

MULTI-AGENT REINFORCEMENT LEARNING WITH SURROGATE MODELS FOR HIGH-DIMENSIONAL DESIGN OPTIMIZATION

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Abstract

Design optimization of complex multidisciplinary systems requires exploration within nonlinear, high-dimensional design spaces. Traditional optimization methods process high-dimensional inputs in a single optimization procedure. Thus, when coupled with finite element analysis (FEA), the search space becomes prohibitively vast, degrading search efficiency and exponentially increasing computational costs. To address these challenges, this study proposes a novel design optimization framework based on multi-agent reinforcement learning (MARL) and a surrogate model, designed to simultaneously maximize computational efficiency and learning stability. The proposed methodology builds on a proximal policy optimization (PPO) algorithm with a multi-actor, single-critic architecture. Instead of tasking a single agent with all high-dimensional design variables, the variables are independently mapped and distributed across the action spaces of multiple agents. This reduces the search space handled by each individual agent, effectively alleviating the curse of dimensionality inherent in single-agent environments, thereby improving learning stability and accelerating convergence speed. The actions derived by each agent are merged into a single complete design configuration and input into a Bayesian neural network (BNN) surrogate environment. A single centralized critic evaluates the global reward returned by the BNN, guiding all agents to cooperatively update their policies toward a global optimum. To guarantee the reliability of the exploration, the predictive uncertainty of the BNN is continuously monitored. In design regions exhibiting high uncertainty, the BNN is bypassed, and the FEA is executed. The resulting data from FEA directly updates the agents and simultaneously retrains the BNN, maintaining the high accuracy of the surrogate environment. Comparative validation against classical optimization algorithms demonstrates that the proposed MARL framework maximizes learning efficiency and search performance in high-dimensional design problems through the distributed processing of design variables. By selectively executing FEA only in regions with high uncertainty, the overall computational load is reduced. This demonstrates its practicality as a highly scalable and reliable optimal design solution applicable to high-dimensional and nonlinear engineering design problems.