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Precision blade manufacturing: Small-sample prediction and optimization using improved meta-learning and Particle Swarm Optimization

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A B S T R A C T

Accurately predicting blade manufacturing deviations from limited experimental data remains challenging due to the complex nonlinear relationship between process parameters and resulting profile deviations in precision casting. To overcome the limitations inherent in traditional approaches and conventional machine learning methods, this study proposes a novel prediction and optimization framework specifically designed for small-sample scenarios, integrating enhanced meta-learning optimization with advanced Particle Swarm Optimization (PSO). We innovatively improve the model-agnostic meta-learning (MAML) algorithm by incorporating a dynamic loss function weighting strategy and a stochastic gradient descent with warm restarts (SGDR) learning rate mechanism, significantly mitigating overfitting and enhancing generalization performance. Additionally, we propose a process parameter optimization model utilizing an improved PSO algorithm with dynamic inertia and adaptive learning factors, designed to effectively navigate high-dimensional optimization landscapes. Experimental validation using orthogonal design data highlights pulling speed as the dominant factor influencing blade deviations (Pearson correlation coefficient ($r = 0.67$). The optimized parameters—low pulling speed (1.5 mm/min) and high pouring temperature (1530 °C)—achieve an 11.54 % reduction in blade deformation. The improved MAML-based prediction model demonstrates superior accuracy, achieving a mean absolute error (MAE) of 2.566×10^{-4} mm, representing a 21.7 % improvement over traditional Adam optimization methods, and exhibits robust predictive capability ($R^2 = 0.92$) in small-sample contexts. This research not only delivers practical insights and precise parameter recommendations for complex blade manufacturing processes but also establishes a robust methodological framework applicable broadly to precision manufacturing domains characterized by limited data availability.

A R T I C L E   I N F O

Keywords:
Precise manufacturing;
Optimization;
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Machine learning;
Small sample learning;
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Izvirni znanstveni članek

Natančna izdelava lopatic: napovedovanje na majhnih vzorcih in optimizacija z izboljšanim metaučenjem ter optimizacijo z rojem delcev (PSO)

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POVZETEK

Napovedovanje odstopanj pri izdelavi lopatic z natančnim litjem na podlagi omejenih eksperimentalnih podatkov je zahtevno zaradi nelinearne odvisnosti med procesnimi parametri in profilnimi odstopanji. Za preseganje omejitev tradicionalnih pristopov in klasičnih metod strojnega učenja je razvit integriran pristop k napovedovanju in optimizaciji, posebej prilagojen scenarijem z majhnim številom vzorcev, ki združuje izboljšano metaučenje z optimizacijo z rojem delcev (PSO). Algoritem modelno neodvisnega metaučenja (MAML) je nadgrajen z dinamičnim uteževanjem funkcije izgube ter mehanizmom stohastičnega gradientnega spusta s periodičnim ponastavljanjem učne hitrosti (SGDR), kar bistveno zmanjša prenaučenje in izboljša posplošitveno sposobnost modela. Poleg tega je razvit model optimizacije procesnih parametrov na osnovi izboljšanega algoritma PSO z dinamično vztrajnostjo in prilagodljivimi učnimi faktorji, primeren za obravnavo visokodimenzionalnih optimizacijskih problemov. Eksperimentalna validacija na podlagi ortogonalnega načrta poskusov pokaže, da je hitrost izvleka prevladujoč dejavnik, ki vpliva na odstopanja lopatic (Pearsonov korelacijski koeficient r = 0,67). Optimizirani parametri – nizka hitrost izvleka (1,5 mm/min) in visoka temperatura litja (1530 °C) – omogočajo 11,54 % zmanjšanje deformacije lopatic. Izboljšani napovedni model na osnovi MAML dosega visoko natančnost s srednjo absolutno napako (MAE) 2,566 × 10^{-4} mm, kar predstavlja 21,7 % izboljšanje v primerjavi z optimizacijo Adam, ter izkazuje robustno napovedno sposobnost (R^2 = 0,92) v pogojih z majhnim številom vzorcev. Raziskava poleg praktičnih spoznanj in natančnih priporočil procesnih parametrov vzpostavlja tudi robusten metodološki okvir, širše uporaben v natančni proizvodnji z omejeno razpoložljivostjo podatkov.

PODATKI O ČLANKU

Ključne besede:
Natančna proizvodnja;
Optimizacija;
Optimizacija z metaučenjem;
Strojno učenje;
Učenje na majhnem številu vzorcev;
Optimizacija z rojem delcev (PSO)

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