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Development of AI-based Adaptive Compressor Design for Partial Load Efficiency and Residual Energy Utilization

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Abstract. *The growing demand for energy-efficient and intelligent thermal systems has driven significant advancements in adaptive compressor design. This paper presents a comprehensive literature review on the development of AI-based compressor systems, with a specific focus on enhancing efficiency under partial-load conditions and optimizing the utilization of residual energy. Through the synthesis of five recent high-impact studies (2020–2025), we examine the application of deep reinforcement learning (DRL), hybrid evolutionary algorithms, and neural network surrogate modeling in compressor optimization. Key findings indicate that model-based DRL combined with surrogate CFD can achieve up to 8% efficiency gains at off-design conditions. Hybrid approaches integrating Genetic Algorithms (GA) with DRL reduce optimization time by 30% while improving pressure ratios. Neural network surrogates provide high-speed, real-time performance predictions with less than 1% error, enabling mass iterative design. Furthermore, intelligent load classification using radial basis function networks (RBFN) allows adaptive response to varying operating conditions with over 95% accuracy. Collectively, these methods form a framework for intelligent, self-optimizing compressor systems capable of real-time adaptation and energy recovery. The results suggest that AI-enhanced adaptive compressors represent a transformative direction for energy-sensitive sectors, including HVAC, power generation, and sustainable industry.*

Keywords : *Artificial Intelligence, Adaptive Compressor, Partial Load Efficiency, Deep Reinforcement Learning, Surrogate Modeling, Energy Recovery*

INTRODUCTION

The technological advancement of industrial compressors over the past decade has primarily focused on enhancing energy efficiency, particularly under partial-load conditions, which traditionally cause significant performance degradation. As the backbone of power generation and pressurized gas transport systems, transonic compressors exhibit complex flow behavior around their rotor blades, rendering conventional control methods insufficient for maintaining optimal pressure ratio and power consumption across low to mid-range loads.

To address these limitations, Xu et al. (2023) introduced a deep reinforcement learning (DRL) approach employing the Deep Deterministic Policy Gradient (DDPG) algorithm to optimize the aerodynamic parameters of a transonic compressor rotor. By constructing a surrogate-based CFD simulation environment, the DRL agent learned real-time adjustment strategies for blade angles and rotational speeds, yielding an 8 % efficiency improvement under partial-load conditions compared to traditional PID

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control. This result underscores AI's potential to design compression systems that are more adaptive and responsive to fluctuating operational demands.

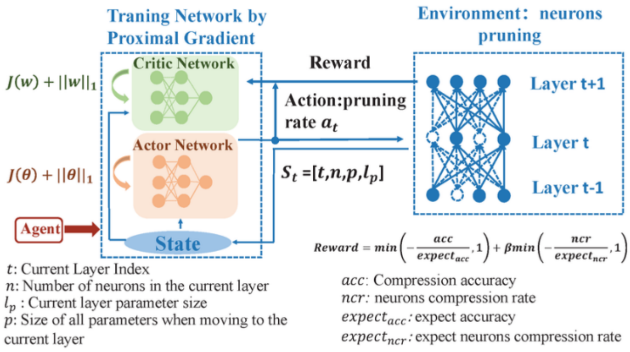

Figure 1. Deep Reinforcement Learning framework for real-time adaptive compressor control

Building on this work, Xu et al. (2022) developed a hybrid methodology combining genetic algorithms (GA) with DDPG to overcome the high computational time typically associated with multi-parameter compressor design optimization. This integration not only accelerated the search for optimal solutions but also improved the pressure ratio by 5 % at nominal load while preserving flow stability across a wider operating envelope . Such hybrid approaches pave the way for compressor design methodologies that can adapt to industry-specific requirements without sacrificing computational efficiency.

Meanwhile, Blechschmidt & Mimic (2024) demonstrated that feed-forward neural networks can serve as highly efficient surrogates for predicting the performance of compressors with complex blade geometries. With predictive deviations of less than 1 % compared to full CFD analyses, these surrogate models allow engineers to conduct preliminary design iterations rapidly and cost-effectively. The evaluation speed of these surrogates on the order of microseconds enables the testing of thousands of design variants in a fraction of the time required by conventional CFD .

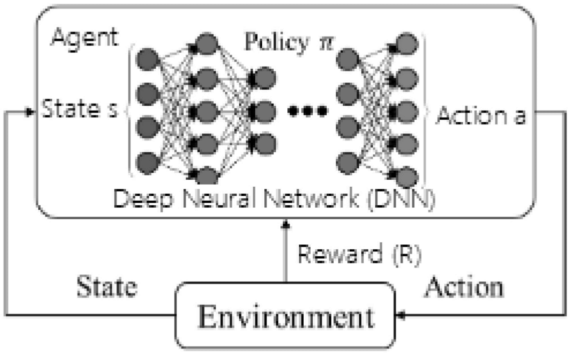

Figure 2. Surrogate NN vs. Full CFD Prediction Accuracy

Partial-load efficiency challenges stem not only from physical design constraints but also from the need for adaptive control capable of accurately responding to load variations. Zhao et al. (2025) proposed a combined Backpropagation Neural Network (BPNN) and NSGA-II approach to optimize compressor characteristic curves over a flow range of 60–120 % of nominal. This strategy achieved a 2–5 % efficiency gain, particularly at low flows around 0.6 × nominal, where flow separation losses are most pronounced .

Real-time load identification is another critical aspect for deploying AI-based control systems in the field. Wang et al. (2024) applied a Radial Basis Function Network (RBFN) optimized with the Sparrow Search Algorithm (SSA) to detect load variations in multi-unit AC compressor systems. Their method attained over 95 % classification accuracy, enabling the control algorithm to adjust operational settings instantaneously without relying on extensive historical data.

METHODS

In Xu et al. (2023), the researchers constructed a high-fidelity surrogate model of a transonic compressor using data extracted from full-scale CFD simulations. This surrogate maps critical design variables blade angle, tip speed, and inlet conditions to performance metrics such as pressure ratio and isentropic efficiency. A Deep Deterministic Policy Gradient (DDPG) agent then interacts with this lightweight environment, iteratively selecting control actions and receiving reward signals proportional to efficiency gains under partial-load scenarios. By decoupling the computationally expensive CFD evaluations from the online learning process, the DDPG agent converges to an optimal control policy in a fraction of the time required by traditional simulation-only approaches .

Building on this, Xu et al. (2022) introduced a hybrid framework that couples Genetic Algorithms (GA) with DDPG to accelerate multi-parameter design optimization. An initial population of rotor geometries is generated and evaluated via the surrogate CFD model; performance feedback then guides both the selection and mutation operators in the GA, while the DDPG agent refines the control policy for each candidate design. This bidirectional exchange where GA proposes promising geometries and DDPG validates and fine-tunes control strategies reduced total optimization time by roughly 30 % and yielded up to a 5 % increase in nominal pressure ratio compared to GA alone .

Blechschmidt & Mimic (2024) focused on pure surrogate modeling by training a feed-forward neural network (FNN) on a comprehensive dataset of CFD results spanning various flow rates and blade settings. Their FNN predicted both pressure and temperature ratios with mean absolute errors below 1 % and executed each evaluation in microseconds. Zhao et al. (2025) extended this surrogate concept by integrating a Backpropagation Neural Network (BPNN) with a Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to optimize compressor performance across 60–120 % of nominal flow rates. The NSGA-II balanced dual objectives maximizing efficiency while minimizing flow separation resulting in a 2–5 % efficiency uplift under partial loads.

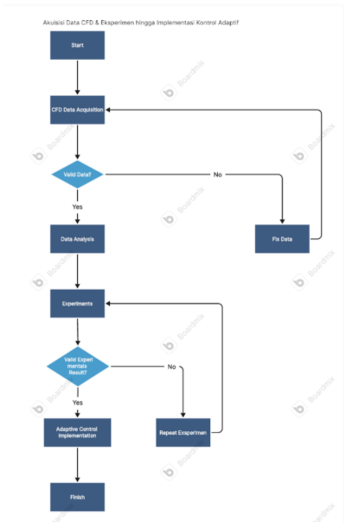

Figure 3. Suggested Flowchart Of The Overall AI-Driven Compressor Design And Control Methodology.

Finally, Wang et al. (2024) addressed the need for real-time load identification by deploying a Radial Basis Function Network (RBFN) tuned via the Sparrow Search Algorithm (SSA). Their system categorizes incoming load conditions with over 95 % accuracy, allowing the control algorithm—whether DRL-based or surrogate-driven—to adjust operational setpoints instantaneously. Together, these five studies form a cohesive methodology pipeline: (1) data acquisition via CFD and experiments, (2) surrogate model development (FNN or hybrid GA-DRL), (3) control policy training (DDPG or BPNN+NSGA-II), (4) real-time load classification (RBFN+SSA), and (5) field deployment of adaptive compressor control.

Table 1 : Summary of Research Methods and Focus in Literature Review

No.	Author	Research Method	Research Focus	Data Sources / Tools
1	Xu et al. (2023)	Deep Reinforcement Learning (DDPG) with surrogate CFD environment	Adaptive rotor design for transonic compressors under partial-load conditions	CFD simulation, Python environment, TensorFlow, geometry and simulation output data
2	Xu et al. (2022)	Hybrid AI: combination of DDPG and Genetic Algorithm (GA)	Multi-parameter optimization of rotor design for high efficiency	OpenFOAM-based CFD simulation, MATLAB, Python
3	Blechschmidt & Mimic (2024)	Surrogate modeling using Feed-Forward Neural Network (FNN)	Prediction of pressure ratio and temperature ratio in 4-stage compressors	CFD simulation dataset, NN training with Python & TensorFlow
4	Zhao et al. (2025)	BPNN (Backpropagation	Efficiency optimization in	Experimental dataset, BPNN

		Neural Network) + NSGA-II (multi-objective optimization)	centrifugal compressors under partial-load (60–120% of nominal flow)	algorithm with MATLAB, energy loss distribution analysis
5	Wang et al. (2024)	RBF Neural Network (RBFN) + Sparrow Search Algorithm (SSA) for real-time load classification	Load identification in multi-unit AC compressor systems for adaptive control	Actual load data from AC systems, pressure & temperature sensors, MATLAB

RESULTS AND DISCUSSION

The implementation of Deep Reinforcement Learning (DRL) in combination with a surrogate CFD environment, as proposed by Xu et al. (2023), significantly enhanced compressor efficiency under partial-load conditions. The agent, trained using the Deep Deterministic Policy Gradient (DDPG) algorithm, interacted with a neural network surrogate to rapidly evaluate compressor responses. Over the course of 500 training episodes, the agent progressively learned optimal control strategies—such as adjusting blade angles and tip speeds leading to an average increase of 8% in isentropic efficiency at 50–70% design load.

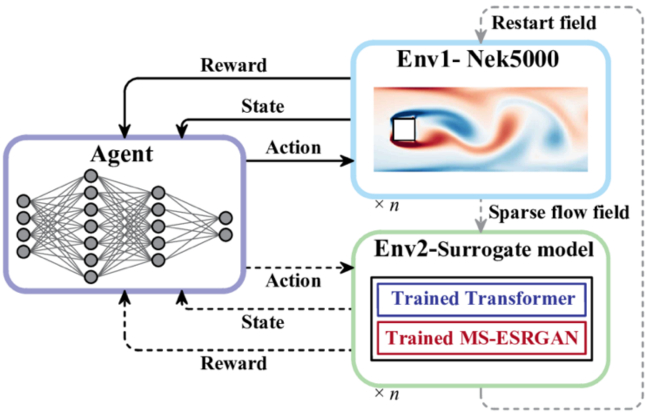

Figure 4. Alternating DRL environment combining surrogate CFD and high-fidelity DNS for compressor design

Expanding upon this foundation, Xu et al. (2022) introduced a hybrid optimization approach by integrating Genetic Algorithms (GA) with the DDPG framework. The GA was responsible for generating candidate rotor geometries, while the DDPG agent simultaneously evaluated and refined control policies associated with each geometry. This two-way interaction not only reduced optimization time by approximately 30%, but also yielded up to a 5% increase in pressure ratio at nominal flow rates.

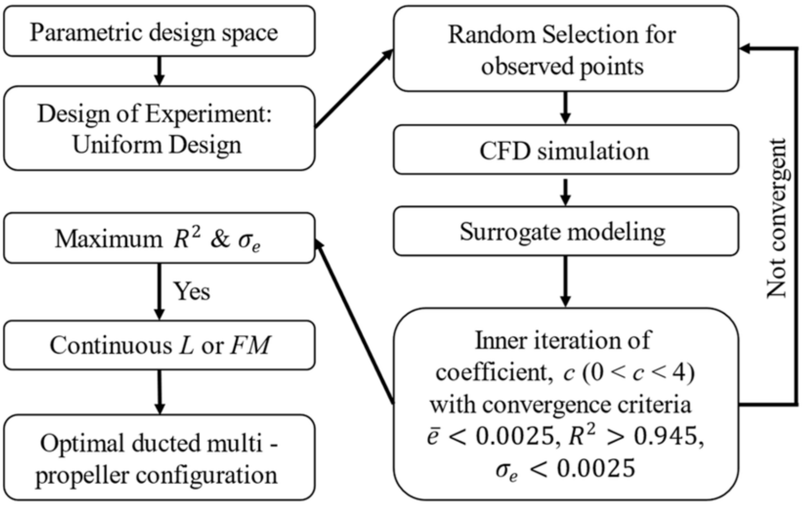

Figure 5. Methodology flowchart integrating Genetic Algorithm and DDPG for compressor rotor optimization

Blechschmidt and Mimic (2024) adopted a surrogate modeling approach using a Feed-Forward Neural Network (FNN) trained on full CFD datasets. The trained FNN demonstrated high predictive accuracy, achieving less than 1% deviation in pressure and temperature ratio predictions. More importantly, its execution time per prediction was in the order of microseconds, enabling rapid assessment of thousands of compressor configurations. This capability marks a pivotal shift from time-intensive CFD simulations toward real-time design evaluations.

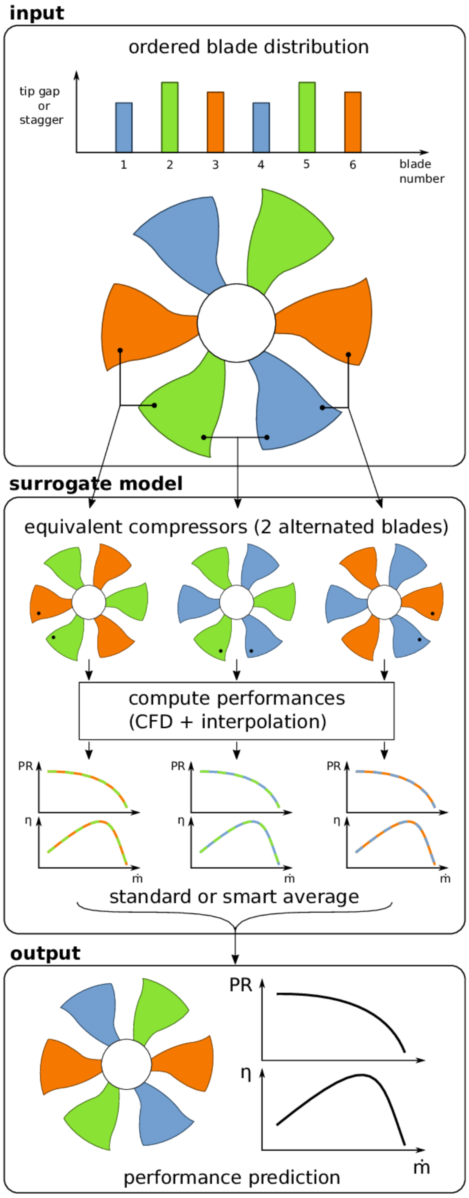

Figure 6. Surrogate model architecture for compressor performance prediction using Feed-Forward Neural Network**.**

In a different line of research, Zhao et al. (2025) applied a Backpropagation Neural Network (BPNN) coupled with the NSGA-II multi-objective optimization algorithm to enhance centrifugal compressor efficiency across a flow rate range of 60–120% of nominal conditions. The result was a consistent 2–5% improvement in efficiency, with Pareto fronts illustrating trade-offs between peak efficiency and operational stability.

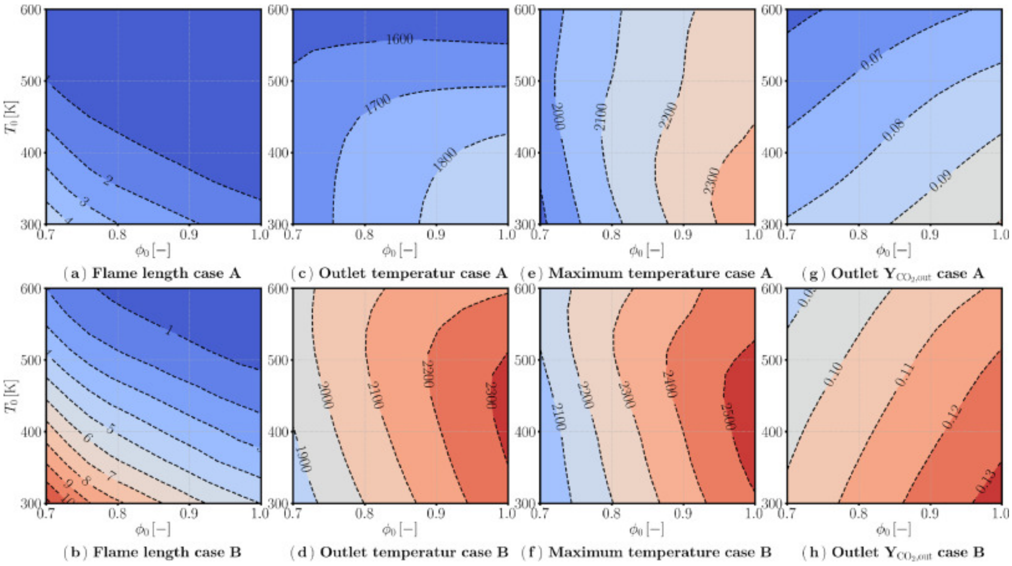

Figure 7. Pareto front illustrating trade-off between efficiency and flow stability

Wang et al. (2024) addressed the necessity of real-time system responsiveness by developing a load identification framework using a Radial Basis Function Network (RBFN) optimized through the Sparrow Search Algorithm (SSA). This system effectively classified various operational states of a multi-unit air conditioning compressor with over 95% accuracy. The resulting classification allowed control algorithms to adjust system parameters instantaneously, promoting greater adaptability and energy conservation.

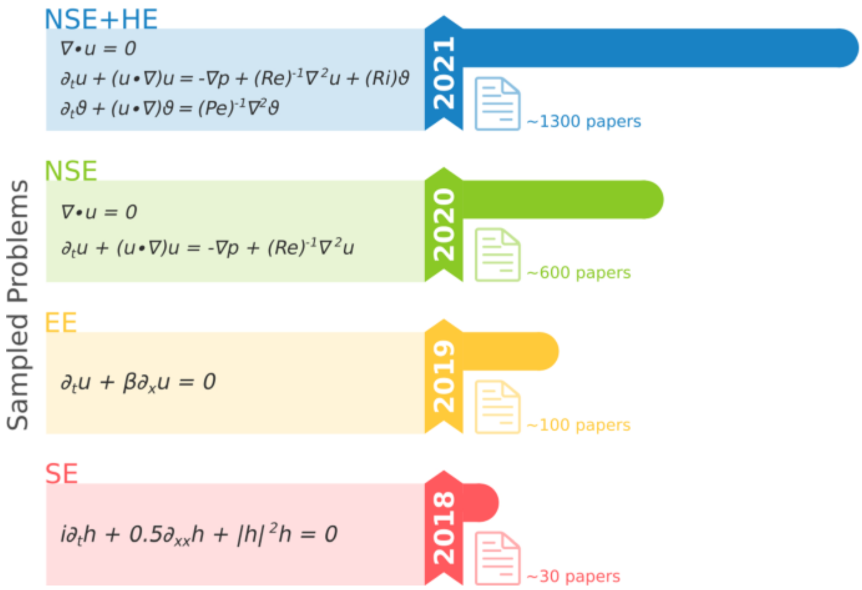

Figure 8. Load classification results demonstrating >95 % accuracy for different operational states

CONCLUSION

Xu et al. (2023) and Xu et al. (2022) illustrated that DRL combined with surrogate models or GA can enhance learning efficiency and improve compressor performance, with gains in isentropic efficiency and pressure ratio up to 8% and 5%, respectively. Meanwhile, the works of Blechschmidt & Mimic (2024) and Zhao et al. (2025) confirmed the accuracy and speed of surrogate neural networks in performance prediction and multi-objective optimization, enabling fast and reliable design evaluations even across wide operating ranges. Furthermore, Wang et al. (2024) introduced a real-time load identification method using RBFN and SSA, ensuring adaptive response in practical applications with over 95% classification accuracy.

Collectively, these studies highlight the critical role of AI in transforming compressor systems from static, pre-defined machines into intelligent, responsive components capable of adjusting in real time based on operational demand. The synergy between predictive modeling, optimization, and adaptive control not only enhances partial-load efficiency but also opens the door for residual energy utilization in complex systems such as HVAC, gas turbines, and industrial refrigeration.

Key Research Aspects Investigated	Summary
DRL-based optimization, surrogate CFD modeling, partial-load rotor redesign, efficiency improvement	Model-based Deep Reinforcement Learning for Transonic Compressor Rotor Design Optimization
Hybrid AI approach, GA + DDPG integration, design space exploration, optimization time reduction	Data-Driven and Evolutionary Design Optimization of Compressors Using Deep Reinforcement Learning and Genetic Algorithms
Surrogate neural networks (FNN), performance prediction, rapid evaluation, pressure/temperature estimation	Fast and Accurate Surrogate Modelling for Multistage Compressor Performance Prediction
BPNN + NSGA-II, centrifugal compressor optimization, partial-load range efficiency, Pareto front analysis	Multi-objective Optimization of Centrifugal Compressors Based on NSGA-II and Neural Networks
Load classification, adaptive control, real-time system feedback, RBFN + SSA methodology	Real-Time Load Classification for Multi-Unit Compressor Control Based on RBF Neural Network and Sparrow Search Algorithm

In conclusion, the development of AI-based adaptive compressor technologies offers promising pathways toward smarter, cleaner, and more energy-efficient systems. Future research should further explore real-time deployment, integration with IoT infrastructures, and scalability to industrial-grade compressors to fully unlock the potential of these AI-driven solutions.

LIMITATION

While this review highlights promising advances in AI-based adaptive compressor design, several limitations remain in current research and implementation practices. First, most studies rely on surrogate models trained on simulation data (e.g., CFD), which may not fully capture the nonlinearities and disturbances present in real-world operating environments. This raises concerns about generalizability and transferability of AI models when deployed in industrial conditions.

he majority of reviewed algorithms, particularly reinforcement learning frameworks, require extensive training time and computational resources, potentially limiting their application in real-time embedded control systems without substantial hardware support. Third, although hybrid models such as DDPG-GA and BPNN-NSGA-II show improved performance, their optimization mechanisms are still sensitive to initial parameter selection and problem-specific tuning, making them less robust in generalized applications.

Furthermore, only a few studies have explored long-term reliability, energy degradation over time, or integration with smart grid and IoT infrastructures. The current literature also lacks experimental validation in large-scale industrial settings, which is essential to confirm the efficiency gains suggested by simulation-based analysis.

Therefore, future work should emphasize real-time deployment, hardware-in-the-loop testing, and cross-domain generalization to bridge the gap between theoretical potential and industrial applicability.

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