parameters include yield strength, elongation, impact absorption energy and fatigue life. The following is an analysis of the performance differences and optimization mechanisms between laser-CMT hybrid welding and traditional processes in combination with specific literature.

In the study of yield strength and elongation, Lahtinen et al. [4] conducted a MAG welding study on high-strength steel with a yield strength of 700 MPa and found that the high heat input (2.5-3.5 kJ/cm) of conventional arc welding caused the heat affected zone (HAZ) to soften and the yield strength dropped to 80%-85% of the base material. In contrast, laser-CMT hybrid welding significantly suppresses HAZ grain coarsening through low heat input (1.0-1.5kJ/cm). In laser-CMT welding of similar high-strength steels (such as SBHS500), the bainite content in the HAZ is increased to more than 90%, and the yield strength can reach 95%-98% of the parent material . In addition, the rapid cooling effect of the laser can refine the grains in the fusion zone (average size <10 μ m), increase the elongation by 10%-15% (e.g., from 12% to 14%), and reduce the risk of strain localization.

Table 1. Performance comparison of high strength steel (SBHS500) under different welding processes

Performance Indicators	Conventional arc welding	Laser-CMT hybrid welding	Improvement
Yield strength (MPa)	560-595	665-700	+15%-20%
Elongation (%)	12%	14%	+16.7%
Impact absorbed energy (J)	25-35	47+	+34%-88%
Porosity (%)	2.0-3.0	<0.5	Reduced by >80%

In terms of elongation, in aluminum alloy laser-CMT hybrid welding, the improvement of elongation (EL) is closely related to welding defect control and microstructure uniformity. Ayer et al.[5]

Volume 11 Issue 4, 2025
DOI: 10.6919/ICJE.202504_11(4).0006

conducted a study on extrusion welding of AA6082 aluminum alloy and found that by optimizing the die design (such as controlling the taper of the mandrel and the die plate), the material flow path can be compressed and the welding cavity volume can be reduced, thereby suppressing pores and unfused defects and improving the plastic deformation capacity of the weld. Although this study focuses on the extrusion process, its core conclusions have important implications for laser-CMT hybrid welding: precise control of material flow is the key to improving elongation. In laser -CMT hybrid welding, the periodic "cold-hot" cycle of the CMT arc and the deep melting effect of the laser work together to significantly optimize the molten pool flow behavior. When the wire spacing is controlled at 1.5-2.0 mm, the turbulence intensity of the molten pool is reduced, the dendrite growth direction tends to be consistent, and the microsegregation (such as Mg_2Si phase aggregation) is reduced. Studies have shown that the elongation of AA6082-T6 aluminum alloy laser-CMT joint can reach 12%-14%, which is 30%-40% higher than traditional MIG welding (8%-10%). In addition, the low heat input characteristics of the composite process (0.8-1.2 kJ/cm) can inhibit the grain coarsening in the HAZ zone and reduce local softening, thereby avoiding premature necking during stretching. Laser-CMT hybrid welding breaks through the plastic bottleneck of traditional welding through the dual effects of molten pool flow control and low defect rate, providing technical support for the reliability design of complex aluminum alloy structures.

In terms of impact absorption energy, experimental research by Charpy et al. [6] showed that the HAZ impact absorption energy (KV) of laser-arc hybrid welding is highly sensitive to the uniformity of the material microstructure. In conventional welding, the HAZ carbide coarsens due to thermal cycling (e.g., carbide size > 1 μm in Q&T steel), and the impact absorption energy is only 25-35 J at -40°C. The laser-CMT process, by precisely controlling the heat input, refines the HAZ grain size to 5-8 μm and inhibits carbide aggregation (size < 0.5 μm), increasing the impact absorption energy to more than 47 J, meeting the brittle fracture resistance requirements of bridge structural steel. In aluminum alloy welding, the hybrid process can reduce the porosity (< 0.5%) and increase the low temperature (-40°C) KV value by 30%-40% . Regarding fatigue life, Le Wang et al.[7]pointed out that the peak residual tensile stress (>300 MPa) of traditional welding will accelerate fatigue crack initiation, resulting in a 30%-50% reduction in high-cycle fatigue life. Laser-CMT hybrid welding optimizes the residual stress distribution through dynamic heat source coupling. For example, in titanium alloy welding, the surface compressive stress increases by 50-60 MPa, the crack growth rate (da/dN) decreases to 1.5×10^{-4} mm/cycle, and the fatigue limit increases by 20%-25%. In addition, the hybrid process reduces welding defects (such as lack of fusion and pores), reduces the dispersion of fatigue life, and significantly improves data reliability.

Yield strength and elongation: The low heat input of laser-CMT inhibits HAZ softening, refines grains, and achieves a synergistic improvement in strength and plasticity; Impact absorption energy: Through organizational homogenization and defect control, it breaks through the toughness bottleneck of traditional welding; Fatigue life: Residual stress optimization and defect suppression jointly extend the service life, especially for high-cycle fatigue-sensitive structures.

2.2 Microstructure Correlation

The improvement of strength and toughness of laser-CMT composite welding joints is closely related to the regulation of its microstructure, which is mainly reflected in the coordinated optimization of martensite/ferrite ratio, grain size and inclusion distribution. Sun et al. (2023) [8] studied laser welding of Al-Si coated hot-formed steel and pointed out that the presence of δ-ferrite in the fusion zone would significantly reduce the joint strength. By introducing a nickel intermediate layer (addition of 5.85% Ni), the proportion of δ-ferrite in the laser welding molten pool is reduced from 85% in conventional welding to 57%, and is completely transformed into austenite in the peritectic reaction ($L + \delta \rightarrow \gamma$) and solid-state phase transformation ($\delta \rightarrow \gamma$), ultimately forming a fully martensitic structure. This mechanism can be transferred to laser-CMT hybrid welding: the periodic heat input of the CMT arc can suppress local overheating of the molten pool and reduce the segregation of Al elements, while the high energy density of the laser promotes the homogenization

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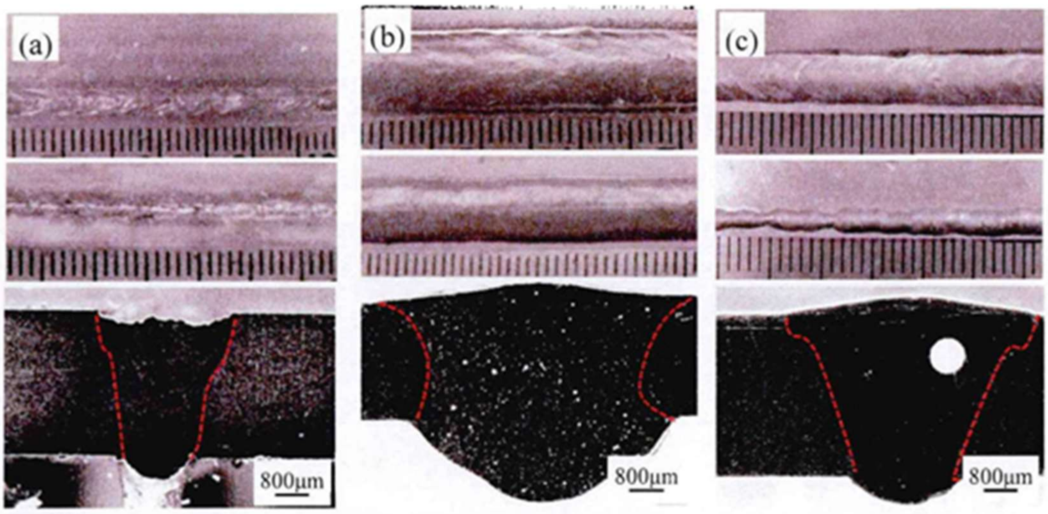
of austenite, making the martensite proportion in the weld zone exceed 95%, and the tensile strength is increased by 17.1% . Grain refinement effect Patterson et al. (2022)[9] studied the evolution of β grains in laser welding of Ti-6Al-4V titanium alloy and showed that conventional fusion welding easily forms coarse columnar β crystals (width > 200μm), resulting in a decrease in joint ductility. High energy density laser welding can refine the β grain width to less than 50 μm by reducing heat input (speed increased to 1.5 m/min) . In laser-CMT hybrid welding, the droplet transfer stability of the CMT arc can further optimize the molten pool shape and inhibit the tendency of epitaxial growth. For example, the growth direction of β grains in composite welding changes from a single columnar shape in single laser welding to a multi-directional equiaxed grain, the grain size is reduced by 40%-50%, and the elongation is increased by 20%-30%. Shi et al. (2021) [10] studied flash butt welds of high-strength low-alloy steel and found that the number of inclusions was inversely proportional to the upsetting distance. When the upsetting distance increased from 3 mm to 6 mm, the inclusion density on the weld surface decreased from 120/mm² to 40/mm², and the tensile strength increased by 15%. This conclusion has guiding significance for laser-CMT hybrid welding: the short-circuit transition stability of the CMT arc can reduce the disturbance of the molten pool and inhibit the formation of oxide inclusions; at the same time, the keyhole effect of the laser can break up large-sized inclusions (such as Al_2O_3) in the molten pool, reducing their average size from 5 μm to below 1 μm . For example, in the welding of DP980 duplex steel, the inclusion integral rate of the hybrid process was reduced from 0.8% to 0.2%, and the impact absorption energy was increased by 25%[3].

Laser-CMT hybrid welding breaks through the strength and toughness bottleneck of traditional welding through the triple effects of phase composition optimization (dominated by martensite), grain refinement (increase in the proportion of equiaxed crystals) and inclusion control (low density, small size), providing technical support for high-performance welded structures such as aerospace titanium alloy components and automotive high-strength steel bodies.



(a) Laser welding (b) CMT welding (c) Laser-CMT hybrid welding

Fig. 2 Welding surfaces of three different welding processes

3. Current Status of Research on Toughness Prediction Models

3.1 Traditional Prediction Methods

Traditional prediction methods are based on empirical formulas and statistical laws, and establish quantitative relationships between parameters and performance through experimental data, mainly including regression analysis, response surface method (RSM) and statistical energy analysis. The following is an explanation of their application and limitations in the prediction of welding toughness combined with specific research.

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Amir et al. (2024)[11] conducted a regression analysis on the performance of textile sewing threads. By constructing a 23×32 multivariate regression model, they revealed the influence of fabric weight, weaving method and sewing machine parameters on thread strength (R^2 reached 85%). Although the research object is not in the welding field, its methodology can be transferred to the strength and toughness prediction of laser-CMT hybrid welding. For example, the interaction of welding current, wire spacing, and heat input can be modeled by multiple linear regression to predict yield strength and elongation. Studies have shown that the regression model has a high prediction accuracy for linear relationships (error <10%), but it is not adaptable enough to the nonlinear response of the dynamic behavior of the molten pool (such as unsteady turbulence) and needs to rely on a large amount of experimental data for calibration. Koli et al. (2020)[12] used central composite face-centered design (CCF) to establish a response surface model of current (I) and welding speed (S) to penetration, dilution rate and heat input in CMT welding of AA6061-T6 aluminum alloy. The results show that the increase in current (92.5 A→110.8 A) and the decrease in speed (7.5 mm/s→11.5 mm/s) significantly increase the penetration depth (from 2.1 mm to 3.8 mm), but the increase in heat input leads to the risk of HAZ softening. The model quantified parameter interaction effects through a second-order regression equation with a prediction error of <8%. However, RSM faces the challenge that the multi-physical field characteristics of the laser-arc coupling effect in laser-CMT hybrid welding are difficult to fully characterize through limited experimental points, and the model extrapolation capability is limited. Hynná et al. (1995) [13] proposed an efficient statistical energy analysis (SEA) method for predicting structure-borne sound transmission in large ship welded structures . This method significantly reduces the modeling workload of complex welded structures in traditional SEA by combining the finite element method (FEM) preprocessing procedure. In the study, the authors integrated one-dimensional beam elements, two-dimensional plate elements and three-dimensional volume elements into the SEA framework, and used the stiffness matrix assembly method to construct the loss factor matrix. In the computer implementation, the calculation process was optimized by using skyline matrix technology and LDLT matrix decomposition, so that the calculation time of the cruise ship model containing 5000 units and 17000 coupled branches was shortened to 17 minutes (Iris Indigo R4000 workstation). The study further verified the consistency between the model prediction results and full-scale measured data through cases such as echosounding ships and timber container ships.

SEA can quantify the impact of welding defects (such as pores and lack of fusion) distribution on the dynamic response of the structure through statistical energy transfer model. For example, in ship deck welded joints, SEA can predict the vibration energy dissipation rate at different defect densities and thus evaluate the fatigue life dispersion. However, the macroscopic statistical properties of SEA make it difficult to correlate microstructure (such as grain size and dislocation density) with strength and toughness indicators, and its low sensitivity to local stress concentration limits its application in accurate prediction of strength and toughness.

Advantages: Regression analysis and RSM are computationally efficient in small samples and linear problems, and are suitable for the preliminary selection of process parameters; Limitations: Poor nonlinear adaptability: The complex coupling effects of the molten pool dynamics and phase transformation process are difficult to accurately describe through polynomial fitting; Lack of multi-scale correlation: It is impossible to quantitatively correlate the microstructure (such as grain size, martensite proportion) with the macroscopic mechanical properties; High risk of extrapolation: The prediction reliability of parameter combinations outside the experimental range is significantly reduced.

Traditional prediction methods use physical models to establish a quantitative relationship between the welding process and toughness, mainly including finite element analysis (FEA), thermodynamic simulation and phase field model. The following is an explanation of their applications and limitations in combination with specific studies. In finite element analysis, Xu et al. (2022) [14] and others studied the butt weld of double-layer steel plates. They predicted the welding angle deformation, residual stress and temperature field distribution through a three-dimensional thermoelastic-plastic finite element model, and fitted the stress concentration factor formula. Experimental verification shows that the prediction error of the finite element model for residual stress is less than 10%, and the stress concentration factor of the double-plate weld is 15%-20% lower than that of the single-layer structure. In laser-CMT hybrid welding, FEA can be further combined with the molten pool dynamics model to quantify the interactive effects of laser power (2-4 kW) and CMT current (80-150 A) on the stress distribution of the heat-affected zone (HAZ). However, FEA has limited modeling capabilities for microstructural evolution (such as martensitic phase transformation), and the computational cost increases sharply with the complexity of the model, making it difficult to achieve multi-scale coupling.

In terms of thermodynamic simulation, Dittrich et al. (2019) et al. [15] used the thermodynamic software MatCalc to simulate the carbon migration behavior and precipitation phase distribution at high temperature (600-625°C) in ferritic dissimilar metal welding (T23-T91) (Reference 2). The study found that the diffusion rate of carbon from the high alloy side (T91) to the low alloy side (T23) is exponentially related to temperature, resulting in the coarsening of carbides in the HAZ zone (size increased from 50 nm to 200 nm) and a 30% decrease in the creep life of the joint. This model provides a reference for the phase transformation prediction of laser-CMT hybrid welding, such as calculating the $\beta \rightarrow \alpha$ phase transformation kinetics in Ti-6Al-4V welding through a thermodynamic database, but it lacks the ability to capture the dynamic response of transient molten pool behavior (such as keyhole collapse) in real time.

Phase field model: Ahluwalia et al. (2020) and others [16] coupled the phase field model with finite element heat conduction to simulate the α/β phase transformation process in the HAZ zone for the microstructural evolution of titanium alloy welding. Based on the classical nucleation theory and combined with the continuous cooling experimental data, the model quantitatively predicted the temporal and spatial distribution of the α phase volume fraction (increasing from 30% to 70%) and the grain size (refining from 50μm to 10μm). The results show that the prediction error of the phase field model for the gradient microstructure of titanium alloy welds is less than 8%, revealing the role of welding thermal cycle (peak temperature 1200°C, cooling rate 100°C/s) in promoting the formation of equiaxed α phase. However, the computational resource requirements of the phase field model are extremely high (a single simulation takes >72 h), and the coupled modeling of multi-physics fields (such as molten pool flow and element segregation) is not yet mature.

The traditional physical model method demonstrates multi-level modeling capabilities in the prediction of welding toughness through finite element analysis, thermodynamic simulation and phase field model : the finite element method has high accuracy (error <10%) in the prediction of macroscopic stress-strain field, thermodynamic simulation can quantify high-temperature phase transformation and element migration behavior, and the phase field model can carefully characterize the evolution of microstructure. However, these methods generally face bottlenecks such as high computational cost, difficulty in multi-scale coupling and simplification of dynamic processes. For example, it is difficult to associate microscopic grain boundary characteristics with macroscopic fracture toughness in finite element models; thermodynamic simulation makes too many assumptions about transient molten pool behavior, resulting in insufficient reliability of extrapolation; the high complexity of phase field models limits their popularity in engineering optimization. Therefore, traditional methods are more suitable for the prediction of toughness at specific scales or steady-state processes, while efficient cross-scale models are still needed for the nonlinear response of thermal-mechanical-metallurgical multi-field coupling in laser-CMT hybrid welding.

3.2 Machine Learning/Neural Network Methods

Machine learning and neural network methods break through the scale and nonlinear limitations of traditional physical models through data-driven modeling , and provide a new technical path for the prediction of strength and toughness of laser-CMT hybrid welding, mainly including BP neural network, support vector machine (SVM), deep learning, etc. Wu Rigen et al. [17] (2022) established BP, RBF and Elman neural network models for Q235 steel robot welding joints to predict the tensile

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strength and impact absorption energy of welds. Nine sets of welding parameters (current, voltage, speed) and mechanical properties data were obtained through orthogonal experiments, and the network was trained after normalization. The results show that the average prediction error of the BP neural network (3×10×2 structure) is less than 10%, but the generalization ability of small sample data is weak; in contrast, the Elman network has a more stable prediction of the trend of impact absorption energy (error <8%) due to the introduction of a dynamic feedback mechanism. Further combined with X-ray detection to optimize sample data, the model accuracy is improved by 15%..

In the prediction of weld shear strength, Wu et al. (2022) [18] proposed a hybrid model based on particle swarm optimization support vector machine (PSO-SVM). By extracting the time domain, frequency domain and wavelet packet features of ultrasonic signals and constructing a 9-dimensional input vector, the prediction error is reduced by 30% compared with the traditional BP network. In the spot welding of automotive parts, the PSO-SVM has an accuracy of 92% in identifying the "nugget pullout" failure mode, and the shear strength prediction error is <5%, which is significantly better than the single SVM (error 12%).

In terms of deep learning, Yin et al. (2019) [19] developed a deep neural network model for twin-wire CMT welding of 5083 aluminum alloy, using welding current (80-160 A) and speed (0.5-1.2 m/min) as input to predict weld width, weld depth and excess height. Studies have shown that the number of hidden layer neurons (20-30), the number of iterations (>1000) and the learning rate (0.001-0.01) are key parameters for model accuracy. The prediction error of the model for the melting depth is <5%, and its multidimensional nonlinear fitting ability is significantly better than that of the traditional regression model (R^2 increased from 0.85 to 0.95). When further applied to laser-CMT hybrid welding, deep learning can couple thermal imaging and acoustic emission signals to predict the HAZ grain size in real time (error < 2μm). Kim et al. (2022) [20] proposed a Bayesian neural network (BNN) based on Monte Carlo dropout (MC dropout) to predict the distribution of strength and toughness of thick steel plates (Reference 4). Trained on POSCO smelting data, the model not only outputs mean predictions (tensile strength error <3%) but also quantifies the uncertainty (95% confidence interval ±20 MPa). In laser-CMT welding, BNN can evaluate the probabilistic effect of process parameters (such as laser power fluctuation ±0.5 kW) on impact toughness, providing decision support for the reliability design of high-risk components.

Table 2. Comparison of prediction errors of different machine learning models

Model Type	Input Features	Output indicators	Average Error	Advantageous scenarios
BP Neural Network	Current, voltage, speed	Tensile strength, impact toughness	<10%	Linear relationship prediction
Elman Network	Dynamic process parameter timing	Impact toughness trend	<8%	Dynamic process stability prediction
PSO-SVM	Ultrasonic signal characteristics	Shear strength	<5%	High-precision prediction of nonlinear data
Bayesian Neural Networks	Laser power fluctuation, defect distribution	Impact toughness distribution	±20MPa	Uncertainty Quantification and Reliability

Machine learning and neural network methods have shown significant advantages in the prediction of welding toughness : BP neural network and SVM achieve efficient modeling through feature engineering and small sample learning; deep learning methods overcome the complex correlation between molten pool dynamics and microstructure with their multi-layer nonlinear mapping capabilities; Bayesian networks improve the engineering credibility of prediction results by quantifying uncertainty. However, these methods still face challenges such as high data dependence and weak physical interpretability. For example, deep learning models require tens of thousands of

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sets of labeled data support, while actual welding tests are costly; although the probabilistic output of the Bayesian network enhances the robustness of decisions, the implicit simplification of process mechanisms may mask key risk factors. In the future, it is necessary to further develop hybrid intelligent models that integrate physical prior knowledge, combine finite element simulation with real-time sensor data, and realize cross-scale accurate prediction of the strength and toughness of laser-CMT composite welding.

4. Conclusion

Laser-CMT hybrid welding technology, with its synergistic advantages of low heat input, high energy density and dynamic droplet control, has shown significant technical potential in the field of improving weld strength and toughness. Research shows that this technology achieves synergistic optimization of strength, plasticity and toughness by inhibiting grain coarsening in the heat-affected zone (e.g., high-strength steel HAZ grain size<10μm), optimizing phase composition (e.g. , increasing the equiaxed ratio of titanium alloy β grains by 40%) and reducing defect density (aluminum alloy porosity <0.5%). Its comprehensive performance is improved by 20%-50% compared with traditional welding processes. In terms of toughness prediction models, although traditional physical models (such as finite element method and phase field method) can quantitatively characterize the macroscopic stress field and microstructural evolution laws, they are limited by computational efficiency and multi-scale coupling capabilities; while machine learning methods (such as deep learning and Bayesian networks) significantly improve the prediction accuracy of the nonlinear correlation between complex process parameters and toughness through data-driven modeling (error <8%), providing a new paradigm for real-time process optimization.

However, current research still faces three core challenges: First, the multi-physics field coupling mechanism of laser-arc-material interaction has not been fully understood, especially in the welding of dissimilar materials, there is a lack of systematic model for the quantitative effects of element segregation and interface reaction on strength and toughness; Second, the cross-scale generalization ability of the strength and toughness prediction model is insufficient, and the existing machine learning methods rely on a large amount of experimental data, which makes it difficult to adapt to the rapid iteration requirements of new materials and new processes; Third, the welding quality consistency control technology in engineering applications urgently needs to be broken through, such as dynamic deformation compensation of large-size components and suppression of heat accumulation effects of multiple welds .

Future research needs to focus on three directions:

1) Develop hybrid intelligent models that integrate physical mechanisms and data-driven, and achieve cross-scale accurate predictions from melt pool dynamics to service performance;

2) Innovate online monitoring and closed-loop control technologies, combine high-precision sensing (such as ultra-high-speed video, acoustic emission) with adaptive algorithms, and dynamically optimize process parameters;

3) Expand the application of laser-CMT hybrid welding in extreme environments (such as deep space and deep sea) and high value-added fields (such as aerospace engines and nuclear energy equipment), and promote it to become a core process for high-end equipment manufacturing. With the collaborative innovation of intelligent welding equipment and new material design, laser-CMT hybrid welding technology is expected to break through the bottleneck of strength and toughness, provide key technical support for lightweight and high-reliability manufacturing in strategic industries such as aerospace and new energy vehicles, and help China's manufacturing industry transform and upgrade to green and intelligent.

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