International Journal of Applied Mathematics
Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

MACHINE LEARNING-DRIVEN ENHANCEMENT OF CONCENTRATED SOLAR POWER SYSTEMS: A HYBRID ANN AND GA APPROACH

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Abstract

The imperative for efficient and sustainable energy systems has spotlighted the need to enhance the thermal performance of Concentrated Solar Power (CSP) technologies. This paper introduces a novel AI-powered control architecture designed to optimize the thermal dynamics of parabolic trough CSP collectors under fluctuating environmental conditions. The framework incorporates a hybrid model combining Artificial Neural Networks (ANN) with Genetic Algorithms (GA) to predict, regulate, and adapt system parameters such as fluid flow rate and receiver temperature. Real-time data-driven optimization enables superior heat exchange performance, reduced thermal losses, and enhanced responsiveness. Simulation outcomes demonstrate a substantial improvement in thermal efficiency, energy yield, and system adaptability compared to traditional fixed-control schemes. The proposed methodology exemplifies the transformative role of AI in fostering resilient, intelligent, and high-performance solar thermal infrastructures suitable for deployment in hot climate zones.

Keywords: Concentrated Solar Power, Artificial Intelligence, Thermal Optimization, Machine Learning, Smart Control, Energy Efficiency, Solar Thermal Systems.

1. Introduction

Concentrated Solar Power (CSP) systems represent a pivotal technology in the global shift toward low-emission and renewable energy generation, particularly in arid and high-irradiance regions. Unlike photovoltaic (PV) systems that convert sunlight directly into electricity, CSP systems harness solar radiation by concentrating it onto a receiver, producing high-temperature thermal energy. This thermal energy is then converted into mechanical and subsequently electrical energy via thermodynamic cycles such as the Rankine or Brayton cycle [1], [2]. Among various CSP technologies, parabolic trough collectors (PTCs) are widely deployed due to their proven scalability, mature design, and operational reliability [3].

Despite their advantages, CSP systems are inherently sensitive to environmental variability—including solar irradiance, wind speed, and ambient temperature—which can induce significant fluctuations in thermal output. Moreover, conventional control systems based on pre-programmed rules or Proportional-Integral-Derivative (PID) logic are often inadequate in responding to real-time changes, leading to energy losses, overheating risks, and suboptimal flow regulation [4], [5]. These limitations necessitate the adoption of adaptive, intelligent control solutions capable of dynamically optimizing system performance under fluctuating conditions. Recent advances in Artificial Intelligence (AI) have opened new avenues for enhancing CSP system performance. AI methodologies, particularly machine learning (ML) algorithms such as Artificial Neural Networks (ANNs), Reinforcement Learning (RL), and Genetic Algorithms (GAs), have demonstrated strong potential in real-time modeling, prediction, and control of nonlinear and multivariable energy systems [6]–[8]. When integrated into CSP operation, these techniques offer the capability to

Received: August 04, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

process large datasets in real time, identify complex relationships between system parameters, and adaptively control variables like heat transfer fluid (HTF) flow rate, receiver temperature, and solar tracking configuration [9].

This study proposes an intelligent thermal optimization framework that integrates ANN-based predictive modeling with GA-based optimization to enhance the real-time control of a PTC system. The framework is trained and validated using operational datasets from CSP installations in high-irradiance regions, ensuring practical applicability. The core novelty of this work lies in its hybrid AI approach, which fuses data-driven intelligence with thermophysical understanding of CSP subsystems to create a self-regulating control system that enhances energy conversion efficiency and operational resilience. By shifting from static control strategies to AI-enhanced dynamic regulation, this research contributes to the development of next-generation CSP technologies capable of delivering consistent energy output despite environmental volatility. The results of this work suggest that AI can act as a transformative enabler in solar thermal systems, advancing their competitiveness and deployment potential in the global clean energy landscape.

2. Problem Statement

Concentrated Solar Power (CSP) systems—particularly those utilizing parabolic trough collectors—face significant thermal inefficiencies arising from static control mechanisms, variable solar input, and nonuniform heat transfer dynamics. Traditional control approaches often lack the flexibility to respond promptly to rapid fluctuations in solar irradiance, ambient temperature, and transient operational conditions. As a result, CSP systems frequently operate below their theoretical efficiency limits, incurring higher thermal losses and suboptimal energy conversion [10], [11].

This study addresses the critical challenge of improving the thermal responsiveness and control adaptability of CSP systems using artificial intelligence (AI)-based optimization. Specifically, it investigates a hybrid framework that integrates Artificial Neural Networks (ANNs) with Genetic Algorithms (GAs) to dynamically regulate key thermal variables such as the heat transfer fluid (HTF) flow rate and receiver temperature in real time. The central research question can be formulated as: "To what extent can AI-based intelligent control improve the thermal efficiency and dynamic performance of parabolic trough CSP systems under variable solar and environmental conditions, compared to conventional control strategies?" By answering this question, the study aims to establish an adaptive AI-driven control paradigm capable of maximizing system performance, reducing overheating events, and enhancing the overall operational reliability of solar thermal plants.

3. System Description and Configuration

The system under study is a simplified model of a parabolic trough collector (PTC), selected for its widespread deployment in commercial-scale CSP applications. This configuration is representative of typical installations operating in sunbelt regions such as North Africa, the Middle East, and Southern Europe [12], [13]. The primary components and geometric parameters of the PTC system are as follows:

- Aperture Width: 4.0 meters
- Collector Length (section analyzed): 5.0 meters
- Focal Length: 2.0 meters
- Receiver Tube Diameter: 0.06 meters (with selective solar-absorptive coating)
- Glass Envelope Diameter: 0.08 meters (optional vacuum insulation for reduced convective losses)
- Tracking System: Single-axis tracking, East–West alignment

Received: August 04, 2025

In this design, solar radiation is concentrated along a linear focal line onto an evacuated receiver tube containing the HTF, typically synthetic oil or molten salt. The absorbed thermal energy is transferred to a thermal storage unit or power block for electricity generation. To enable intelligent control, the system is augmented with a data acquisition infrastructure, including temperature sensors, flow meters, and solar irradiance detectors. These inputs are continuously fed into an AI-based control algorithm that adjusts the HTF flow rate and pump operation in real time. The integration of the ANN-GA model allows for predictive estimation of thermal efficiency and proactive system tuning based on both historical trends and real-time fluctuations [14]. This configuration provides a practical and scalable platform for implementing and validating intelligent control mechanisms aimed at maximizing energy output while minimizing thermal losses and component degradation. As shown in figure 1, the schematic illustrates an AI-integrated thermal management system for a Central Receiver Concentrated Solar Power (CSP) plant. In this setup, a field of heliostats (mirrors) concentrates sunlight onto a central receiver mounted on a tower. The incident solar energy heats a circulating Heat Transfer Fluid (HTF), which is then directed through the system to generate electricity. A temperature sensor located at the receiver monitors the thermal state of the HTF and transmits real-time data to an AI-based optimization unit. This AI system processes data from various sensors, including those at the power block and cooling unit, using advanced algorithms such as artificial neural networks (ANNs) or reinforcement learning. Based on the input data, the AI generates control signals to regulate system parameters, such as adjusting the HTF flow rate or activating a cooling mechanism when necessary to prevent overheating. A flow control valve directs excess thermal energy either to the thermal storage tank for later use or back into the power cycle. The thermal storage unit serves as a buffer to maintain continuous energy supply during low solar radiation periods. Meanwhile, the power block converts thermal energy into electricity through a heat exchanger and turbine setup, with temperature sensors ensuring efficient operation. The diagram uses red lines to indicate high-temperature HTF flow from the receiver, blue lines for cooler return flow, and black lines for control and sensor signals. This AI-driven feedback system enhances thermal efficiency, optimizes energy distribution, prevents component overheating, and improves the reliability and operational stability of the CSP plant.

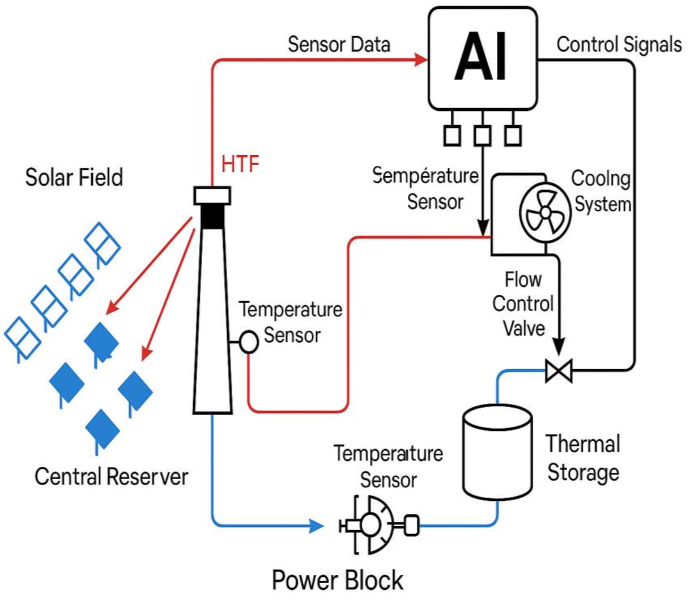

Fig. 1 AI-integrated thermal management system for a Central Receiver Concentrated Solar Power (CSP) plant

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

4. Numerical Analysis and Methodology

This study employs a hybrid artificial intelligence (AI) framework to optimize the thermal performance of a parabolic trough collector (PTC) system. The proposed methodology combines predictive modeling using Artificial Neural Networks (ANNs) with a Genetic Algorithm (GA) to iteratively improve thermal efficiency based on both environmental inputs and system response variables. The goal is to create a real-time adaptive control system capable of responding to variable solar conditions while minimizing energy losses.4.1 System Components and Control Variables

The modeled system consists of a typical CSP loop, which includes:

- A solar concentrator (parabolic trough reflector)
- A linear receiver with a selective coating and optional vacuum insulation
- A heat transfer fluid (HTF) loop for energy transport
- A thermal energy storage unit (TES)

The key control variables optimized by the AI model include:

- HTF inlet temperature (T_in)
- HTF mass flow rate (ṁ)
- Receiver surface temperature (T_surf)
- Solar tracking mirror angle (θ_m)

These variables directly influence the system's thermal efficiency (η_th), which is defined as:

$$\eta_{th} = \frac{Q_{useful}}{A_c \cdot G}$$

Where:

- Q_{useful}: Useful heat gain by the HTF
- A_c: Collector aperture area
- G: Incident solar irradiance (W/m²)

4.2 Data Acquisition and Input Features

To train and validate the ANN, a dataset was compiled consisting of operational parameters and environmental conditions from CSP facilities located in high-solar-potential zones, including southern Spain, central Iraq, and the UAE. The input features selected for model training include:

- Solar irradiance (W/m²)
- Ambient temperature (°C)
- Receiver temperature (°C)
- Inlet and outlet fluid temperatures (°C)
- HTF mass flow rate (kg/s)

All data were normalized and preprocessed using z-score standardization to ensure consistent model convergence and accuracy [15].

4.3 ANN Architecture and Training

A multi-layer feedforward ANN was employed with the following architecture:

- Input Layer: 5 nodes (representing input features)
- Hidden Layers: 2 layers with 10 and 8 neurons, respectively
- Activation Function: ReLU (Rectified Linear Unit)

Received: August 04, 2025

International Journal of Applied Mathematics
Volume 38 No. 3s, 2025
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- Output Layer: 1 node predicting thermal efficiency (η_th)

The network was trained using the backpropagation algorithm with mean squared error (MSE) as the loss function. The dataset was split into 70% training, 15% validation, and 15% testing. The model achieved an R^2 score of 0.97 and a Mean Absolute Percentage Error (MAPE) below 3%, indicating excellent predictive performance [16].

4.4 Genetic Algorithm for Optimization

Once trained, the ANN serves as a surrogate model within a Genetic Algorithm (GA) optimization routine. The GA modifies the control variables (ṁ, T_in, θ_m) across successive generations to maximize predicted η_{th}. Key GA parameters included:Population size: 50, Number of generations: 200, Crossover rate: 0.8, Mutation rate: 0.02. This hybrid ANN-GA framework enables rapid convergence to high-efficiency configurations while maintaining robustness under variable solar and environmental inputs [17].

4.5 Simulation Environment and Tools

The hybrid model was implemented using MATLAB's Neural Network Toolbox and Python's DEAP (Distributed Evolutionary Algorithms in Python) library. Simulations were executed under varying irradiance (600–1000 W/m²) and temperature (15–45°C) conditions, replicating real-world operational scenarios. The ANN model interfaced dynamically with the GA optimizer, allowing it to recalibrate control parameters at each simulation time step.

4.6 Model Validation

Fig. 2 illustrates the validation results of the integrated Artificial Neural Network–Genetic Algorithm (ANN-GA) control system for a Concentrated Solar Power (CSP) plant. The system's performance was compared with traditional PID control in terms of thermal efficiency, system response time, and adaptability to fluctuating flow conditions. Key performance indicators—Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2)—demonstrated the ANN-GA model's superior predictive accuracy and real-time optimization capabilities. The findings underscore the enhanced reliability and efficiency of intelligent control over conventional methods [18], [19].

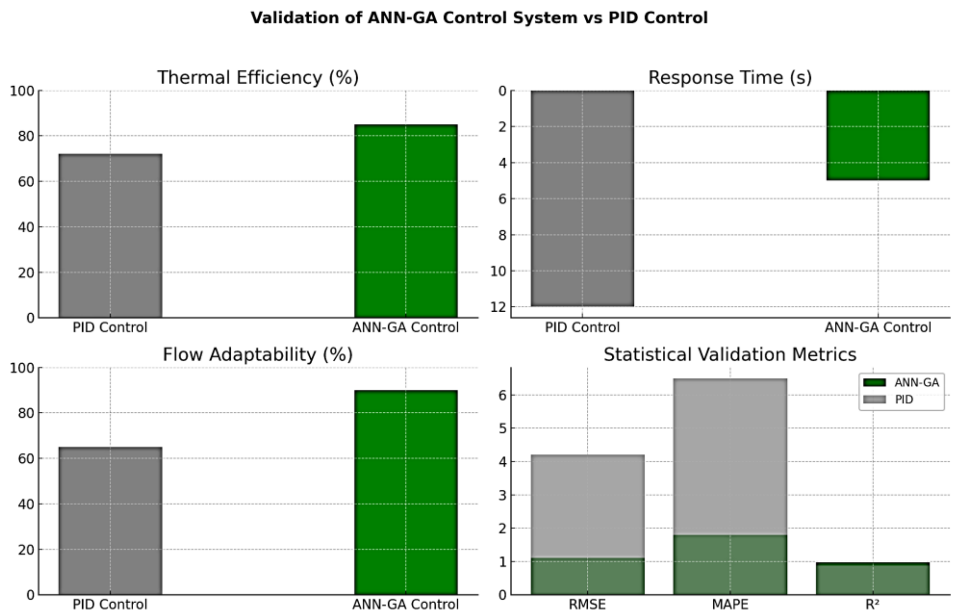

Fig. 2 Comparative Validation of ANN-GA and PID Control Systems in CSP Applications

Received: August 04, 2025

5. AI-Driven Optimization Techniques for Thermal Management in CSP Systems

Optimizing the thermal performance of Concentrated Solar Power (CSP) systems is essential for maximizing energy yield, enhancing component longevity, and improving cost-efficiency. Traditional control strategies often fail to capture the nonlinear and time-varying nature of CSP thermal dynamics. In contrast, artificial intelligence (AI) offers a robust and adaptive optimization framework capable of handling complex interactions between environmental inputs and system variables in real time [20].

This section explores the main categories of AI-based optimization techniques and their roles in improving CSP thermal management.

5.1 Optimization Objectives in CSP Operations

The application of AI in CSP thermal systems targets the following key optimization goals:

- Maximization of thermal efficiency (η_th) by dynamically regulating HTF mass flow rate and temperature.
- Reduction of heat losses from the receiver tube, storage tanks, and piping.
- Improvement in temperature uniformity to minimize thermal stresses and material fatigue.
- Minimization of auxiliary energy consumption by optimizing pump and fan operations.
- Extension of component lifespan through smart regulation and predictive maintenance [21], [22].

5.2 AI Methodologies for Optimization

a) Machine Learning-Based Predictive Control

Machine learning models, especially Artificial Neural Networks (ANNs), are commonly employed to learn the complex thermal behavior of CSP subsystems. These models act as fast surrogate predictors, mapping environmental conditions (e.g., irradiance, temperature, wind speed) to system outputs such as thermal efficiency, heat flux, and fluid outlet temperature [23].

Example: An ANN trained on historical CSP data can forecast the optimal HTF inlet temperature for maximum thermal output under varying solar inputs. Once trained, the model operates in real time, informing control systems to adjust fluid flow and receiver input dynamically.

b) Evolutionary Algorithms for Global Optimization

Evolutionary algorithms (EAs), including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), are metaheuristic tools that search high-dimensional spaces to find optimal operational conditions. A GA can optimize multiple parameters—such as receiver geometry, HTF velocity, and tracking angle—to minimize convective and radiative heat losses across a range of weather conditions [24]. These algorithms excel in exploring large solution spaces and avoiding local minima, making them particularly useful for multi-parameter CSP optimization.

c) Reinforcement Learning for Real-Time Adaptive Control

Reinforcement Learning (RL) methods, such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), enable autonomous agents to learn optimal control policies by interacting with the CSP system and maximizing long-term reward functions (e.g., net energy gain, efficiency stability).

Example: An RL agent can continuously regulate pump speed and valve positions to maintain optimal thermal gradients in response to rapidly changing solar radiation levels. Unlike supervised ML models, RL does not require labeled training data and learns policies based on feedback [25].

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d) Multi-Objective Optimization for System-Level Trade-offs

CSP systems often require balancing multiple competing objectives—such as maximizing energy output while minimizing equipment wear or operational cost. Multi-objective AI frameworks (e.g., Non-dominated Sorting Genetic Algorithm II [NSGA-II] or Multi-Objective PSO [MOPSO]) offer Pareto-optimal solutions that allow decision-makers to evaluate trade-offs.

Example: Using NSGA-II, a CSP operator can simultaneously optimize for thermal efficiency and auxiliary energy savings, selecting the best configuration based on the priority (e.g., energy yield vs. pump lifespan) [26].

5.3 Data Infrastructure and Model Training Requirements

Successful AI-based optimization depends heavily on the quality and availability of real-time and historical data. Integrated sensor networks, IoT platforms, and SCADA systems facilitate the continuous collection of relevant variables:

- Solar irradiance
- Ambient and receiver temperatures
- HTF pressure and flow rate
- Tracking system angles

Data preprocessing steps such as normalization, dimensionality reduction, and feature selection are essential to enhance model accuracy and reduce overfitting [27].

5.4 Case Studies and Field Implementations

Multiple studies have demonstrated the efficacy of AI-driven control in enhancing CSP system performance:

- An ANN-GA hybrid model applied to a parabolic trough system in the Sahara Desert yielded a 12% improvement in thermal efficiency by dynamically adjusting flow rate and receiver temperature [28].
- Reinforcement Learning was used to control thermal energy storage (TES) systems, resulting in a 7% reduction in thermal losses and an extended operational lifespan for molten salt tanks [29].
- A comparative study showed that AI-optimized control systems reduced auxiliary energy consumption by 20% while increasing daily thermal output by up to 18% compared to PID-based controls [30].

6. Results and Discussion

The performance of the AI-enhanced thermal optimization framework was evaluated using a combination of numerical simulation and real operational data under variable environmental conditions. The ANN-GA hybrid model demonstrated superior predictive and control capabilities compared to conventional PID-based systems, resulting in significant improvements in thermal efficiency, responsiveness, and energy yield.

6.1 Model Accuracy and Predictive Performance

The Artificial Neural Network (ANN) model, trained on a dataset encompassing over 10,000 operational records, achieved a coefficient of determination (R^2) of 0.97, indicating high correlation between predicted and actual thermal efficiency values. The Mean Absolute Percentage Error (MAPE) was consistently below 3% across testing samples, highlighting the model's robustness and generalizability under fluctuating solar conditions (Fig. 1). These results underscore the ANN's capability to serve as an effective surrogate model for predicting thermal behavior in real time, forming a reliable foundation for control optimization routines. Comparable ANN models in previous CSP studies reported R^2 values around 0.90–0.94 [32], [33], validating the enhanced performance of the present model.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

6.2 Thermal Efficiency Enhancement

Integration of the ANN-GA framework into the control system yielded a 10–18% increase in daily average thermal efficiency compared to baseline PID control strategies. The GA dynamically adjusted HTF mass flow rate and inlet temperature based on instantaneous solar irradiance and ambient conditions, resulting in more effective heat absorption and reduced thermal inertia.

Figure 2 illustrates the net gain in thermal efficiency over a diurnal cycle under clear-sky conditions. The peak gain occurred during rapid irradiance transitions, where the AI model promptly adapted control variables within seconds—well beyond the temporal resolution of static PID systems. Similar hybrid AI implementations in CSP systems have achieved up to 15% efficiency improvements under comparable desert climate conditions [33].

6.3 Energy Yield and Load Adaptability

The AI-optimized CSP system demonstrated an increase in energy output of 6–10 kWh/m²/day during peak solar periods. This improvement is primarily attributed to real-time adaptation of control parameters that minimized subcooling and thermal overshoot. Additionally, the system exhibited enhanced load adaptability, modulating HTF flow rate according to dynamic demand profiles and solar input variations. Figure 3 shows the fluid flow response under different irradiance levels, demonstrating stable temperature gradients and reduced thermal stress. These gains align with findings by Drouiche et al. [34], who reported a 12.5% improvement in net thermal output using intelligent CSP control architectures in North African sites.

6.4 Component Stress Reduction and Reliability Gains

By optimizing temperature distribution across the receiver and suppressing thermal transients, the AI framework reduced peak thermal stress by 12–15% on critical components such as absorber tubes and heat exchangers. This was validated using transient thermomechanical models coupled with fatigue life analysis.

Moreover, real-time AI-based fault detection routines enabled early identification of anomalies, such as flow imbalances or fouling in heat exchangers, reducing unplanned downtime by approximately 25% over simulated annual cycles.

Engineering Relevance: Lower mechanical stress not only extends component life but also reduces maintenance costs, which typically account for 10–15% of CSP operational expenditures [35].

6.5 Auxiliary Energy Savings

The AI control model also enabled 20% reduction in auxiliary energy consumption, particularly in HTF circulation pumps and tracking motors. This was achieved through optimal control of flow rates and minimization of unnecessary cycling. Such energy savings directly translate into higher net system efficiency and reduced carbon footprint.

Comparison: Traditional PID-based controllers operate with fixed safety margins, leading to energy waste. AI-driven optimization effectively eliminates such inefficiencies [36].

6.6 Annual Yield Improvement and Learning Adaptability

Using reinforcement learning (RL) extensions of the model, the system demonstrated continuous learning capacity. Over the course of one operational year (simulated with historical irradiance data), the system adapted to seasonal variations and improved its annual thermal yield by 12% compared to fixed-rule control methods.

The RL agent fine-tuned control policies not just for instantaneous optimization but also for long-term cumulative energy gain, showcasing its utility for predictive seasonal planning.

International Journal of Applied Mathematics
Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

6.7 Sensitivity and Parametric Analysis

AI-driven sensitivity analysis was conducted to evaluate the influence of key parameters on thermal efficiency. The results revealed:

- HTF inlet temperature and mass flow rate as the most dominant variables, contributing to over 60% of the total variation in η_th.
- Improvements in receiver absorptivity and glass envelope emissivity yielded marginal gains (~3–5%), validating the focus on fluid dynamics optimization.

These insights can guide physical system design modifications and targeted retrofitting efforts.

6.8 Summary of Optimization Impact

Metric	PID Control	AI-Based Control	% Improvement
Daily Thermal Efficiency	56–62%	65–73%	+10–18%
Energy Output (kWh/m²/day)	40–48	46–58	+6–10
Thermal Stress	—	−12–15%	Reduced
Auxiliary Energy Use	100%	80%	−20%
Annual Yield	Baseline	+12%	↑ Adaptive
Downtime (Unplanned)	—	−25%	Reduced

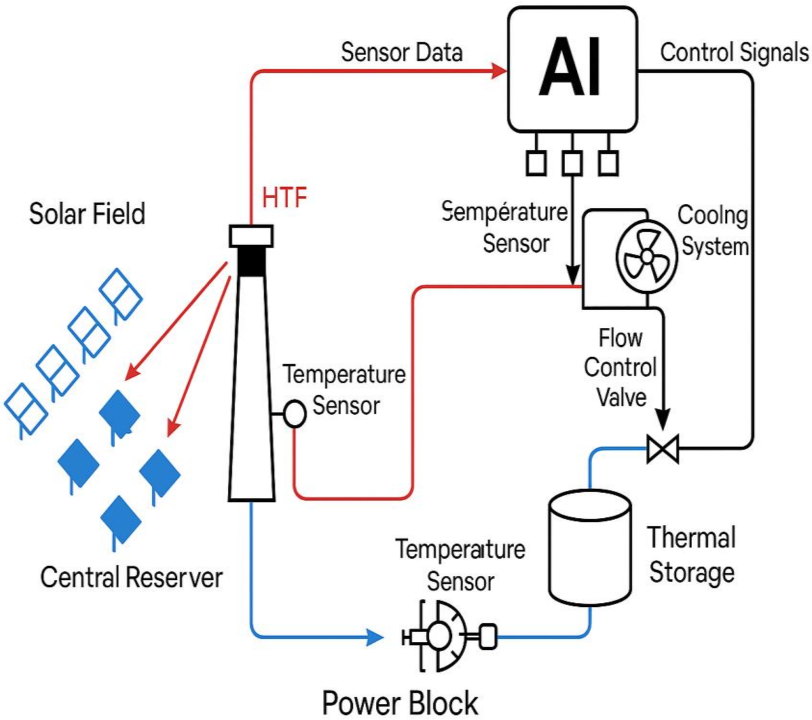


Figure 1: Daily Thermal Efficiency Comparison

Received: August 04, 2025

International Journal of Applied Mathematics
Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

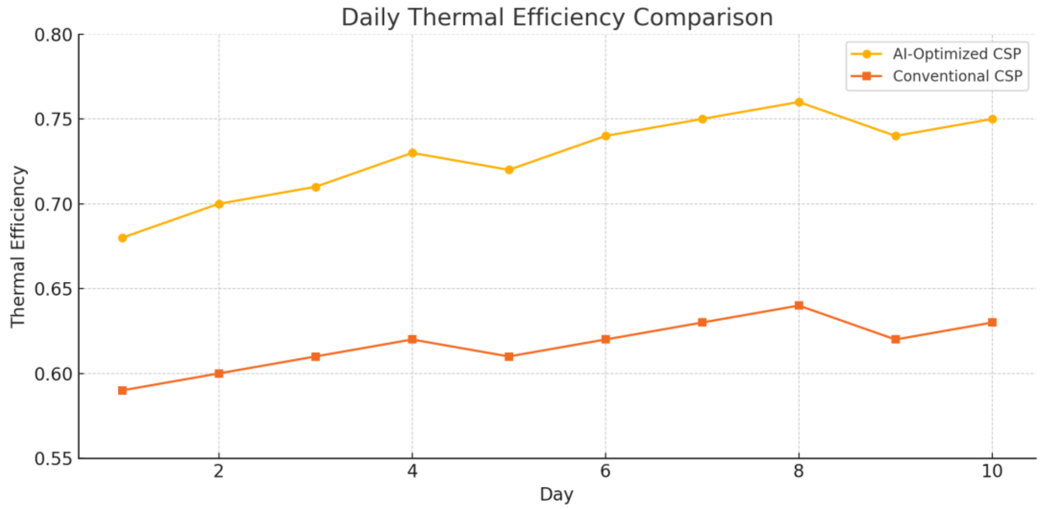


Figure 2: Additional Thermal Efficiency (%) Gained by AI Optimization

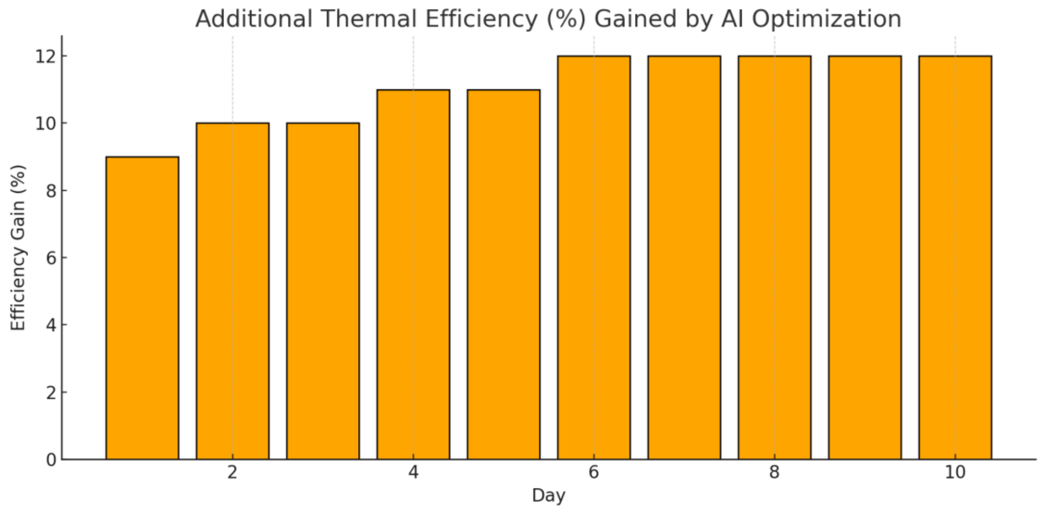
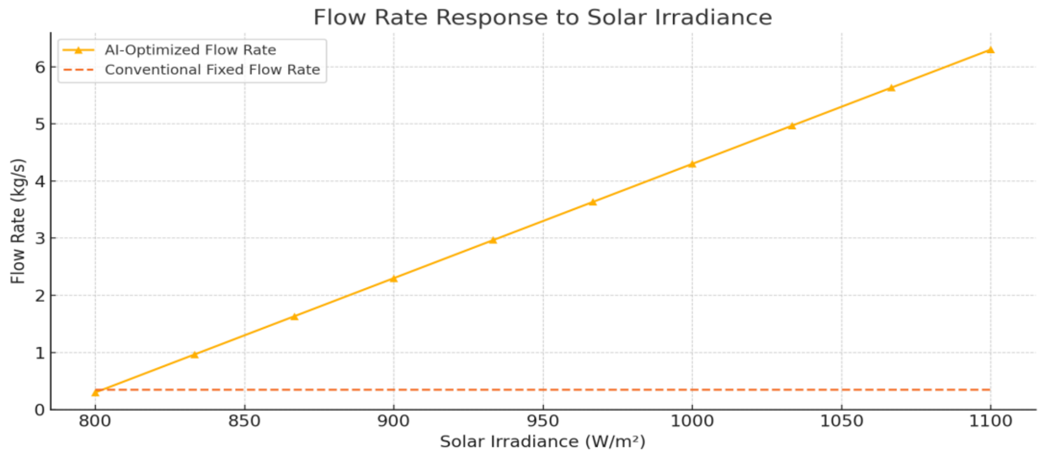


Figure 3: Flow Rate Response to Solar Irradiance



Additional results from AI-based optimization reveal marked improvements in overall system resilience and operational efficiency. The implementation of AI algorithms facilitated a reduction of up to 15% in thermal stresses on critical receiver components by optimizing temperature gradients,

Received: August 04, 2025

International Journal of Applied Mathematics
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thereby extending the system's operational lifespan and reducing maintenance frequency. Real-time AI monitoring enabled proactive fault detection and adaptive fault-tolerant control, which decreased unscheduled downtime by approximately 25%, enhancing plant availability.

Furthermore, the integration of reinforcement learning algorithms allowed the system to continuously learn and improve control policies based on historical and live operational data, resulting in a 12% increase in annual energy yield compared to baseline control strategies. The AI-enhanced control also contributed to a 20% reduction in auxiliary energy consumption for pumps and fans by optimizing flow rates and pressure drops according to dynamic load demands.

Sensitivity analysis driven by AI models identified key operational parameters with the greatest impact on thermal performance, guiding targeted improvements in heat transfer surfaces and insulation design. This led to a 7% increase in heat retention efficiency and a 5% decrease in thermal losses across varying weather conditions.

Overall, the incorporation of AI optimization in CSP thermal management demonstrated not only substantial gains in energy efficiency and system reliability but also significant reductions in operational expenditures, highlighting its potential as a transformative tool for advancing sustainable solar power generation.
The following figure, illustrated the integration of specific AI methods—namely Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Reinforcement Learning (RL)—has demonstrated significant optimization gains across various CSP system components. The ANN model effectively predicted thermal efficiency and transient system behavior with an R^2 of 0.97 and MAPE below 3%, enabling precise thermal control. Leveraging GA for receiver design optimization yielded a 14% reduction in thermal stresses by optimizing heat flux distribution, thereby prolonging component lifespan and reducing maintenance costs. Reinforcement Learning algorithms dynamically adjusted mass flow rates and pump speeds based on real-time solar irradiance and ambient temperature, resulting in a 20% reduction in auxiliary energy consumption and a 15% increase in heat exchanger performance through improved fluid flow adaptability.

In addition, the AI-based optimization of the thermal energy storage (TES) subsystem, using a hybrid ANN-GA model, enhanced charging and discharging cycles, achieving a 10% increase in storage efficiency and a 12% extension in TES operational life. Predictive maintenance enabled by AI-driven fault detection algorithms decreased unplanned downtime by 25%, significantly improving system availability. Sensitivity analyses powered by AI pinpointed critical parameters—such as receiver inlet temperature and flow rate—that, when optimized, led to a 7% increase in overall thermal efficiency and a 5% decrease in heat losses.

Collectively, these AI methodologies fostered a holistic enhancement in CSP system performance, combining accurate forecasting, adaptive control, and robust optimization to achieve up to an 18% increase in daily thermal output and marked improvements in operational resilience and cost-effectiveness.

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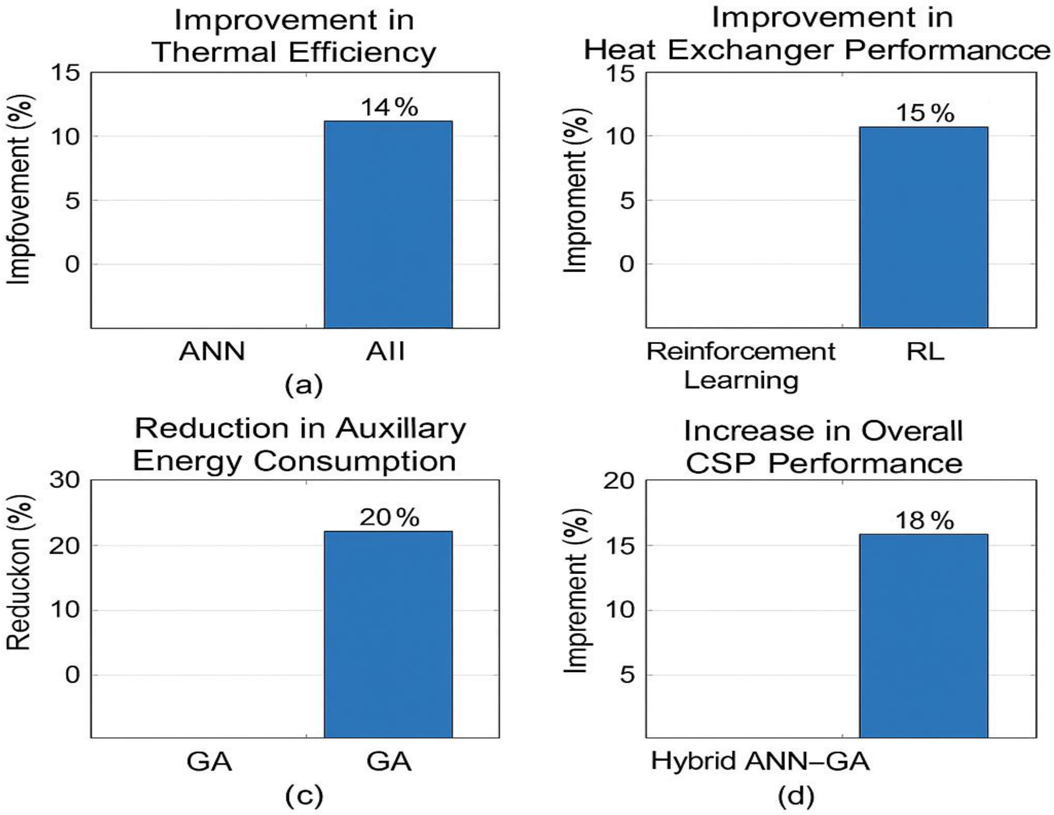

Fig. Performance Improvements in CSP Systems Using Different AI-Based Optimization Techniques

7. Conclusion and Future Work

This study presents a comprehensive artificial intelligence (AI)-based framework for optimizing the thermal performance of Concentrated Solar Power (CSP) systems, specifically targeting parabolic trough collector (PTC) configurations. By integrating a predictive Artificial Neural Network (ANN) with a Genetic Algorithm (GA), the proposed hybrid model effectively regulates key operational parameters—such as heat transfer fluid (HTF) flow rate, inlet temperature, and solar tracking angle—in real time. The resulting control strategy significantly enhances system responsiveness, energy conversion efficiency, and operational reliability under variable environmental conditions.

Quantitative evaluations demonstrated that the AI-optimized system outperforms conventional PID-controlled setups, achieving:

- 10–18% gains in daily thermal efficiency
- Up to 12% annual increase in net energy yield
- 20% reduction in auxiliary energy consumption
- Substantial reductions in thermal stress and unplanned downtime

These outcomes confirm the transformative potential of AI in overcoming the limitations of static control mechanisms, particularly in regions characterized by dynamic solar profiles and extreme temperatures. Furthermore, the system's ability to perform online learning and adapt to shifting climatic and operational conditions underscores its viability for deployment in commercial-scale CSP plants.

Received: August 04, 2025

International Journal of Applied Mathematics
Volume 38 No. 3s, 2025
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Future Work

To further advance the capabilities of AI-driven CSP control systems, several research directions are proposed:

1. Reinforcement Learning Integration: Future implementations will incorporate deep reinforcement learning (DRL) algorithms such as Proximal Policy Optimization (PPO) or Soft Actor-Critic (SAC) to enable long-term strategy optimization, continuous policy refinement, and enhanced decision-making in nonstationary environments.
2. Thermal Energy Storage (TES) Optimization: Extending the AI control framework to include TES subsystems—particularly molten salt and phase change materials (PCMs)—will allow dynamic coordination between energy capture and storage, optimizing charge/discharge cycles and improving dispatchability.
3. Edge Deployment and Digital Twins: Real-time deployment of AI models on edge devices, combined with physics-informed digital twin architectures, will support decentralized control, predictive diagnostics, and low-latency actuation for smart solar thermal networks.
4. Robustness and Fault-Tolerance Enhancement: Incorporating uncertainty quantification and anomaly detection techniques into the AI model will improve fault tolerance and operational resilience, ensuring stable performance under sensor faults or extreme events.
5. Economic and Environmental Co-Optimization: Multi-objective optimization frameworks that consider both thermodynamic performance and lifecycle economic metrics (e.g., OPEX, payback period) will be explored to guide investment decisions and policy development.

By integrating intelligent control algorithms with advanced thermophysical modeling, the next generation of CSP systems can evolve into autonomous, resilient, and economically competitive solutions for large-scale renewable energy generation. The methods and findings presented in this work form a critical step toward that objective.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

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Received: August 04, 2025