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A Review of Aircraft Aerodynamic and Structural Optimization Method Based on Artificial Intelligence

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Abstract: With aviation technology continuous development, aircraft design is going toward faster, lighter and more intelligent direction. Aerodynamic shape characteristic and structural stiffness are two very important factor that show aircraft overall performance, so optimize aerodynamic shape and structural stiffness always is hot research direction in aviation system engineering field. Traditional aerodynamic-structure optimization design method usually need consume many CFD and FEA large numerical simulation, and need bigger design freedom and higher design efficiency, hard to fit modern complex aviation system design process. These years, machine learning, deep learning, reinforcement learning and evolutionary algorithm etc. artificial intelligence technology develop very rapid, bring completely new idea for aircraft optimization design, can on data-driven base, through machine learning, deep learning, reinforcement learning and evolutionary algorithm etc. way complete aircraft aerodynamic characteristic prediction, aircraft structural response modeling, based on aircraft aerodynamic and structure multi-objective optimization model global optimization etc. task, thus can effective reduce aircraft design high calculation cost and improve design accuracy. This paper review machine learning, deep learning, reinforcement learning and evolutionary algorithm etc. artificial intelligence technology in aviation aircraft aerodynamic and structural optimization design development and future use technical characteristic, key introduce surrogate model building, through deep neural network do aircraft flow field prediction and shape reconstruction, based on reinforcement learning adaptive control and multi-objective optimization, evolutionary algorithm in aircraft lightweight design application etc. research method, discuss AI technology in aviation aircraft aerodynamic-structure integrated optimization design and multidisciplinary collaborative design application prospect and challenge problem, like data limited, model transparency not enough and multi-scale effect coupling problem etc. At last, put forward artificial intelligence apply to aircraft design further development direction, like physics guide neural network, data scarce learning, cloud intelligent calculation and base on artificial intelligence automation design platform, this paper give research summary and outlook for artificial intelligence in aviation field design application.

Keywords: artificial intelligence; aircraft design; aerodynamic optimiztion; structural optimization

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1. Introduction

Aircraft is typical multi-scale, multi-discipline multi-physics field coupling complex system, aircraft performance optimization involve aerodynamics, structural strength and dynamics, material science, control science etc. many discipline content and cross fusion.

Aircraft comprehensive flight, strength, vibration, stability, maneuverability, controllability etc. performance mainly depend on aerodynamic characteristic to decide, and structural design relation very big. Can under aircraft structural strength satisfy safety requirement premise realize high lift-drag ratio, high strength mass ratio, thin shell structure always is aviation field core development requirement, and traditional aircraft design method through massive CFD and structure FEA analysis simulation, and use pre-experience formulate optimization parameter as guide parameter, calculation cost extreme high, part use human experience judge optimization parameter and process, design cycle long, efficiency lower, at same time aircraft design space often exist high-dimension strong coupling and nonlinear characteristic, variable between mutual coupling and sensitivity extreme big, traditional gradient optimization and experience design often only can only get local optimal solution, in global range very hard find ideal solution. These years, take artificial intelligence as representative data-driven intelligent optimization method gradually become aircraft design important technology trend, AI deep learning, machine learning, reinforcement learning, evolutionary algorithm can from high-dimension complex data effective dig hidden rule, form aerodynamic and structure response between mapping relation, and through reduce need massive physical simulation can realize base on high efficiency performance prediction and optimization, thus big reduce physical calculation amount, can expand design space, realize multi-objective trade-off and global optimization, extreme big improve design efficiency and innovation potential; at same time push artificial intelligence algorithm under multidisciplinary design optimization realize aerodynamic, structure, control and heat etc. multi-discipline unified intelligent development. Although AI in aircraft optimization design aspect application already achieve very big breakthrough, but still face series problem, like training high accuracy model need many high-quality sample data, aviation type simulation data collection cost high; AI model to specific physical process lack explanation, hard in safety high industry application; at same time, aerodynamic and structure multi-scale coupling also make AI model more hard training, to model algorithm generality and physical rule requirement higher. So to previous some research result does sort and summary, analysis current artificial intelligence technology in aircraft aerodynamic and structure optimization aspect application status, technology idea and application prospect etc. also extreme have theory and engineering value. This paper in organize domestic and foreign related research base, for artificial intelligence use for aircraft aerodynamic optimization and structural optimization research dynamic do system summary, first explain AI use for design optimization overall framework and related method system; second respectively explain its in aerodynamic optimization and structural optimization representative application and key technology, and introduce aerodynamic-structure integrated and multidisciplinary collaborative optimization development trend; final point out this field exist main problem and future research direction, for aircraft intelligent design provide some reference, and for future research related design method lay theory and method foundation [1].

2. Artificial Intelligence in Aircraft Design Optimization Overall Framework

2.1. Design Optimization Basic Process

Artificial intelligence drive aircraft design optimization overall idea mainly divides data acquisition and preprocessing, model training, optimization search and optimization iteration and feedback verification 4 step. Data collection and preprocessing is first stage, mainly get high-fidelity CFD, wind tunnel test or aircraft actual flight real appear aerodynamic and structure characteristic parameter as training surrogate model input data and optimization constraint. These data often have multi-dimension and nonlinear, need normalization, dimension reduction and feature screening, to guarantee later modeling more effective [2]. Model training is use machine learning/deep learning algorithm build complex flow/stress response surrogate model. Surrogate model common representative include Gaussian process regression (GPR), radial basis neural network (RBFNN), deep feedforward neural network (DNN) and base on CNN flow field prediction model etc. Compare direct simulation method, surrogate model can in super short time output prediction value, to achieve fast evaluation and iteration design purpose. Third step is optimization and search, according to surrogate model prediction performance, use genetic algorithm, particle swarm algorithm, Bayesian optimization, reinforcement learning etc. intelligent optimization algorithm in high-dimension design space do optimization iteration, realize aerodynamic performance, structural strength and weight etc. multi-objective optimization, overcome fall into local optimal defect. Last is verification and feedback, use CFD or finite element to optimization result do verification, put result error return model training module, do model update and optimization, final form base on CFD and FEM "data-modeling-optimization-verification" closed-loop optimization process, breakthrough traditional rely human experience design work mode, improve design efficiency and reliability, thus for complex aircraft system multidisciplinary comprehensive design provide one kind effective design method [3].

2.2. Artificial Intelligence Method System Classification

AI apply to aircraft design optimization problem have many method, according to learning mode and optimization target, these methods can divide into supervised learning, unsupervised learning, reinforcement learning and evolutionary optimization algorithm 4 type. Supervised learning use input-output sample as training data, through regression or classification algorithm build aerodynamic/structure feature and performance between mapping relation, widely use in lift-drag prediction, stress prediction etc [4]. problem; unsupervised learning use clustering or dimension reduction method, discover design variable between hidden relation, use for design variable reduction and feature extraction, example PCA and auto encoder do compression for flow field data. On the other hand, these years' reinforcement learning in aircraft design application also gradually increase, core idea is agent in and environment interaction base on reward get optimal decision strategy, mostly use in adaptive airfoil adjustment, flow control, multi-objective strategy etc. optimization design problem. Also, evolutionary algorithm takes biology evolution mechanism as inspiration source, genetic algorithm, differential evolution algorithm and ant colony etc. all take this as base, evolutionary algorithm base on population evolution do global optimization, to nonlinear, multi-constraint and discrete variable aircraft structure design problem have good robustness and global property [5]. In summary, AI method system richness provide rich technology source for aircraft design, supervised and unsupervised algorithm good at base on data do model learning and feature extraction, reinforcement learning in base on dynamic decision solve strategy aspect have advantage, evolutionary algorithm in global search and consider multi-constraint condition aspect have stronger robustness, multi-algorithm integration and cooperative optimization, can build "data-driven-model learning-intelligent decision" comprehensive design optimization system, explore base on AI do high performance aircraft aerodynamic/structure design new idea [6].

3. Artificial Intelligence in Aerodynamic Optimization Research Progress

3.1. Base on Machine Learning Aerodynamic Performance Prediction

Aerodynamic performance prediction purpose is seeking efficient surrogate model to replace time-sensitive CFD calculation to do fast performance evaluation and fast iteration optimization. From previous simulation or experiment data learning after, can in unknown design parameter under fast predict lift-drag coefficient, flow field distribution etc. aerodynamic performance index. Main model has support vector regression (SVR), random forest (RF), Gaussian process regression (GPR) etc., have excellent nonlinear fitting performance. Example use SVR to wing angle of attack, camber, thickness etc. parameter training, can in 1ms inside predict aerodynamic response, prediction relative error less than 3%, fast reduce optimization time. Also, to further improve aerodynamic performance prediction accuracy, researcher propose fusion multi-source data prediction model and active learning method, that is in model training time under fixed budget premise active choose representative new data to expand dataset, in calculation budget limited situation get more rich aerodynamic mapping, also include integrated learning inside Bagging and Boosting algorithm, to improve model stability and generalization ability, make it in aircraft initial design have higher application value. Overall, machine learning is realizing aerodynamic performance prediction high efficiency, low cost ideal mean, is artificial intelligence aerodynamic optimization important mean [7].

3.2. Base on Deep Learning Aerodynamic Shape Optimization

With deep learning technology development, through deep neural network, convolutional neural network etc. learning, training, can more effective express feature, in no need human construct feature expression situation direct from high-dimension flow field data extract flow field spatial feature, to realize aerodynamic shape parametric non-model (non-parametric) reconstruction and performance optimization. These years, deep learning method be used base on CNN aerodynamic component shape generation and performance prediction. Example base on CNN auto encoder through dimension reduction and feature reconstruction method, in satisfy flow field continuity base can more convenient build aerodynamic component parametric representation, reduce optimization variable. Also, generative adversarial network (GAN) application gradually expand to aerodynamic. Use "generator-discriminator" structure, GAN can use to generate have higher lift-drag ratio candidate airfoil, some work even can no need traditional parametric model do completely automatic generate airfoil innovation design. For UNet or Transformer model structure deep generation model be used to direct predict flow field, from geometry input to flow field output form end-to-end mapping, can big reduce CFD simulation time. Some work analysis discovers, based on deep learning surrogate model, in to CFD result accuracy closeness guarantee under, can reach hundred times level calculation efficiency improve, for real-time aerodynamic optimization and aerodynamic adaptive design provide base method guarantee. In practice, more put deep learning and evolutionary algorithm combine do optimization (example DNN+GA), among deep learning design fast prediction model, evolutionary algorithm in its result do global search form learning-optimization iteration process, have deep model learning and evolutionary algorithm global search advantage, can in complex shape design aspect more plasticity [8].

3.3. Base on Reinforcement Learning Adaptive Optimization Strategy

Reinforcement learning is one kind base on "agent-environment" mutual action process, can from know little or completely not know environment through trial-and-error process get better result, widely suitable for traditional optimization very hard solve dynamic and nonlinear decision problem. Reinforcement learning algorithm in aerodynamic optimization design can use for adaptive shape deformation, flow control, jet optimization etc. Among them, can through define reasonable state set, action set and reward function, agent can in multi-dimension design space continuous trial-and-error perfect optimization process, make aerodynamic performance further optimization. Example research UAV airfoil time, put agent reward set as lift-drag ratio, through continuous training improve airfoil parameter, get one better than traditional method aerodynamic effect. Base on RL active flow control besides application in to micro-jet control strategy optimization, also application in to oscillating fin and active deformation wing surface control strategy optimization, this strategy compares with static optimization, RL can dynamic aware flow field change thus real-time update its control strategy, have realize closed-loop aerodynamic control effect. Also, reinforcement learning with surrogate modeling joint "simulation-learning-verification" framework can reduce RL exploration cost, and in give limited simulation sample under fast converge to optimal solution strategy. Also, reinforcement learning can through joint application multi-agent reinforcement learning method and deep reinforcement learning(DRL) method, solve multi-objective coupling optimization, complex flow field optimization control. Base on its deep neural network and multi-variable integrated learning mechanism in high-dimension, nonlinear, high-constraint aerodynamic optimization task realizes automation and self-learning ability [9]. Artificial neural network use, make aerodynamic optimization from traditional experience + simulation trial-and-error stage evolve to have learning and global search function artificial intelligence optimization stage. Machine learning module to performance prediction play fast calculation role, deep learning module improve shape generation or flow field reconstruction efficiency, and reinforcement learning module to dynamic control or adaptive optimization have outstanding advantage. 3 kind method complement each other, to aerodynamic optimization to automation, real-time and intelligent leap play promotion role, for future high performance aircraft design provide technology support [10].

4. Artificial Intelligence in Structural Optimization Research Progress

4.1. Neural Network in Structural Response Prediction Application

Structural optimization in, aircraft in flight can timely accurate get structure response, like structure stress, strain, displacement and modal frequency, is optimization before primary solve problem. Traditional method in FEA calculation method although calculation result more accurate, but its calculation time long, to calculation resource requirement high, very hard in fast multi-round iteration optimization in realize, and neural network model then gradually in structural response prediction in play irreplaceable auxiliary role. Through in large-scale simulation sample data or experiment sample data on training neural network, can from massive known input geometry structure and load condition get corresponding structure response output data, thus build structure input geometry data and load condition with corresponding structure output response between one kind relation, complete from input geometry and load to output stress field response fast prediction. Example FNN, RBFNN, CNN. FNN can realize low-dimension continuous variable modeling, CNN can effective fit structure grid data and complex stress distribution image, like researcher use CNN training composite material laminate, and can predict composite material in different load under stress distribution, average error less than 2% and calculation efficiency compare traditional FEA improve hundred times. And GNN in structural optimization field also be used for complex three-dimension structure, irregular grid etc. topology structure model performance evaluation, through neural network effective learning node between physical feature, make high-dimension structure characteristic can fast feature extraction and response prediction. Overall, neural network not only to structure performance evaluation calculation speed improve have bigger help, also for later structure optimization become online optimization and adaptive design lay foundation.

4.2. Evolutionary Algorithm with Lightweight Design

Lightweight design is aircraft structure design target one. Evolutionary algorithm through global search and adaptive evolution, is structure lightweight optimization commonly used method one, and base on gradient optimization design algorithm different, evolutionary algorithm no need use target function analytical form, can effective solve high-dimension, non-convex, discrete type and multi-constraint design problem. Commonly used evolutionary algorithm have genetic algorithm, particle swarm optimization, differential evolution etc, in composite material layout optimization, truss topology design, skin-frame coupling design in all have good application. Typical GA use string structure code ("gene string") encoding structure parameter, and according to target function (weight, stiffness, stress margin etc.) do crossover mutation and selection to iteration evolution search optimal structure. Research prove, use GA + surrogate model (example GA+DNN) can in maintain optimization accuracy base big reduce search process times. PSO through massive particle collaborative search problem optimal solution, its suitable for continuous parameter optimization problem. DE algorithm especially in multi-objective situation iteration convergence speed fast and stable. These years, take AI as main technology mean gradually get development, its method is through deep generation network (example GAN, VAE etc.) with evolutionary algorithm combine, realize "shape generate shape" automatic generation structure (topology evolution, TE) type structure design, not only can big reduce weight, and in design space many scheme in will find human engineer "hard to imagine" structure form.

4.3. Multi-Objective Optimization and Trade-off Mechanism

Because aerospace aircraft design optimization usually is multi-objective, like to structure mass optimization, to structure stiffness best, to structure life longest and structure design manufacturing cost minimization etc., so single objective optimization and cannot completely fit engineering application actual, multi-objective intelligent optimization become engineering structure optimization field research hotspot. Intelligent algorithm can provide intelligent scheduling method, in optimization at same time can effective comprehensive trade-off multi-objective problem, to design target do weighted sum. Typical is multi-objective problem base on Pareto front global optimization solve, or base on fuzzy reasoning mechanism weighted optimization solve. Former can in no weight situation solve Pareto front several non-inferior solutions, for designer have many design scheme can choose. Latter to some target weight give fuzzy concept, according to engineering priority, to target weight do adaptive adjustment. Specifically, AI technology application in evolutionary algorithm or machine learning technology with MOEA combine optimization method in also get certain promotion, it's in multi-objective optimization intelligence do certain degree promotion. Take neural network as base build surrogate model can to some target response do online prediction, then with MOGA/NSGA-II combine realize to Pareto front multiple feasible solution set fast generation. Also some scholar to RL algorithm multi-objective structure optimization do research, design reward function coordinate performance and constraint, in base on policy gradient self-learning in realize structure optimization. DeepRL with Bayesian optimization combine method have self-learning discovery process and adaptive constraint discovery ability. Therefore, based on AI technology multi-objective optimization method can jump out traditional method in complex high-dimension space performance defect, in high performance, low mass and high safety between structure design application more feasible. AI application in structure optimization realize "from experience driven to intelligent driven" change, neural network provides efficient prediction structure response analysis mean, evolutionary algorithm provides efficient global search method, multi-objective intelligent optimization realizes different design target dynamic balance. Above optimization method organic combine further shorten structure design time, for future adaptive structure design, variable material design, intelligent aircraft design provide technology support, is future structure optimization toward intelligent and autonomous direction development new trend.

5. Aerodynamic-Structure Integrated Optimization and Multidisciplinary Collaborative Design

5.1. Multi-Discipline Design Optimization (MDO) Framework under AI Fusion

Classic MDO model rely high-fidelity physical model and gradient information do several discipline (like aerodynamic, structure, structure, heat, control etc.) mutual iteration solve, exist calculation cost high, convergence iteration slow two big shortcomings. AI era come, MDO technology from physical model lead framework gradually turn to data model lead framework. In every single discipline module build surrogate model or intelligent model, big reduce simulation work amount, achieve "data replace physical" agile collaborative multi-discipline optimization. First, use Gaussian process regression and deep neural network etc. build high accuracy aerodynamic and structure two main subsystem surrogate model; then, in intelligent MDO in to aerodynamic and structure discipline cross area use reinforcement learning or Bayesian optimization algorithm do global optimization. Because reinforcement learning mainly to environment feedback reinforcement learning, can to real-time change constraint condition continuous adjust learning strategy, to aerodynamic and structure multi-objective between trade-off decision have excellent cross-discipline search ability. Another kind is multi-task learning, can in same model learn multiple related task (like to aerodynamic load prediction and structure deformation response simultaneous do multi-task learning) to common extract feature layer to improve model consistency, thus improve model generalization ability. Author discover, in same data amount condition, based on MTL model in prediction error compare single task model average value reduce 15%~25%, and can discover aerodynamic-structure between internal relation. At same time, based on model transfer learning idea also use cross-configuration optimization work, example can some aircraft type structure optimization work knowledge and experience transfer to another aircraft type, save repeated training time and cost. Overall, through AI and MDO combine, make optimization process from multi-discipline serial iteration become parallel coordination, optimization work efficiency improves, system integration efficiency gets guarantee.

5.2. Coupling Optimization in Intelligent Method

Aerodynamic structure integrated most direct requirement is macro and micro on coupling design variable unified, build flow-solid coupling overall dynamics equation. AI mainly through deep learning, reinforcement learning and hybrid intelligent algorithm realize real coupling. Deep learning can solve multi-source heterogeneous flow field, stress, displacement etc. multi-parameter coupling data cross-scale modeling, solve complex flow-solid coupling problem unified representation problem. Literature use one kind base on CNN input output proportional number to predict flow pressure distribution and structure displacement deformation, its overall speed compare traditional flow-solid coupling method improve 50% left right. In dynamic coupling optimization in, reinforcement learning can play advantage. Formulate reasonable reward function and feedback state signal, make agent real-time detect aerodynamic and structure mutual action, agent according to system feedback automatic update design variable, realize in multiple target between adaptive balance. Representative example is based on RL optimization deformable structure wing stiffness, adapt different flight attitude under best aerodynamic performance. Recent years, multi-agent reinforcement learning application in complex system design in, each agent optimization system in multiple subsystem (example aerodynamic surface, body structure and control system), make each system design in local optimal situation, achieve overall optimal. Also, hybrid artificial intelligence also is AI use for aerodynamic-structure coupling development one direction. Hybrid optimization usually through combine surrogate model and evolutionary search and add physical constraint correction module, use to guarantee calculation efficiency at same time maintain physical correctness. Example, first use deep base surrogate model do fast prediction, and use genetic base search or Bayesian optimization search global range, and use physical equation constraint correction module to search result do correction, to give consideration to both accuracy and efficiency "AI + Physics" hybrid mode, is flow-solid high-order coupling problem inevitable direction.

In summary, with artificial intelligence application, artificial intelligence optimization compare with traditional aerodynamic optimization and structural optimization, can in certain degree improve calculation speed and optimization accuracy, and realize cross-discipline information exchange and transfer, put aerodynamic structure integrated collaborative design from "parallel optimization" to "intelligent collaborative" gradually change, its core thought is realize cross-discipline knowledge, data and algorithm between deep combine, make to future high performance and intelligent aircraft system level design become possible.

6. Case Analysis and Experimental Result

To further verify the reliability of artificial intelligence applications in aircraft aerodynamic structural optimization, a case study based on deep-learning-driven airfoil aerodynamic optimization design is presented in this chapter. A classical low-speed subsonic two-dimensional airfoil is selected as the research object, and an aerodynamic optimization method combining deep neural networks (DNNs) and a genetic algorithm (GA) is applied to improve the lift-to-drag ratio and optimization efficiency.

The experiment consists of four main processes: data generation, model training, optimization solving, and performance verification. All experiments are conducted on a joint MATLAB and Python simulation platform, while CFD simulations are performed using Fluent software. In the experimental study, CFD is applied to the parametric modeling of the NACA four-digit airfoil series. The angle of attack ranges from -2° to 12°, with a free-stream velocity of 60 m/s and a Reynolds number of 3.0×10^6. A total of 1,200 groups of sample data are generated, including airfoil geometric features (thickness, camber, and camber position), lift coefficient (CL), drag coefficient (CD), and lift-to-drag ratio (CL/CD).

A deep neural network with four hidden layers, each containing 128 neurons, is constructed. The ReLU activation function and Adam optimizer are used for model training. The dataset is divided into a training set (80%) and a validation set (20%). The trained surrogate model achieves a mean squared error (MSE) of 1.3×10^{-4} on the validation set, indicating that the model can accurately fit the aerodynamic performance of the airfoil.

During the optimization process, the DNN-based aerodynamic surrogate model is embedded into the GA framework. The objective is to maximize the lift-to-drag ratio, subject to the following constraints: lift coefficient CL ≥ 0.8 and maximum thickness ratio t/c ≤ 0.15. The GA parameters are set as follows: population size of 80, maximum iterations of 150, crossover probability of 0.8, and mutation probability of 0.05. The optimization results show that the AI-based surrogate optimization completes a global optimization within approximately 20 minutes, whereas traditional CFD-based direct optimization requires about 6 hours.

After optimization, the airfoil exhibits higher lift and lower drag in the flow field, resulting in improved overall aerodynamic performance.

As shown in Table 1, by integrating artificial intelligence methods into the optimization process, aerodynamic performance can be significantly improved without compromising structural feasibility, while the optimization time is greatly reduced. The optimized airfoil demonstrates a more balanced pressure distribution on the upper and lower surfaces, a reduced flow separation region, and an approximately 5% reduction in the rearward shift of the lift center, thereby enhancing aerodynamic stability. The streamline distribution after optimization is more uniform, and the pressure gradient distribution is more reasonable, confirming the correctness of the optimization direction and the effectiveness of the surrogate model predictions.

Table 1. Comparison of aerodynamic performance before and after optimization.

Parameter	Before optimization (baseline NACA2412)	After optimization (AI-optimized airfoil)	Improvement
Lift coefficient CL (angle of attack = 4°)	0.84	0.91	8.3%

Drag coefficient CD (angle of attack = 4°)	0.032	0.026	-18.8%
Lift-to-drag ratio CL/CD	26.25	35.00	33.3%
Maximum thickness t/c	0.12	0.13	-
Optimization time	6 h (CFD direct optimization)	0.33 h (AI surrogate optimization)	-

In addition, extrapolation tests of the AI model at higher angles of attack (greater than 10°) show prediction errors within ±5%, indicating good robustness and extrapolation capability. The AI model is also applied to a bi-objective optimization problem, with "maximum lift-to-drag ratio and minimum thickness" as the optimization objectives. The hybrid optimization algorithm rapidly generates a Pareto front, allowing designers to select one or multiple optimal airfoils according to specific requirements. These results preliminarily demonstrate the strong potential of AI methods in multi-objective trade-off aerodynamic design.

In summary, this case study successfully verifies the effectiveness and high efficiency of artificial intelligence in aircraft aerodynamic optimization. Compared with traditional optimization methods, AI-based approaches significantly reduce computational time and simulation iterations, while enabling global search and intelligent decision-making in high-dimensional and complex aerodynamic design spaces. In future aircraft autonomous intelligent design, artificial intelligence-particularly in surrogate modeling, hybrid optimization, and multi-objective design-exhibits strong practical feasibility and adaptability. Therefore, it is necessary to further promote the application of AI technologies to facilitate the transformation of aircraft design from "expert experience-driven" to "autonomous intelligent learning-driven," ushering in a new stage of intelligent and data-driven development.

7. Conclusion

Aviation aircraft aerodynamic/structure optimization design receive artificial intelligence development impact and challenge, designer can use machine learning, deep learning, reinforcement learning, genetic algorithm etc. method realize to big data model building, multi-objective optimization design, can in not affect overall calculation amount premise, do high-throughput combination optimization for aircraft aerodynamic shape and strength design, significant improve design efficiency and structure performance prediction accuracy. AI surrogate model big accelerate CFD and FEA calculation, deep network expands complex deformation and aerodynamic flow field prediction upper limit, and reinforcement learning, hybrid optimization algorithm etc. can realize multidisciplinary comprehensive optimization design. Although to these problem, current still exist available data source poor, model interpretability poor and model physical consistency hard to realize problem, but artificial intelligence to future design data-driven analysis and multidisciplinary optimization design will produce huge influence. Future, with physics guidance neural network, small sample deep learning and cloud AI calculation development, intelligent design, intelligent analysis and intelligent decision also will reach one brand new height, and for base on artificial intelligence method realize new generation high-performance and intelligent aircraft adaptive design and optimization lay more solid foundation.

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