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Exergy analysis and optimization in high-temperature gas-cooled reactors: A review of multi-objective approaches based on evolutionary algorithms

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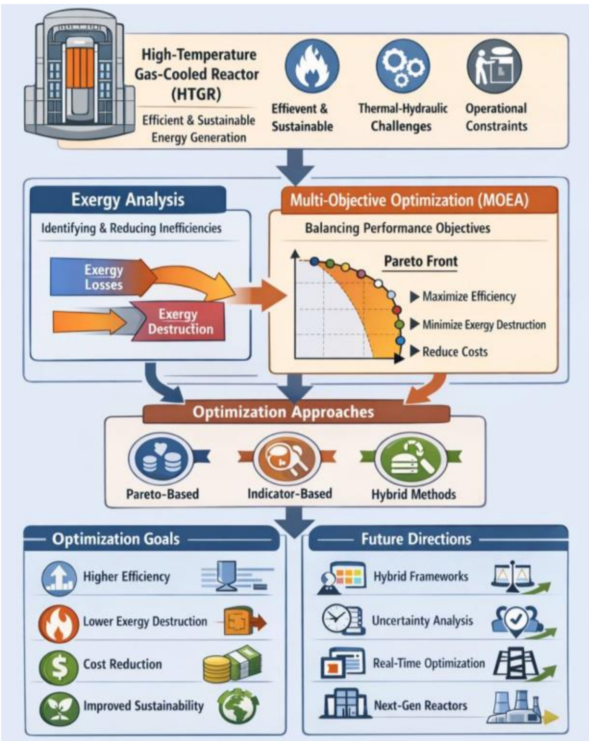
Abstract

High-Temperature Gas-Cooled Reactors (HTGRs) have emerged as one of the most promising technologies for sustainable, efficient, and safe system energy generation. Despite their advantages, the thermodynamic performance of HTGRs is often limited by inherent irreversibility, complex thermal-hydraulic interactions, and operational constraints. Exergy analysis has proven to be a powerful tool for identifying, quantifying, and minimizing these inefficiencies, offering critical insights into system design and operational improvement. Alongside this, multi-objective optimization provides a systematic framework to enhance multiple performance indicators simultaneously, enabling engineers to balance competing objectives such as maximizing thermal efficiency, minimizing exergy destruction, reducing operational costs, and improving overall system sustainability. This review focuses on the integration of Multi-Objective Evolutionary Algorithms (MOEAs) with exergy-based analysis for HTGR optimization. Key methodologies, including Pareto-based, indicator-based, and hybrid evolutionary approaches, are examined in detail, highlighting their effectiveness in navigating complex trade-offs and achieving convergence in high-dimensional design spaces. The study synthesizes recent advancements in algorithm development, performance evaluation, and application strategies, emphasizing the potential of MOEAs to significantly improve reactor thermodynamic efficiency while providing robust decision-making tools for reactor designers. Finally, current challenges and future research directions are discussed, including the development of hybrid optimization frameworks, incorporation of uncertainty quantification, real-time operational optimization, and the extension of these methodologies to next-generation reactor systems, aiming to foster sustainable and high-performance energy solutions.

Graphical Abstract



1. Introduction

Exergy analysis has become an essential tool in modern thermodynamics and energy engineering, providing a more complete and insightful assessment of energy systems compared to conventional energy analysis. While energy is conserved according to the first law of thermodynamics, it does not provide information on the quality or usability of energy within a system. Exergy, on the other hand, quantifies the maximum useful work obtainable as a system comes into equilibrium with its environment, effectively capturing both the quantity and quality of energy. This distinction allows exergy analysis to identify irreversibility and inefficiencies that are often overlooked in traditional energy assessments. By highlighting the locations and magnitudes of these losses, exergy analysis enables engineers and researchers to optimize system performance, improve resource utilization, and reduce waste. The applicability of exergy analysis spans a wide range of energy conversion and utilization systems, including power plants, combined heat and power systems, refrigeration cycles, and emerging renewable energy technologies. Beyond identifying inefficiencies, exergy-based assessments provide valuable insights into environmental impacts by quantifying the exergy destruction associated with emissions and resource depletion. This makes exergy analysis not only a powerful diagnostic tool but also a strategic framework for sustainable energy design and management. Over the past decades, integrating exergy principles has become crucial for comparative evaluation of conventional and innovative technologies, guiding the development of more efficient, cost-effective, and environmentally responsible energy systems. Consequently, exergy analysis bridges the gap between theoretical thermodynamic evaluation and practical engineering optimization, making it an indispensable methodology for advancing modern energy science and technology [1-4].

The development of next-generation reactors has become a key focus in the pursuit of sustainable and low-carbon energy solutions. These advanced reactors are designed to address the limitations of conventional systems by offering higher thermal efficiency, enhanced safety features, and greater operational flexibility. Innovations such as high-temperature operation, modular construction, advanced fuel technologies like TRISO particles, and passive safety systems enable these reactors to perform reliably under extreme conditions while minimizing the risk of accidents. Furthermore, next-generation designs aim to integrate seamlessly with industrial processes, providing not only electricity but also high-temperature heat for hydrogen production, desalination, and other industrial applications. By advancing both technological capabilities and safety standards, the development of these reactors represents a critical step toward a more sustainable, versatile, and resilient energy infrastructure systems for the future [5-6].

Next-generation reactors, particularly High-Temperature Reactors (HTRs), represent a significant evolution in energy technology, combining enhanced safety, higher efficiency, and versatile operational capabilities. Unlike conventional light-water reactors, HTRs operate at outlet temperatures ranging from 750°C to over 900°C, which substantially improves thermal efficiency and enables the direct coupling of reactors to various high-temperature industrial processes. These advanced reactors often use helium or carbon dioxide as inert coolants and graphite as a moderator, providing chemically stable, high-conductivity environments that minimize corrosion and enhance passive safety. Moreover, the use of TRISO fuel particles ensures robust containment of fission products, even under extreme temperature conditions, thereby further improving the overall safety profile of the system [7-8].

The high-temperature operation of these reactors opens the door to a wide array of industrial applications beyond electricity generation. HTRs can efficiently drive high-temperature chemical processes, including hydrogen production via thermochemical cycles, water desalination for producing fresh water, and synthetic fuel generation, offering an integrated approach to meeting both energy and industrial heat demands. Additionally, their modular and flexible design allows for scalable construction, shorter deployment times, and potential use in cogeneration systems where electricity and process heat are simultaneously supplied. By combining robust safety features, operational versatility, and high thermal efficiency, next-generation HTRs are positioned as a cornerstone technology for sustainable, multi-purpose energy systems capable of addressing the growing global demand for clean energy and industrial process heat [8-11].

Optimizing HTGRs requires a comprehensive understanding of both energy and exergy performance, as traditional energy analysis alone cannot capture the intrinsic inefficiencies in complex systems. Exergy analysis provides a rigorous thermodynamic framework to quantify inefficiencies and identify locations where useful work is lost due to entropy generation, high-temperature gradients, or material limitations. By revealing the sources and magnitudes of thermodynamic losses, exergy-based assessment enables engineers to target critical subsystems, improve fuel utilization, enhance thermal efficiency, and reduce environmental impacts. In the context of HTGRs, exergy analysis is particularly valuable due to the high operating temperatures and diverse applications, from electricity generation to hydrogen production and process heat, where optimal use of available energy resources is essential for system sustainability and economic feasibility [12-13].

Building on exergy analysis, multi-objective optimization techniques, especially those based on evolutionary algorithms such as genetic algorithms, particle swarm optimization, and NSGA-II, have proven effective in simultaneously improving multiple conflicting performance criteria. These approaches allow designers to optimize reactor operating conditions, coolant flow rates, fuel configurations, and heat exchanger designs while balancing trade-offs between thermal efficiency, safety, operational flexibility, and environmental impact. By integrating exergy-based evaluation with evolutionary multi-objective optimization, researchers can generate Pareto-optimal solutions that guide the design and operation of HTGR systems toward maximum performance. Such optimization frameworks not only enhance energy and exergy efficiency but also provide actionable insights for the sustainable and safe deployment of next-generation high-temperature energy systems [12-15].

Despite the considerable body of research devoted to the analysis and optimization of HTGRs, many fundamental aspects of their thermodynamic behavior, efficiency improvement, and system-level optimization remain insufficiently understood. Previous studies have often emphasized conventional energy analyses or isolated exergy assessments, without fully addressing the complex interactions among reactor subsystems, heat transfer mechanisms, and multi-objective trade-offs involving efficiency, safety, and sustainability. Ryszard Bartnik and Hnydiuk-Stefan investigated the energy efficiency and economic feasibility of retrofitting coal-fired power plants by integrating high-temperature gas-cooled reactors (HTGRs) and turboexpanders to achieve supercritical steam parameters by 2025. Their study adopted an incremental approach to assess the potential advantages of this modernization, emphasizing the integration of the Joule and Clausius–Rankine cycles [16]. In 2024, Yujia Zhou et al. conducted the first comprehensive analysis of the thermodynamic, economic, and environmental performance of an HTGR–SCO_2 system using the energy, exergy, economic, and environmental (4E) evaluation framework. They proposed a cascaded SCO_2 configuration consisting of two serially connected sub-cycles on the cold side of the reactor heat exchanger, demonstrating that this arrangement effectively enhances heat utilization from the HTGR through optimized top and bottom cycle designs [17]. In 2021, H. Neser et al. performed a comparative evaluation of three energy-based fault detection and isolation (FDI) techniques—namely, enthalpy–entropy error-based, residual-based, and eigendecomposition-based methods. A Brayton cycle-based power conversion unit (PCU) served as the case study, simulated under both normal and faulted conditions, and analyzed using energy representations such as enthalpy–entropy diagrams and attributed graphs [18]. Qi Wang et al. (2026) proposed a flexibly configured cogeneration system driven by two types of small modular reactors (SMRs), integrated with a typical petrochemical complex for combined electricity and steam production. The system was analyzed under two operational schemes from both energy and exergy perspectives [19]. Finally, Jiarui Zhao et al. (2023) developed a comprehensive mathematical model for a marine power secondary circuit system and introduced an enhanced adaptive multi-objective particle swarm optimization algorithm (AMOPSO-APD). Optimization of key design parameters under safety and performance constraints resulted in a 10.57% reduction in system weight, a 13.68% reduction in volume, and a 4.26% improvement in efficiency [20].

The increasing global demand for sustainable and efficient energy has intensified the focus on HTRs as promising candidates for next-generation energy systems. Despite their potential, the complex thermodynamic behavior of HTRs and the inherent inefficiencies in their processes pose significant challenges in achieving optimal performance. Exergy analysis provides a rigorous framework to quantify these inefficiencies and assess the true potential of energy conversion in such reactors. Moreover, the integration of multi-objective optimization techniques, particularly those based on evolutionary algorithms, allows simultaneous improvement of multiple conflicting performance criteria, such as thermal efficiency, safety, and fuel utilization. Therefore, this study aims to comprehensively review the state-of-the-art exergy analysis and multi-objective optimization methodologies applied to HTRs, highlighting their effectiveness, limitations, and future research opportunities. By consolidating existing knowledge, this work not only emphasizes the critical role of exergy-based assessment in maximizing reactor efficiency but also underscores the importance of evolutionary optimization as a strategic tool for the design and operation of advanced energy systems.

2. Theoretical Framework

The theoretical framework of this study integrates the principles of exergy analysis, multi-objective optimization, and evolutionary computation to evaluate and enhance the performance of HTGRs. Exergy analysis provides a powerful thermodynamic foundation for identifying sources of irreversibility and quantifying the real potential of energy conversion processes. In energy systems, especially HTGRs, where heat transfer occurs at very high temperatures, exergy-based assessment becomes essential for maximizing system efficiency and minimizing entropy generation.

2.1. Multi-Objective Exergy Optimization Approaches

Traditional energy analysis methods are often insufficient for complex systems because they do not account for the quality or usability of energy. Exergy analysis, by contrast, measures the *useful work potential* of energy flows relative to the environment, providing a more rational basis for optimization. In practical applications, the design of HTGR systems involves multiple conflicting objectives such as maximizing exergy efficiency, minimizing component mass, reducing fuel consumption, and ensuring safety margins. Hence, multi-objective exergy optimization methods are used to balance these trade-offs. The Pareto optimality concept is typically employed to identify the set of non-dominated solutions, representing optimal compromises among the competing design criteria [21-23].

2.2. High-Temperature Gas-Cooled Reactors

HTGRs embody several technological innovations that distinguish them from other Generation IV systems. Their modular reactor architecture typically consists of either prismatic block or pebble-bed configurations, both designed for high reliability and ease of maintenance. The prismatic design employs hexagonal graphite blocks containing fuel compacts and coolant channels, while the pebble-bed type utilizes spherical fuel elements that continuously circulate through the reactor core. These modular configurations allow for passive decay heat removal through natural convection and radiation, ensuring inherent safety even in loss-of-coolant scenarios. From a thermal-hydraulic standpoint, HTGRs exhibit excellent heat transfer performance due to the low density and high specific heat capacity of helium coolant. This feature enables compact heat exchangers and enhances the coupling efficiency between the reactor and secondary power conversion systems. The reactors can be integrated with advanced thermodynamic cycles such as Brayton, Rankine, or supercritical CO_2 ($S\text{-}CO_2$) cycles to further elevate thermal efficiency and reduce specific fuel consumption. Among these, the direct helium Brayton cycle is particularly attractive because it eliminates the need for an intermediate heat exchanger, simplifying system design and minimizing exergy losses across heat transfer interfaces [24]. The schematic diagram of a HTGR is shown in **Fig. 1**.

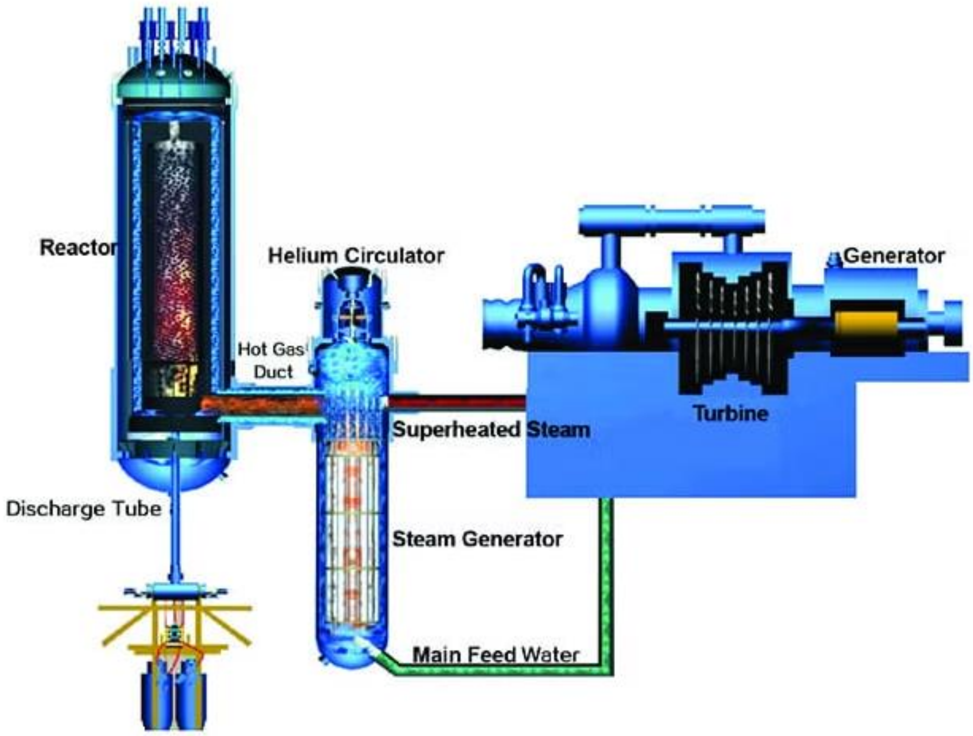


Fig 1. Schematic diagram of HTGR, showing the prismatic core, graphite moderator, and helium coolant circulation loop [24].

In terms of fuel technology, HTGRs rely on TRISO (Tri-structural Isotropic) coated fuel particles, which represent one of the most robust fuel forms developed to date. Each fuel particle consists of a uranium kernel encased in multiple protective layers of carbon and silicon carbide, forming a miniature containment structure capable of withstanding temperatures exceeding 1600 °C. This design not only retains fission products effectively but also allows for higher fuel burnup, extending the operational lifetime of fuel elements and reducing waste generation. Consequently, the fuel design aligns closely with the sustainability and proliferation-resistance goals of next-generation systems. Furthermore, the multi-functionality of HTGR technology extends its role beyond power generation to serve as a central node in integrated energy systems. Coupled with high-temperature electrolysis or thermochemical cycles such as the Sulfur–Iodine (S–I) or Copper–Chlorine (Cu–Cl) processes, HTGRs can facilitate large-scale hydrogen production without carbon emissions. Similarly, their steady and controllable heat output makes them ideal for district heating, industrial steam generation, and process heat supply for industries such as metallurgy, ammonia synthesis, and petrochemical refining. This operational flexibility positions HTGRs as a bridge between the electric and thermal energy sectors, contributing significantly to decarbonization and sectoral coupling in future low-carbon energy infrastructures [25-27]. A schematic representation of a cogeneration plant with its flow diagram showing simultaneous production of electricity, desalinated water, district heating, and cooling using waste heat from a HTGR is demonstrated in **Fig. 2**.

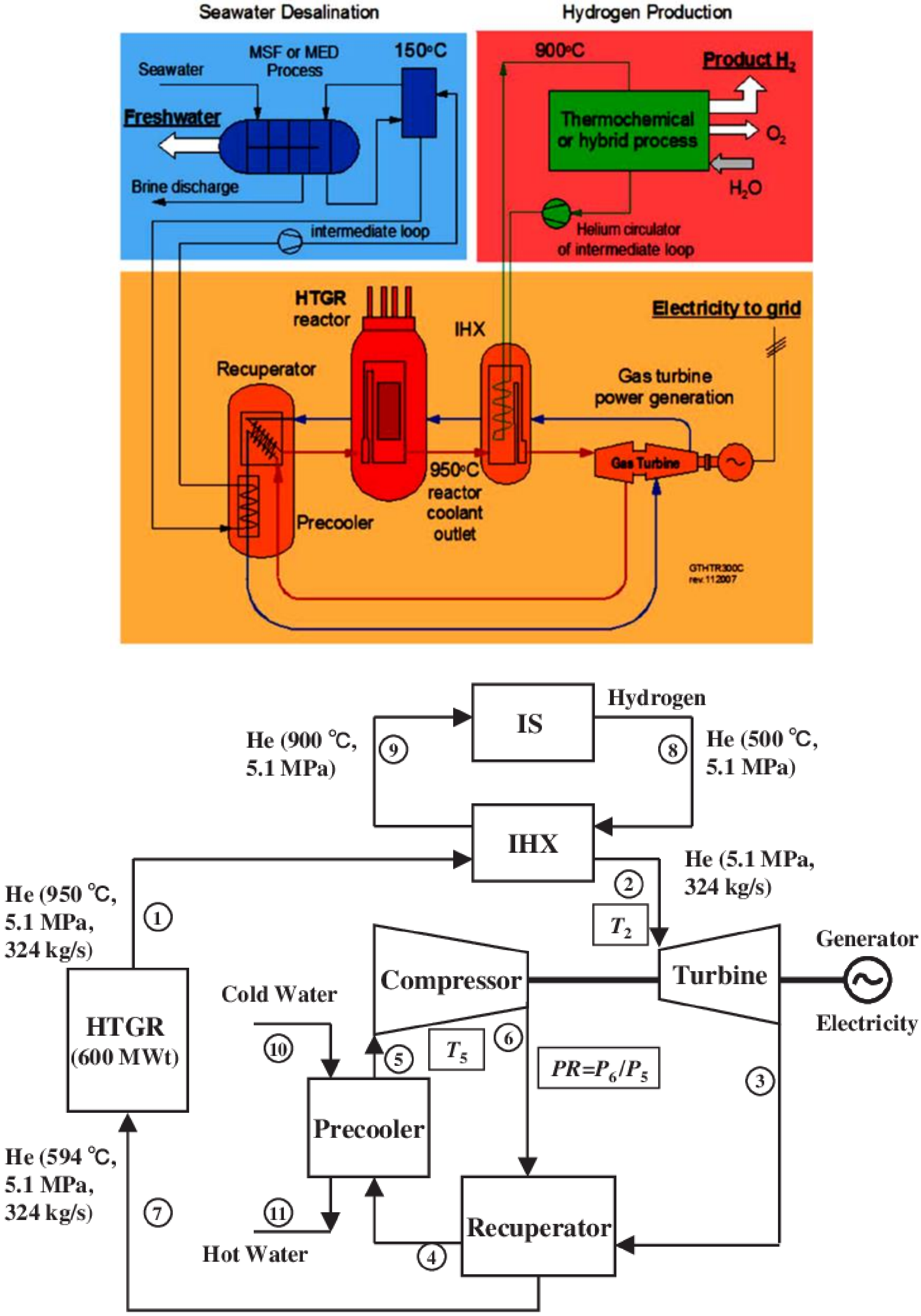


Fig 2. HTGR-based cogeneration system producing electricity, desalinated water, heating, and cooling [27].

From an economic and deployment perspective, Small Modular HTGRs are gaining attention due to their scalability, factory fabrication potential, and shorter construction timelines. These modular units can be deployed incrementally to match local energy demand and reduce upfront capital risk, while maintaining the same safety and efficiency standards as larger systems. Coupled with advanced digital control systems, predictive maintenance, and exergy-based optimization algorithms, modular HTGRs offer a pathway toward autonomous, intelligent, and economically viable power plants that align with the broader vision of sustainable energy transitions [28].

2.3 Multi-Objective Evolutionary Algorithms

To address the nonlinear, non-convex, and highly coupled nature of HTGR optimization problems, Multi-Objective Evolutionary Algorithms (MOEAs) have become indispensable. These algorithms, such as NSGA-II (Non-dominated Sorting Genetic Algorithm II), MOPSO (Multi-Objective Particle Swarm Optimization), and their adaptive or hybrid variants, are capable of efficiently exploring large and complex design spaces without requiring gradient information. By integrating exergy analysis with MOEAs, researchers can identify optimal configurations that enhance thermal efficiency, reduce exergy destruction, and maintain structural safety. The Pareto front obtained from such optimization provides valuable decision-making support, enabling designers to select configurations that achieve the best trade-off between performance, cost, and sustainability [29-31]. **Fig. 3** shows the integration of exergy analysis with MOEAs for HTGRs optimization.

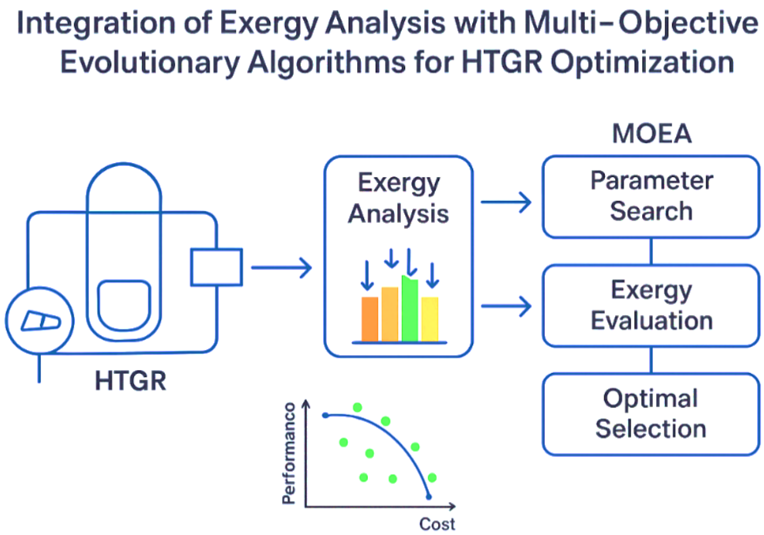


Fig.3. Integration of exergy analysis with MOEAs for HTGR optimization [30-31].

3. Discussion

Recent studies increasingly emphasize the integration of exergy analysis with multi-objective optimization frameworks to enhance the performance of high-temperature gas-cooled reactors (HTGRs). The majority of the reviewed literature identifies exergy efficiency and total exergy destruction rate as the primary objective functions, frequently combined with economic metrics or safety constraints to ensure a holistic system evaluation. Among optimization techniques, algorithms such as the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) are most widely employed. These approaches yield well-distributed Pareto fronts that effectively illustrate trade-offs among thermal efficiency, reactor safety, and fuel utilization. Optimized HTGR configurations, particularly those incorporating combined Brayton or supercritical CO_2 (S–CO_2) cycles, achieve overall exergy efficiencies ranging from 45% to 55% a marked improvement over conventional Rankine-based system. This advancement underscores the critical interplay between reactor thermodynamic behavior and optimization methodology. The convergence of these approaches not only facilitates more efficient reactor designs but also supports informed decision-making in balancing performance, safety, and economic viability [32–34].

Comparative analyses indicate that NSGA-II remains the most reliable algorithm for HTGR applications due to its effective balance between convergence speed and solution diversity. However, hybrid approaches such as GA–PSO and NSGA-III coupled with surrogate models or response surface methods demonstrate superior capability in managing multi-variable, nonlinear interactions in exergy optimization. Furthermore, several studies have shown that adaptive MOEAs, which dynamically tune control parameters, outperform classical algorithms in maintaining diversity along the Pareto front. This improvement enables more robust optimization outcomes under varying operational constraints, such as coolant temperature and pressure [35–38].

Exergy destruction analysis across different HTGR configurations consistently identify the reactor core, intermediate heat exchanger, and turbine as the dominant sources of irreversibility, collectively accounting for 60–75% of total exergy losses. By incorporating evolutionary optimization, multiple studies have achieved a 10–20% reduction in total exergy destruction primarily by optimizing coolant flow distribution, pressure ratios, and turbine inlet temperatures. Additionally, advanced Brayton and S–CO_2 cycles effectively minimize exergy losses in secondary systems due to reduced temperature gradients and enhanced thermal recovery effectiveness [38-40].

Another emerging trend involves the integration of HTGRs with hydrogen production cycles such as sulfur–iodine (S–I) and copper–chlorine (Cu–Cl). Multi-objective optimization in these hybrid systems typically aims to maximize both exergy efficiency and hydrogen yield under economic and safety constraints. Optimized S–I cycle coupled with HTGRs can achieve overall exergy efficiencies up to 50%, while Cu–Cl cycles show slightly lower performance but offer improved material compatibility and reduced operational risk. These findings highlight the potential of exergy-based optimization as a systematic framework for identifying optimal integration pathways between heat and industrial hydrogen production [41-42].

Despite the remarkable progress achieved in integrating exergy analysis with MOEAs for HTGR optimization, several challenges persist. One of the most critical limitations lies in the substantial computational cost of simulating large-scale, multi-parameter HTGR systems within evolutionary frameworks. Since MOEAs require thousands of function evaluations to generate a well-distributed Pareto front, their application to high-fidelity reactor models often involving detailed neutronic, thermohydraulic, and material coupling demands considerable computational resources and processing time. This computational intensity restricts the number of design variables explored and limits the practical adoption of such techniques in real-world design environments or online operational frameworks [43-44].

Another major constraint arises from uncertainty in material properties and degradation mechanisms at extremely high operating temperatures (typically above 900 °C). Because HTGR components such as the reactor pressure vessel, fuel compacts, and heat exchangers undergo prolonged exposure to elevated temperatures, inaccuracies in data for thermal conductivity, creep resistance, and corrosion introduce uncertainty into exergy destruction estimates. Consequently, optimization results may deviate from actual performance if such material uncertainties are not accounted for through robust uncertainty quantification or sensitivity analyses. This underscores the need for reliable high-temperature material databases and experimentally validated models to support predictive, exergy-based optimization of next-generation reactors [45-46].

A further methodological limitation concerns the absence of standardized objective functions that comprehensively integrate thermodynamic, safety, economic, and environmental criteria within a unified optimization framework. Many studies still emphasize exergy efficiency and thermal performance while treating safety margins, fuel cycle costs, and lifecycle economic indicators as secondary considerations. This fragmentation limits the ability to conduct holistic optimization and hinders cross-study comparability. Developing standardized metrics and benchmarking protocols for exergy-based optimization would substantially enhance reproducibility, transparency, and consistency across the field. **Fig. 4**. illustrates the Pareto fronts representing the trade-offs between exergy efficiency and total exergy destruction rate for different optimization algorithms. NSGA-II shows a balanced distribution and faster convergence, while hybrid GA–PSO achieves a slightly wider coverage of the solution space. Additionally, the limited utilization of Artificial Intelligence (AI)-assisted surrogate modeling and digital twin technologies represents another significant gap. While some recent works have demonstrated the feasibility of coupling MOEAs with surrogate models such as Gaussian process regression, artificial neural networks, or response surface methodologies to approximate complex reactor responses at a fraction of the computational cost, such applications remain relatively isolated. Broader adoption of AI-driven surrogate models could dramatically accelerate convergence, enhance global search capability, and facilitate multi-scale integration of reactor physics and system-level performance. Furthermore, the emergence of digital reactor twins' virtual replicas continuously updated through sensor data and physics-based simulations offers a transformative pathway toward real-time exergy monitoring and adaptive optimization during reactor operation. Integrating MOEAs and machine learning algorithms within digital twin platforms may enable self-optimizing, self-correcting HTGR systems capable of dynamically adjusting control parameters in response to changing operational or environmental conditions [47-50]. The **Table 1** summarizes representative studies focusing on exergy-based multi-objective optimization of HTGRs. It highlights the optimization method, key objective functions, principal design variables, and the achieved performance improvements in terms of exergy efficiency and total exergy destruction reduction [42].

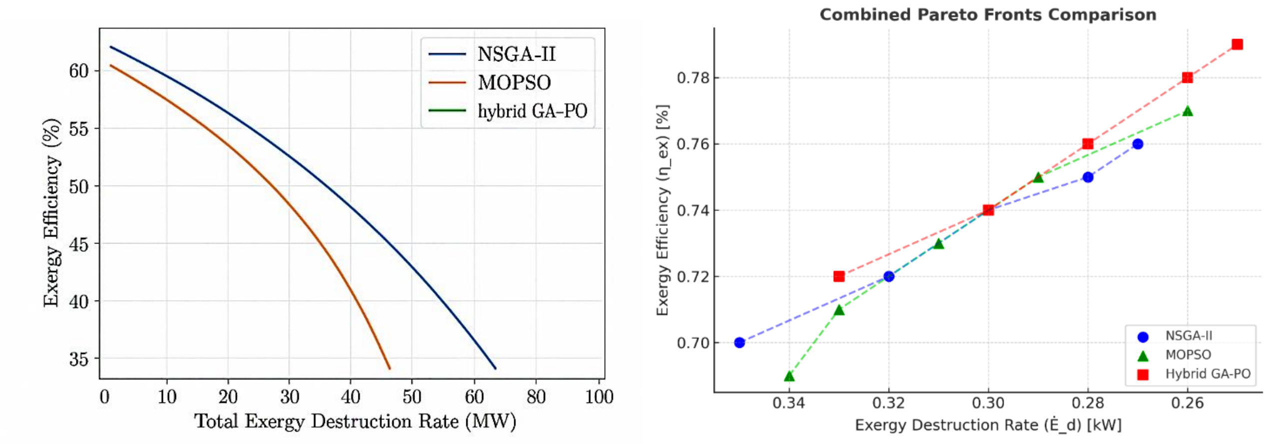


Fig 4. Comparison of Pareto front distributions obtained by NSGA-II, MOPSO, and hybrid GA–PSO algorithms for HTGR exergy optimization [48-50].

Table 1. Comparative summary of recent exergy-based multi-objective optimization studies on HTGR systems [42].

Optimization Method	Objective Functions	Key Parameters Optimized	Reported Exergy Efficiency (%)	Reduction in Exergy Destruction (%)
NSGA-II	η_{ex}, Cost	Pressure ratio, T inlet	48.5	12
MOPSO	η_{ex}, Safety index	Coolant flow, Core geometry	46.8	10
GA–PSO Hybrid	η_{ex}, Fuel utilization	Flow distribution, Heat recovery	50.2	15
Adaptive NSGA-III + ANN	η_{ex}, Cost, Risk	Pressure ratio, Material type	52.1	18
NSGA-II + S–CO_2	η_{ex}, H_2 yield	Cycle temperature, Recompression ratio	54.5	20

Looking ahead, future research should focus on developing hybrid optimization frameworks that combine the exploratory strength of MOEAs with the predictive learning capability of AI. Such hybrid approaches can substantially reduce computational demands, enhance convergence stability, and improve robustness under uncertainty. In parallel, embedding exergy-based models into digital twin environments could enable continuous, closed-loop optimization throughout the reactor's lifecycle from design and commissioning to operation and maintenance. Ultimately, these advancements are expected to pave the way toward next-generation intelligent systems that are not only thermodynamically optimized but also capable of autonomous decision-making, predictive diagnostics, and real-time performance enhancement supporting the global transition to safer, cleaner, and more sustainable energy infrastructures [49,51]. Finally, the distribution of total exergy destruction among major components of the HTGR system, including the reactor core, turbine, compressor, heat exchanger, and recuperator is shown in **Fig. 5**.

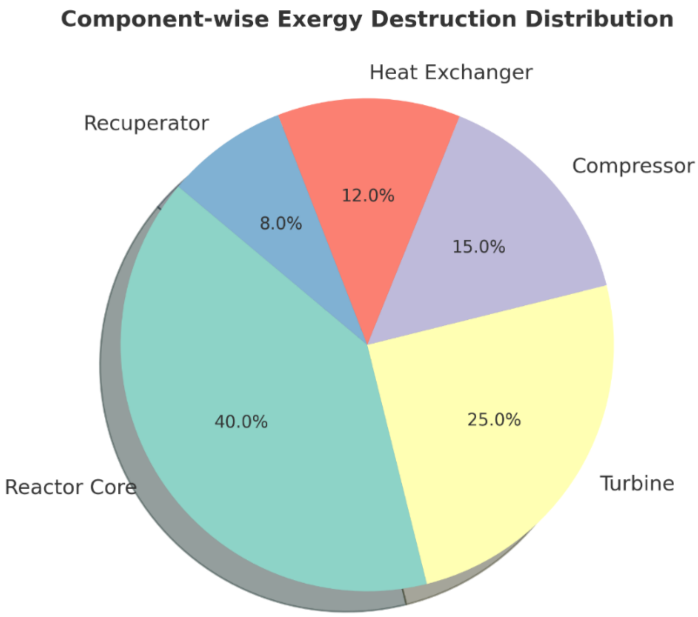


Fig 5. Exergy destruction distribution across major HTGR components, with the reactor core showing the highest contribution [51].

The thermoeconomic Pareto front illustrates the trade-off between exergy efficiency (η_ex) and system cost for the optimized HTGR configurations. As expected, the results show an inverse relationship between the two objectives — designs with higher exergy efficiency generally involve higher investment or operational costs, while lower-cost solutions are associated with reduced thermodynamic performance. The Pareto-optimal front (highlighted in red) represents the set of non-dominated solutions, where any further improvement in exergy efficiency would require an increase in cost, and vice versa. This curve provides valuable insight into the economic–thermodynamic compromise inherent to HTGR systems. From the observed trend, the steeper segment of the Pareto front corresponds to the region where small gains in efficiency result in disproportionately large cost increases — indicating diminishing economic returns for very high-efficiency designs. Conversely, the flatter region of the front identifies cost-effective configurations, where moderate efficiency improvements can be achieved with minimal additional cost. Therefore, the optimal operating zone can be identified near the knee point (or "elbow") of the Pareto curve, which provides a balanced compromise between performance and economic feasibility. This point can serve as a reference for decision-making in HTGR thermoeconomic optimization, especially when design priorities favor both energy utilization and cost control [39-40]. **Fig. 6** illustrates the thermodynamic trade-off between system cost and exergy efficiency on the Pareto front.

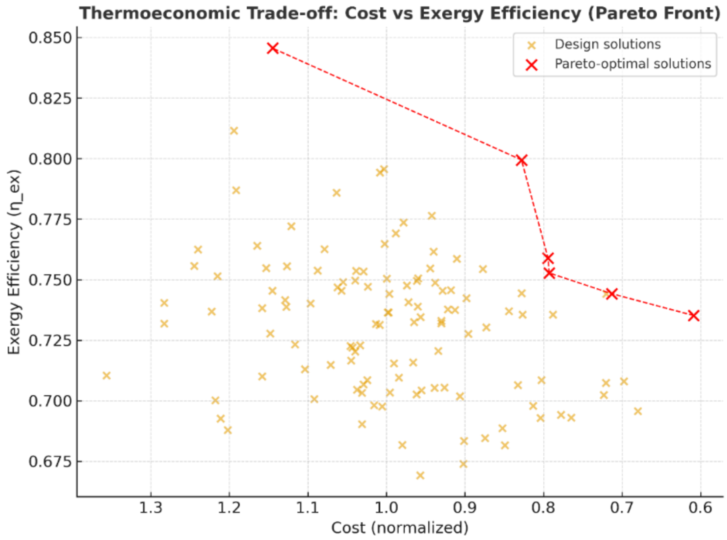


Fig 6. The thermodynamic trade off; cost vs exergy efficiency [40].

4. Conclusion

HTGRs represent a pivotal step toward achieving sustainable, efficient, and inherently safe energy systems. The integration of exergy analysis with multi-objective optimization frameworks, particularly those based on MOEAs, has proven to be a powerful strategy for enhancing reactor thermodynamic performance while balancing competing criteria such as efficiency, safety, and cost-effectiveness. The reviewed studies demonstrate that methods like NSGA-II, MOPSO, and their hybrid or adaptive variants are capable of generating well-distributed Pareto fronts, effectively elucidating trade-offs between exergy efficiency and total exergy destruction. Optimized HTGR configurations, especially those coupled with advanced Brayton or supercritical CO_2 (S–CO_2) cycles, consistently achieve exergy efficiencies between 45% and 55%, representing significant improvements over conventional cycles. However, despite these advancements, several methodological and computational challenges persist. The high computational demand of MOEAs, uncertainties in high-temperature material properties, and the absence of standardized multi-criteria performance metrics remain key barriers to broader implementation. Addressing these issues requires the incorporation of robust uncertainty quantification, high-fidelity material databases, and unified benchmarking frameworks that integrate thermodynamic, safety, economic, and environmental indicators within a single optimization platform. Looking forward, the convergence of AI, surrogate modeling, and digital twin technologies offers a transformative pathway toward real-time, adaptive exergy optimization of HTGRs. Hybrid AI–MOEA frameworks can substantially reduce computational costs, enhance global search capability, and enable continuous optimization across all reactor life stages from conceptual design to operational management. Ultimately, the evolution of such intelligent, self-optimizing systems will accelerate the transition toward next-generation reactors that are not only thermodynamically superior but also capable of autonomous decision-making, predictive diagnostics, and dynamic performance enhancement. These developments mark a decisive step toward a more resilient, efficient, and sustainable energy future.

Ethical Consideration

The authors of the article certify that all ethical principles related to research have been completely met.

Conflicts of Interest

The authors declared that they have no conflicts of interest in this paper. Also, we declare the following financial interests that represent a conflict of interest in connection with the research works submitted.

Data availability

The data that has been used is confidential.

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