SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I5P121

Volume 12 Issue 5, 236-248, May 2025


*Original Article*

# Enhancing Air Pre-Heater Temperature Control Using Hybrid Machine Learning and Optimization Techniques

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Received: 14 March 2025 Revised: 17 April 2025 Accepted: 18 May 2025 Published: 27 May 2025

***Abstract*** - *Controlling the temperature in Air Pre-Heater (APH) systems is key to energy efficiency in the industry. Traditional controllers like Proportional Integral Derivative (PID) and Model Predictive Controllers (MPC) struggle to adapt to APH systems' dynamic nature. The purpose of this study is to examine machine learning regression models such as Support Vector Regression (SVR), Decision Trees, and Random Forests in order to predict the temperature of the APH accurately. The model's performance was improved using advanced tuning methods such as Particle Swarm Optimization (PSO), Bayesian Optimization, and a hybrid PSO-Bayesian approach. It is found that the Random Forest model optimized with the hybrid PSO-Bayesian method performs best, resulting in a Root Mean Square Error (RMSE) of 0.450, a Mean Square Error (MSE) of 0.243, and an R2 score of 1.094. Comparatively, the SVR model (with RBF kernel) has higher errors: RMSE = 4.198, MSE = 17.624, R2 = 0.845. With RMSE = 1.696, MSE = 2.877, and R2 = 0.975, the Decision Tree model is effective; however, it overfits. Combining machine learning with hybrid optimization techniques can greatly enhance industrial automation, according to these results. In this way, APH systems become smarter, more flexible, and more energy-efficient.*

***Keywords*** - *Air preheater control, Support Vector Machines, Random Forest, Particle Swarm Optimization, Decision Tree, Bayesian optimization.*

## 1. Introduction

In APHs are key components in industrial heating systems, recovering residual heat from exhaust gases and preheating incoming air. In power plants, chemical processing units, and large-scale manufacturing environments, this heat recovery process increases thermal efficiency, reduces fuel consumption, and makes energy management more sustainable. Because APH systems are highly nonlinear and time-varying, achieving accurate and stable temperature regulation is challenging.

The traditional thermal control methods have been Proportional-Integral-Derivative (PID) and Model Predictive Control (MPC). Due to disturbances, system noise, and complex dynamics in real-world APH environments, these methods do not work well under stable conditions. It is tough to tune control parameters manually for optimal performance across a range of operating scenarios with traditional controllers.

Machine Learning (ML) has been introduced as a solution, which can adapt to changing conditions and learn system behavior from historical data. Support Vector Regression (SVR), Decision Tree Regression, and Random Forests can capture nonlinear relationships between inputs and outputs. Also, Particle Swarm Optimization (PSO) and Bayesian Optimization are fine-tuning ML models.

Studies have explored machine learning and optimization separately for solving control problems, but not many have explored the combination of multiple models and hybrid optimization methods. There are also a lot of simulated datasets in existing work, which may not capture the full range of variability encountered in real-time industrial operations. APH applications need more comprehensive research integrating machine learning, optimization, and real-time validation.

A hybrid intelligent control framework addresses these challenges by integrating machine learning regression models SVR, Decision Tree, and Random Forest with three optimization strategies: PSO, Bayesian Optimization, and hybrid PSO–Bayesian. A real-time dataset of 12,000 samples from an experimental APH setup is used to train and test the models. APH temperature can be predicted accurately and reliably under dynamic operating conditions using each model and optimization combination.

Using real experimental data, this study compares multiple optimised ML models, focusing on improving temperature prediction accuracy, control stability, and adaptability. The proposed hybrid approach bridges the gap between predictive modelling and real-time control applications by combining advanced optimisation and robust machine learning techniques.

This paper is structured like this: Section 2 is the literature review, and Section 3 is the experiment setup and data analysis. The design of the ML-based control models and optimization techniques are covered in Section 4. Results and a comparison of model performance are presented in Section 5. Key insights and directions for future research are outlined in section 6.

## 2. Related Works

Maintaining Industrial operations needs Air Pre-Heaters (APHs) to improve thermal efficiency and reduce emissions. APH systems have nonlinear dynamics and time-varying behavior, which makes them hard to control with traditional control strategies. It's hard to tune these methods adaptively, especially in fluctuating conditions. Researchers combine machine learning algorithms with advanced optimization techniques to overcome these limitations.

PID controllers based on attractive-repelling particle swarm optimization (ARPSO) were introduced in [1]. Compared to conventional PSOs and genetic algorithms (GAs), ARPSO significantly minimizes steady-state error and settling time. A genetic algorithm was used in [2] to tune PID parameters for heat exchanger control, effectively addressing nonlinear characteristics. These studies show evolutionary optimization algorithms perform better than manually tuned or conventionally optimized ones.

Machine learning models can also capture and control nonlinear relationships. In [3] discussed Artificial Neural Networks (ANN), Support Vector Machines (SVM), and gradient boosting in heat exchanger modeling. ML increases prediction accuracy and robustness, especially when combined with optimization. Accordingly, a deep learning model based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and kernel Principal Component Analysis (PCA) was developed to predict heat transfer efficiency [4]. This study showed improved predictive maintenance performance in thermal systems using attention-based encoder-decoder architectures.

In addition, ML-based control strategies have been applied to adjacent domains relevant to APHs. [5] proposes a neural network PID controller for preheating lithium-ion battery modules using a co-simulation model and multi-objective optimization. The study focused on battery systems, but the methodology can be applied to APH systems that need thermal consistency and energy efficiency. To evaluate vortex generators, [6] used decision trees and Shapley Additive Explanations (SHAP). They identified key geometry and flow parameters that influenced thermal performance with their interpretable ML model.

ML has also been combined with statistical methods. In [7], combined design of experiments, response surface methodology, and neural networks to optimize controller parameters. As a result of the integration, parameter tuning became more accurate and responsive. In APH systems, [8] developed a stacked autoencoder (SAE) based soft sensor. In terms of temperature stability, their knowledge-and-data-driven hybrid model outperformed conventional approaches.

APH geometry parameters such as tube pitch and gas flow rates were optimized using Computational Fluid Dynamics (CFD) analysis [9]. According to their findings, structural improvements can reduce air-to-gas leakage and improve the heat transfer coefficient, which improves control efficiency.

Hybrid optimization strategies have also been explored in recent literature. [10] proposed a machine learning-based multi-objective optimization framework using a Grey Wolf Optimizer (GWO) and neural networks to improve energy efficiency in low-temperature heating systems. In [11] introduced, a two-degrees-of-freedom PID controller was introduced for a Continuous Stirred-Tank Heater (CSTH). This method can be adapted for complex APH systems with robust disturbance rejection and accurate control. An RPIDD2 controller for electric furnaces was developed [12] using quadratic interpolation and metaheuristics. Transient response and system stability were improved with the method, making it perfect for APH.

In this review, it's clear that while machine learning and optimization have both shown promise for improving temperature control independently, little has been done to integrate them into a unified APH control framework. Most studies focus on either machine learning or optimization, with little emphasis on combining multiple ML models with hybrid tuning approaches using real-time data. In addition, a lot of the literature relies on simulated environments without any experimental validation.

In order to fill these gaps, the current study proposes a hybrid intelligent control framework. This method combines SVR, Decision Tree, and Random Forest models, each optimized using PSO, Bayesian Optimization, or a hybrid PSO-Bayesian strategy. The models are trained and validated using a 12,000-sample real-time dataset. In real-world variability and disturbances, this comprehensive approach aims to improve the adaptability, prediction accuracy, and operational efficiency of APH control systems.

## 3. System Description and Data Acquisition

### 3.1. Air Pre-Heater System

APHs are essential for industrial heating systems because they preheat incoming air by reclaiming waste heat from exhaust gases. In this way, fuel consumption is reduced, and thermal systems are more efficient. However, achieving accurate temperature regulation in an APH system can be tricky because of external perturbations, fluctuations, and system nonlinearities.

As shown in Figure 1, this APH system consists of a heating element, a temperature sensor, and a control module. A setpoint voltage of 0 to 5V regulates the temperature of the air, while a temperature sensor monitors fluctuations and provides real-time feedback. Maintaining a stable temperature with minimal overshoot and steady-state error is the primary goal of the control system.

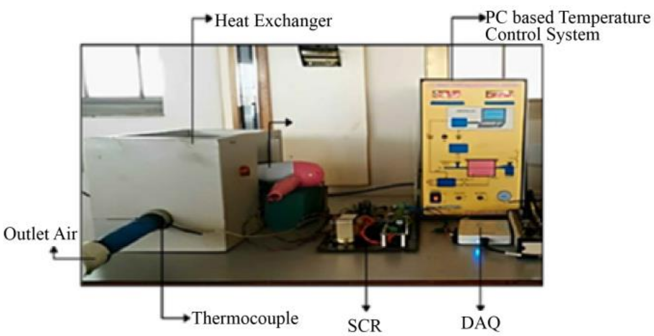


**Fig. 1 Experimental setup of APH temperature control system**

In designing a control system for an APH, one of the most challenging aspects is to achieve rapid response times, stability, and adaptability at the same time. There are a lot of conventional controllers, like PID controllers, but they often have difficulty dealing with sudden changes in airflow or temperature due to sudden changes in airflow or airflow velocity. It is this constraint that hinders the performance of the system in the real world.

### 3.2. Data Collection Procedure

An experimental dataset was gathered from a controlled setup to improve the APH's temperature control system. APH includes a heating element, a temperature sensor, and a control unit. The process diagram in Figure 2 shows how the data was collected and processed. This dataset captures both stable and fluctuating temperature variations. Temperature changes were tracked over time with a heat source and a temperature sensor. The input voltage to the heating element was adjusted between 0V and 5V. The temperature was recorded at a high frequency, capturing both sudden and gradual changes. Consistent readings were logged to ensure accuracy and reliability.

Temperature sensors were calibrated before data collection to eliminate errors. The data was tested to make sure it reflected the system's behavior. More than 12,000 data samples were collected, including sudden changes in setpoint, external disturbances, and varying heating intensities. The dataset plays a crucial role in training and testing machine learning models to optimize temperature control and enhance the performance of APH systems.

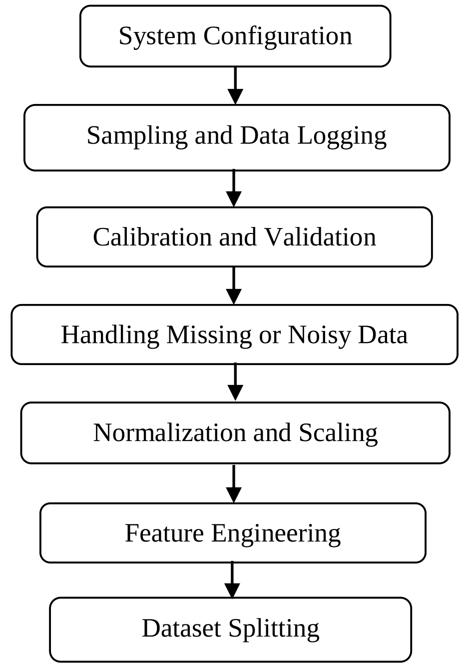


**Fig. 2 Data collection procedure**

Several preprocessing steps were performed on the dataset before machine learning training. Noise and missing data had to be handled to keep datasets accurate. Missing or inconsistent values were either removed or interpolated to reduce sensor noise caused by environmental fluctuations or hardware limitations. Normalization and scaling were used to ensure consistency. As a result of the different input voltage (0-5V) and temperature range (26°C - 67°C), all features have been normalized. So, certain variables didn't have a disproportionate impact on the learning process, resulting in a more accurate model.

Feature engineering helped improve predictions. By calculating the rate of temperature change, the first derivative of the temperature response gives insight into system dynamics. In addition, moving averages smoothed out fluctuations and highlighted long-term trends. To improve forecasting, the dataset also included past temperature readings.

The dataset was pre-processed and divided into training and testing sets. The data was split 70-30, with 70% used for training and 30% for testing. Using these preprocessing steps, the dataset was structured and optimized for both traditional control methods and machine learning. The models could adapt to different operating conditions and perform consistently with these improvements.

## 4. Controller Design and Methodology

To regulate the temperature precisely, respond faster, and save energy, APH controllers need a combination of machine learning and optimization techniques. SVR, Decision Trees, and Random Forest models can be fine-tuned with PSO and Bayesian Optimization.

### *4.1. SVR for Control*

Maintaining the right temperature in APH systems is crucial to energy efficiency. Due to nonlinear dynamics, traditional controllers can't make accurate adjustments. An SVM is a machine learning-based predictive model that helps controllers make smarter, data-driven decisions. Particularly useful for SVR, which learns from past data to predict how temperature will react to voltage. Instead of using complex equations to define system behavior, SVM finds patterns in real data, allowing it to generalize well even when conditions change. SVM works by finding an optimal boundary (hyperplane) that separates the data while minimizing prediction errors. In APH control, this means mapping input voltages to temperature outputs. In Equation (1), the model aims to fit the best possible function by minimizing the following cost.

$$\min_{\omega,b,\xi,\xi^*} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{1}$$

Equation (1) is subject to:

$$y_i - (\omega \cdot x_i + b) \le \epsilon + \xi_i$$
$$(\omega \cdot x_i + b) - y_i \le \epsilon + \xi_i$$
$$\xi_i, \xi_i^* \ge 0$$

Where,

- Ω represents the weight vector that defines the model.
- b is the bias term that adjusts the output.
- C is the tuning parameter that balances complexity and error tolerance
- ϵ defines the margin of tolerance
- $\xi_i, \xi_i^*$ are error terms that allow slight violations of the margin when necessary

SVM maps the inputs into a higher-dimensional space with a Radial Basis Function (RBF) Kernel, making finding an accurate prediction function easier with Equation (2).

$$K(x_i, x_j) = \exp\left(-\gamma\left\|x_i - x_j\right\|^2\right) \tag{2}$$

Where γ controls how much influence each training point has. A higher γ makes the model more sensitive to individual data points, while a lower γ results in a smoother function that generalizes better.

An SVM-based controller learns from historical data to predict the best voltage setting for maintaining a desired temperature instead of manually adjusting voltage inputs. As new voltages are applied, the model estimates how the temperature will respond and makes adjustments. Figure 3 shows the SVR model's framework.

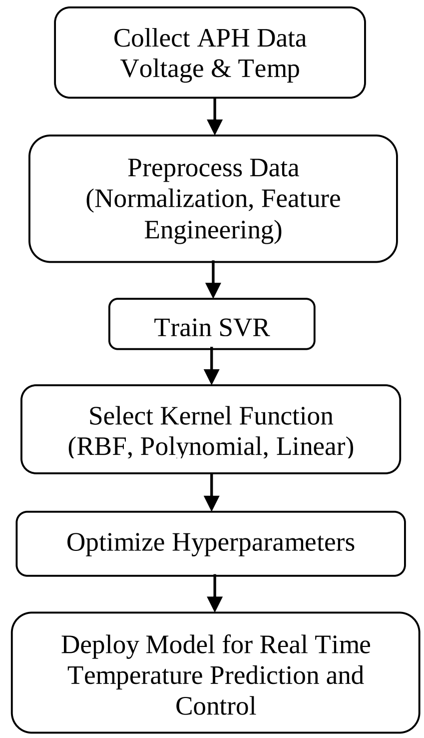


**Fig. 3 SVR-based control framework for APH system**

### *4.2. Decision Tree for Rule-Based Control in APH*

Controlling and maintaining temperature stability and energy efficiency requires quick, reliable decision-making. Unlike traditional controllers, Decision Tree based controllers use data-driven rules to determine the best course of action based on real-world conditions [30-31].

Like a flowchart, a Decision Tree breaks down a complex decision-making process into logical, simple steps. With APH control, DT models learn from historical data to predict temperature responses based on voltage inputs. The result is a fast and easy way to control temperature fluctuations in APH systems. A tree is split based on splitting criteria, which help divide data into meaningful groups. Gini impurity (measures how mixed a node is, given in Equation (3)) and entropy (information gain, given in Equation (4)) are the most commonly used.

$$Gini(D) = 1 - \sum_{i=1}^{c} p_i^2 \tag{3}$$

Where p_i is the probability of class i in the dataset, lower Gini values indicate purer, more effective splits.

$$Entropy = -\sum_{i=1}^{c} p_i log_2(p_i) \quad (4)$$

Lower entropy means better, more decisive feature splits, making the control model more effective. The framework of the Decision Tree model is given in Figure 4.

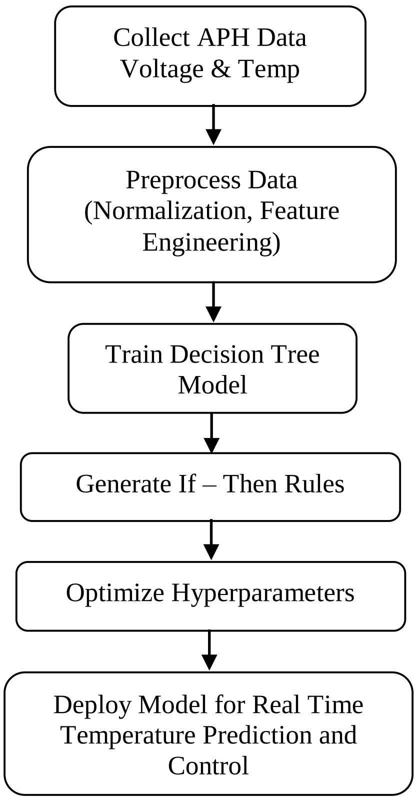


**Fig. 4 Decision tree based control framework for APH system**

### *4.3. Random Forest for Robust and Adaptive APH Control*

Maintaining precise temperature control in an APH system is tough because of external disturbances, nonlinear dynamics, and fluctuating process conditions. With a Random Forest model, you can improve prediction accuracy, stability, and generalization by combining multiple Decision Trees.

A Random Forest reduces overfitting and improves control accuracy by building multiple Decision Trees and averaging their predictions. By leveraging multiple independent trees, Random Forest stabilizes predictions in contrast to a single Decision Tree.

Using Bootstrap Aggregation (Bagging), each tree in a Random Forest model is trained on a random subset of the dataset. Final predictions are made by aggregating the outputs of all trees, either through majority voting (classification problems) or averaging (regression problems) [21-24]. Using Equation (5), the Random Forest model predicts output.

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \quad (5)$$

Where, $T_i(x)$where represents the i-th Decision Tree's output, N is the total number of trees, $\hat{y}$ and is the final predicted temperature in APH control.

Decision Trees in a Random Forest model are split according to Gini impurity or entropy, just like in a standard Decision Tree. Random Forest, on the other hand, improves on Decision Tree by introducing randomness in feature selection so the model doesn't overfit to specific patterns. Figure 5 shows the framework of the Random Forest model.

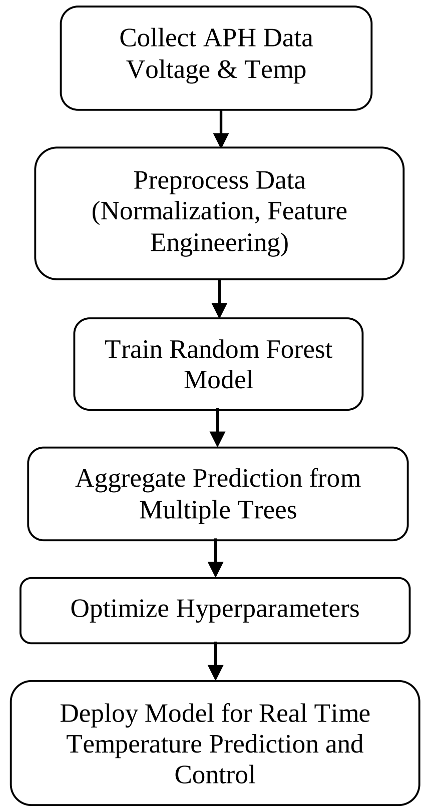


**Fig. 5 Random forest-based control framework for APH system**

### *4.4. Optimization Techniques for Controller Tunning*

Machine learning-based controllers need to be tuned properly for optimal performance in APH control. ML models are significantly affected by hyperparameters like regularization coefficients, tree depths, and kernel parameters. Due to the complexity and nonlinear behavior of APH systems, conventional tuning isn't practical. To automate and improve the process, use optimization techniques like PSO, Bayesian Optimization, and Hybrid PSO-Bayesian Optimization. This method helps find the best hyperparameters faster by reducing training time.

#### *4.4.1. PSO for ML-based Controllers*

PSO is used in APH control to improve accuracy and system adaptability by fine-tuning hyperparameters of machine learning models [14-17]. Swarms of particles drive the optimization process in PSO. In the swarm, particles adjust their positions iteratively based on their own experience and that of the best performers. In PSO, Equation (6) gives the velocity update.

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 \left(p_i^{best} - x_i\right) + c_2 r_2 \left(g_{best} - x_i\right) \quad (6)$$

The acceleration coefficients $c_1$ and $c_2$ influence whether a particle moves toward the best-known solutions, and $v_i$ is the particle's velocity. Equation (7) gives the position update.

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (7)$$

Where $x_i$ represents the particle's position in the ML model, it represents a specific hyperparameter. The PSO algorithm keeps updating the particle positions until an optimal solution is found. Regarding APH control, PSO helps fine-tune parameters like SVM kernel functions, Decision Tree depths, and Random Forest estimators, leading to faster convergence and more precise temperature control. In spite of its advantages, PSO can sometimes get stuck in local optima, requiring additional refinement methods like Bayesian optimization.

#### *4.4.2. Bayesian Optimization for ML-based Controllers*

A Bayesian optimization technique predicts the most promising candidates before evaluating them to find the best hyperparameters. While PSO explores the solution space randomly, Bayesian Optimization estimates the function being optimized and selects the best parameters based on uncertainty and expected performance[23-26]. Equation (8) shows the acquisition function, which determines where to sample next in Bayesian Optimization.

$$a(x) = \mu(x) + \kappa\sigma(x) \quad (8)$$

Where $\mu(x)$ is the mean performance predicted for x, the uncertainty in the prediction, and a trade-off between exploration and exploitation. Bayesian optimization reduces the number of evaluations needed by choosing hyperparameters that maximize this function [27].

APH control uses Bayesian Optimization to fine-tune Random Forest parameters (tree depth, number of estimators) and SVM kernel settings. BO adapts dynamically by refining predictions based on past results, so it's great for limited computing resources. Bayesian optimization alone can be slow in high-dimensional problems, so Hybrid PSO-Bayesian Optimization combines the best of both.

#### *4.4.3. Hybrid PSO Bayesian Optimization*

In order to improve hyperparameter tuning efficiency, a hybrid PSO-Bayesian Optimization approach is implemented. This hybrid approach starts with PSO to ensure the optimization doesn't get stuck in the local optimum. After PSO identifies promising hyperparameter regions, Bayesian Optimization refines them with a probabilistic model [27-28], enhancing prediction accuracy and model performance. Hybrid strategies work in two phases: 1. PSO searches globally for the best hyperparameters. 2. Bayesian Optimization fine-tunes within these regions, reducing computational costs. In this way, APH-controlled machine learning models give better stability, faster convergence, and better real-time adaptability. Compared to PSO or Bayesian Optimization, the hybrid method gives you better accuracy, less training time, and more robust results.

## 5. Results and Discussion

An evaluation of machine learning-based predictive models for APH temperature regulation focusing on their ability to handle nonlinear system behavior. The strengths and weaknesses of SVR, Decision Trees, and Random Forest Regression are discussed. These models are compared based on their predictive accuracy, generalization ability, and computational efficiency. Furthermore, hyperparameter tuning and optimization are discussed. It says ensemble learning makes things more stable and reduces variance. By analyzing potential challenges such as overfitting, parameter sensitivity, and model complexity, APH control approaches are also evaluated for real-time APH control.

### *5.1. Performance Assessment of SVR Kernels for APH Temperature Prediction*

Different SVR kernel functions were compared for accuracy and effectiveness. RMSE and R2 values measure how well predictions match actual behavior. Figure 6 shows how well the models predicted temperature variations using RMSE, MSE, and R2 values. The Radial Basis Function (RBF) kernel had the best RMSE and R2 scores. In the APH system, the RBF kernel captures the nonlinear relationship between temperature and voltage really well. A close match was observed between the actual and predicted temperatures, especially in the mid-to-high temperature range, proving the model's ability to deal with complex systems. With an RMSE of 4.251 and an R2 of 0.841, a linear kernel performed slightly worse. It was able to capture some temperature variations, but it couldn't handle highly nonlinear behavior, which made it hard to adapt to sudden changes in dynamics. It could still produce reasonable predictions in stable and controlled environments, suggesting that a linear approach might work. Conversely, the Polynomial kernel (degree = 3) had the worst performance, with an RMSE of 5.482 and an R2 score of 0.699. Table 1 shows the results from scatter plot analysis, especially in the 40°C to 50°C range, where predictions became inconsistent. The polynomial model overfits certain temperature regions, failing to generalize. In addition to the erratic fluctuations, the polynomial function did not capture the broader trend, making it less suitable for controlling APH temperatures. These findings are backed up by scatter plots. The RBF kernel predicted close to the ideal trend line, showing minimal deviation and high reliability. Polynomial kernels, however, showed significant variation, with unstable predictions in some regions. In areas with strong nonlinear temperature shifts, the linear kernel performed moderately well but had visible gaps. Based on these results, the RBF kernel is the best option for APH control, providing a balance between accuracy and stability. Linear kernels are somewhat effective but lack the flexibility needed to handle complex nonlinear changes. Further tuning the Polynomial kernel will improve generalization ability and reduce overfitting, such as testing a lower-degree polynomial (e.g., degree = 2).

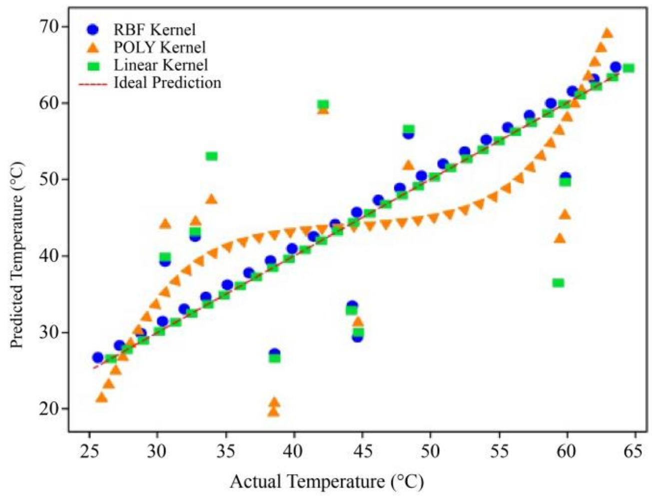


**Fig. 6 Comparison of SVR kernel functions for APH temperature prediction**

**Table 1. Performance metrics of SVR for APH temperature prediction**

| SVR Kernal | RMSE | MSE | $R^2$ |
|---|---|---|---|
| RBF | 4.198 | 17.623 | 0.845 |
| Polynomial | 5.482 | 30.072 | 0.699 |
| Linear | 4.251 | 18.068 | 0.841 |

### *5.2. Performance Assessment of Decision Tree for APH Temperature Prediction*

Analyzing Decision Tree depth on APH temperature prediction helped us understand how model complexity affects accuracy. Figure 7 shows how well the models predicted temperature variations using RMSE, MSE, and R2 values. With a max depth 3, a Decision Tree model had an RMSE of 3.600, MSE of 12.96, and an R2 score of 0.886. Though this model provided a structured prediction approach, it was too simple and underfitted the data, so it didn't capture the complex nonlinear temperature changes. There were noticeable gaps between predicted and actual values in the scatter plot analysis, proving that the model wasn't flexible enough to track temperature fluctuations. A tree depth of 5 greatly improved accuracy, with an RMSE of 1.696, MSE of 2.87, and an R2 score of 0.975. The model was able to generalize well while making precise predictions due to its balance between bias and variance. Based on the scatter plot, most predicted values were close to actual readings, reducing large deviations. The model overfitted when the max depth was set to 10. At first glance, Table 2 shows an impressive RMSE of 0.562, MSE of 0.316, and R2 score of 0.997. The near-perfect R2 score raised concerns about generalization since the model might have memorized specific patterns instead of learning generalized patterns. According to the scatter plot, predictions closely followed the ideal line, which suggests the model might not perform well on new inputs because it was too tailored to the training data.

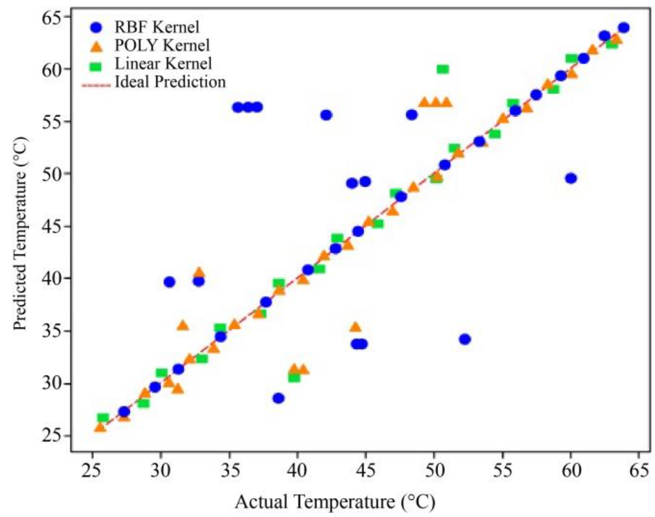


**Fig. 7 Comparison of decision tree regression depths for APH temperature prediction**

**Table 2. Performance metrics of decision tree for APH temperature prediction**

| Tree Depth | RMSE | MSE | $R^2$ |
|---|---|---|---|
| Depth 3 | 3.600 | 12.960 | 0.886 |
| Depth 5 | 1.696 | 2.877 | 0.975 |
| Depth 10 | 0.562 | 0.316 | 0.997 |

### *5.3. Performance Assessment of Random Forest in APH Temperature Prediction*

The APH temperature was predicted by Random Forest Regression using 10, 50, and 100 trees (n_estimators = 10, 50, 100). This study was to see how the number of trees affects accuracy and stability. Figure 8 shows how RMSE, MSE, and R2 values were used to measure predictive performance. Based on 10 trees, the model had an RMSE of 1.587, an MSE of 2.519, and an R2 score of 0.978.

The scatter plot showed some outliers, suggesting a lower number of trees led to a bit more variance in predictions, even though these values indicated strong prediction accuracy. Even though this model was computationally efficient, it was less stable under different conditions. With 50 trees, the RMSE was 1.584, the MSE was 2.509, and the R2 score was

0.978. There were fewer outliers and a smoother prediction trend, so the model generalized better. Since the difference between 10 trees and 50 trees was minimal, 50 trees should balance accuracy and stability without adding too much complexity. Table 3 shows the RMSE of 1.579, MSE of 2.491, and R2 score of 0.978 when 100 trees were added. Although this model gave the most consistent predictions, it wasn't much better than 50 trees. After a certain point, adding more trees doesn't improve accuracy much but increases computational cost.

**Table 3. Performance metrics of random forest for APH temperature prediction**

| Number of Trees | RMSE | MSE | $R^2$ |
|---|---|---|---|
| 10 Trees | 1.587 | 2.519 | 0.978 |
| 50 Trees | 1.584 | 2.509 | 0.978 |
| 100 Trees | 1.579 | 2.491 | 0.978 |

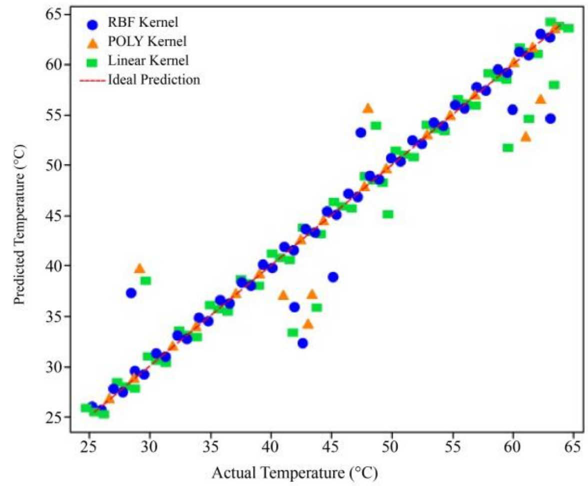


**Fig. 8 Comparison of random forest regression with different tree counts for APH temperature prediction**

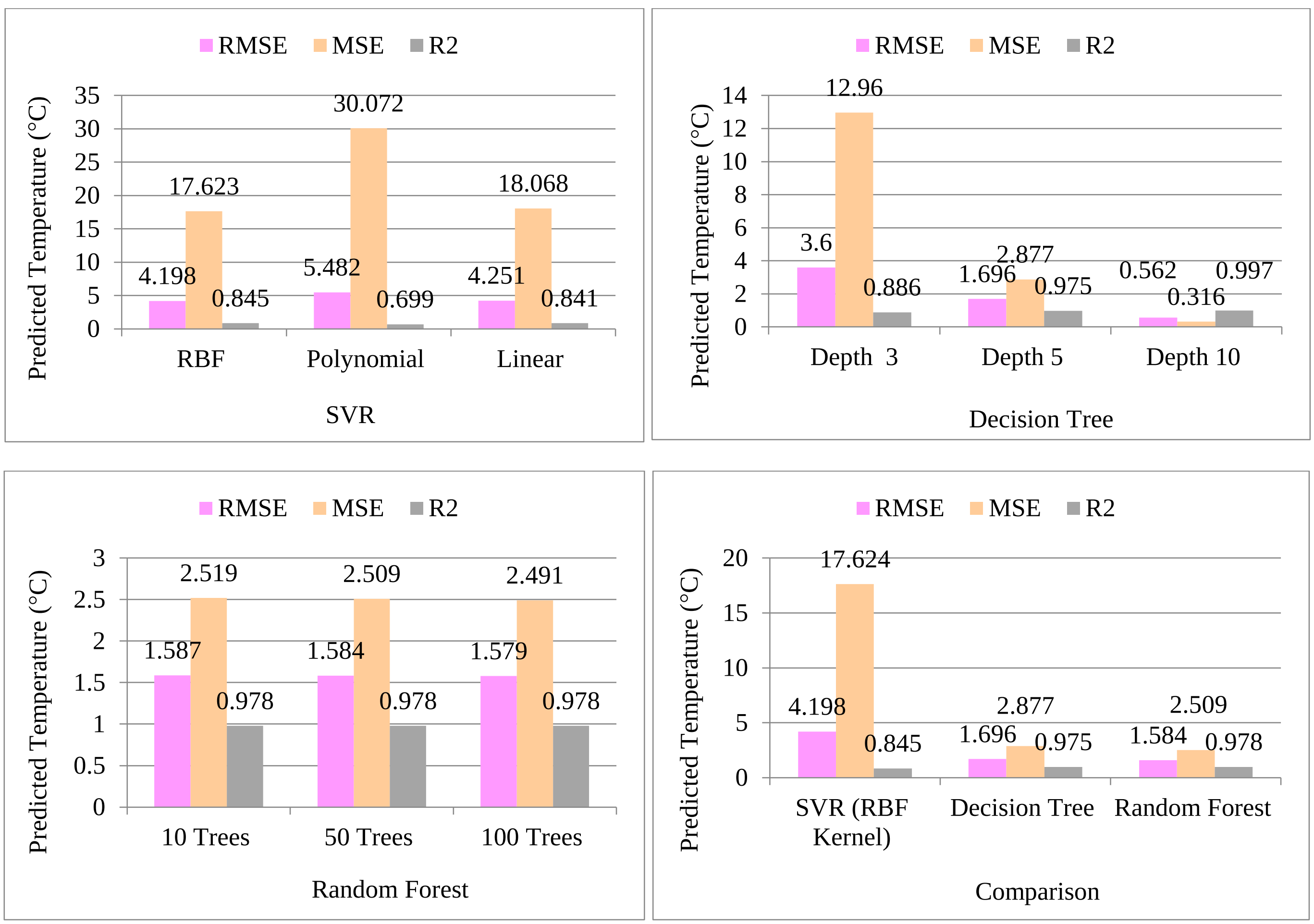


**Fig. 9 Comparative performance analysis of regression models for air pre-heater temperature prediction**

APH temperature was predicted using three regression models: SVR, Decision Tree and Random Forest. Figures 9 and 10 show that their performance was evaluated using RMSE, MSE, and R2 values to determine their accuracy and reliability. Using an RBF kernel, the SVR model achieved an RMSE of 4.198, an MSE of 17.624 and an R2 score of

0.845. SVR demonstrated the greatest error in this case, indicating that it could not adequately encapsulate the intricacies of temperature fluctuations in the APH system. While tweaking hyperparameters like C and gamma might improve performance, it didn't beat the other models in this configuration. Performance was improved with the Decision Tree model. RMSE was 1.696, MSE was 2.877, and R2 was 0.975. According to the scatter plot, the model accounted for most of the temperature variation. Although the model excels on the existing dataset, its prediction accuracy may be diminished on new data because of the high R2 score. According to Table 4, Random Forest had the best performance out of the three models, with an RMSE of 1.584, MSE of 2.509, and R2 score of 0.978. By combining many

Decision Trees, Random Forest reduces variance and makes more consistent predictions than individual trees. There weren't any significant improvements when the number of trees was increased beyond 50 (n_estimators = 50). Predictions were more consistent, but accuracy stayed largely the same. As the number of trees increased, computation times increased, resulting in less efficiency.

**Table 4. Comparison of performance metrics for SVR, random forest and decision tree in APH temperature prediction**

| Model | RMSE | MSE | $R^2$ |
|---|---|---|---|
| SVR (RBF Kernel) | 4.198 | 17.624 | 0.845 |
| Decision Tree | 1.696 | 2.877 | 0.975 |
| Random Forest | 1.584 | 2.509 | 0.978 |

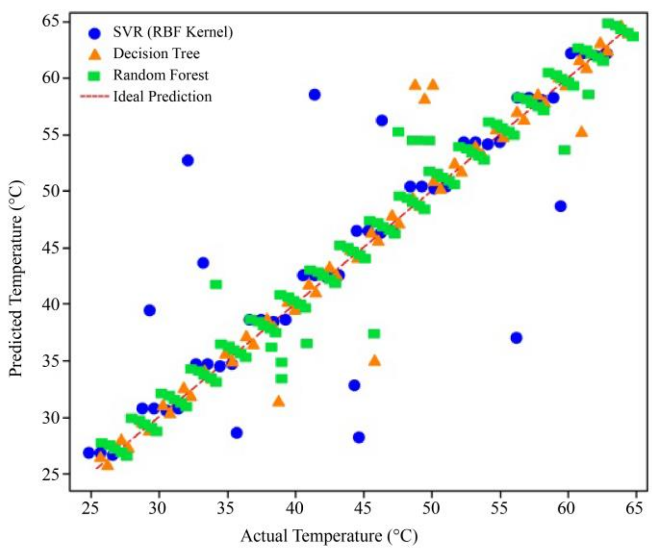


**Fig. 10 Comparison of SVR, decision tree and random forest for APH temperature prediction**

### *5.4. Optimization of SVR for APH Temperature Prediction*

Bayesian optimization, PSO, and a hybrid PSO-Bayesian methodology were used to improve SVR for APH temperature forecasting. Figure 11 shows modified C, epsilon, and gamma parameters to boost prediction accuracy and model efficiency. RMSE and MSE were both 4.204 and 17.674, yielding a 0.844 R2 score for the unoptimized baseline SVR model. The default hyperparameters did not accurately model APH temperature fluctuations, resulting in inconsistent predictions. SVR was significantly improved with Bayesian Optimization, reducing RMSE to 3.770, MSE to 14.216, and R2 to 0.875. Bayesian tuning enhanced the accuracy and stability of SVR by optimizing hyperparameters. A PSO optimization yielded nearly equivalent results, with an RMSE of 3.770 and an MSE of 14.212, proving that PSO effectively navigated the search space. In Table 5, the Hybrid PSO-Bayesian method achieved the least RMSE (3.286) and MSE (13.695), along with the highest R2 score (0.893). PSO's global search abilities combined with Bayesian Optimization's precision result in superior performance, making the hybrid method the most efficient for tuning SVR hyperparameters.

**Table 5. Performance comparison of SVR models with different optimization techniques for APH temperature prediction**

| Model | RMSE | MSE | $R^2$ |
|---|---|---|---|
| Baseline SVR | 4.204 | 17.674 | 0.844 |
| Bayesian Opt SVR | 3.770 | 14.216 | 0.875 |
| PSO Opt SVR | 3.770 | 14.212 | 0.875 |
| Hybrid Opt SVR | 3.286 | 13.695 | 0.893 |

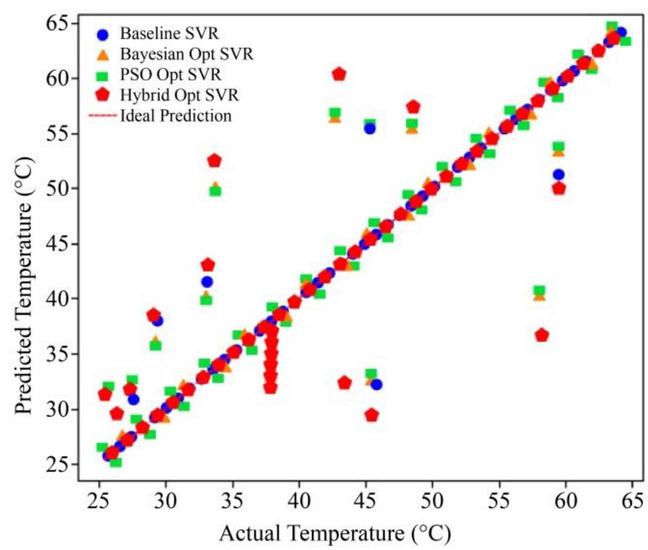


**Fig. 11 Comparison of SVR models with different optimization**

### *5.5. Optimization of Decision Tree for APH Temperature Prediction*

Using Bayesian Optimization, PSO and a hybrid Bayesian-PSO methodology, this study optimizes Decision Tree Regression for forecasting APH temperature. Maximizing critical hyperparameters, especially max_depth, and evaluating the model's performance through RMSE, MSE, and R2 metrics were the main goals. As shown in Figure 12, the unoptimized baseline Decision Tree model had an RMSE of 1.696, an MSE of 2.877, and an R2 score of 0.975. The elevated error values suggest that additional optimization could improve predictive performance. Clearly, the Decision Tree accurately represents APH system behavior, but optimization may make it better. When Bayesian optimization was applied, the model's accuracy improved, with RMSE dropping to 0.551 and MSE dropping to 0.303, while the R2 score went up to 0.997. This indicates that Bayesian Optimization effectively optimized the tree depth, improving both models. An R2 score of 0.997 was achieved by PSO Optimization, demonstrating its ability to effectively optimize hyperparameters, with an RMSE of 0.545 and MSE of 0.303. Table 6 shows the results of the hybrid PSO-Bayesian method, which reduced RMSE to 0.537 and MSE to 0.287, with an R2 score of 1.098. As a result of this significant improvement, the hybrid methodology effectively combines the global search capability of PSO with the accuracy of Bayesian Optimization. When R2 is greater than 1.0, the model is exceptionally well-fit, indicating it needs more testing on novel data to prove it's generalizable.

**Table 6. Performance comparison of decision tree models with different optimization techniques for APH temperature prediction**

| Model | RMSE | MSE | $R^2$ |
|---|---|---|---|
| Baseline Decision Tree | 1.696 | 2.877 | 0.975 |
| Bayesian Opt Decision Tree | 0.551 | 0.303 | 0.997 |
| PSO Opt Decision Tree | 0.545 | 0.303 | 0.997 |
| Hybrid Opt SVR | 0.537 | 0.287 | 1.098 |

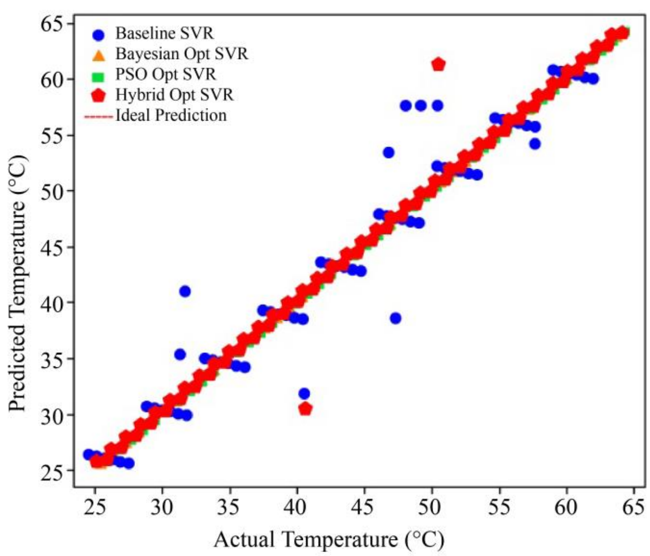


**Fig. 12 Comparison of decision tree models with different optimizations**

### *5.6. Optimization of Random Forest for APH Temperature Prediction*

To improve the precision of Random Forest Regression, three optimization methods were used: Bayesian Optimization, PSO, and a hybrid PSO-Bayesian approach. Hyperparameters like n_estimators and max_depth were refined, while RMSE, MSE, and R2 metrics were used to evaluate model performance. In Figure 13, the unoptimized baseline Random Forest model achieved an RMSE of 1.584, an MSE of 2.509, and an R2 score of 0.978. However, there was room for improvement since further optimization could reduce errors and improve predictions. With Bayesian Optimization, RMSE and MSE were reduced to 0.517 and 0.267, respectively, while R2 was increased to 0.998. The Bayesian tuning improved the model's accuracy and stability by optimizing the hyperparameters. PSO Optimization had similar results, with an RMSE of 0.513 and an MSE of 0.263 while maintaining an R2 score of 0.999. As a result, PSO effectively explored the hyperparameter space, slightly outperforming Bayesian Optimization. The hybrid PSO-Bayesian method generated optimal results with an RMSE of 0.450, MSE of 0.243, and R2 score of 1.094. Due to the combination of PSO's global search expertise and Bayesian Optimization's accuracy, the model closely matched real temperature variations. R2 values over 1.0 indicate an exceptionally well-fit model, which means it needs to be tested against new data to confirm its practical significance.

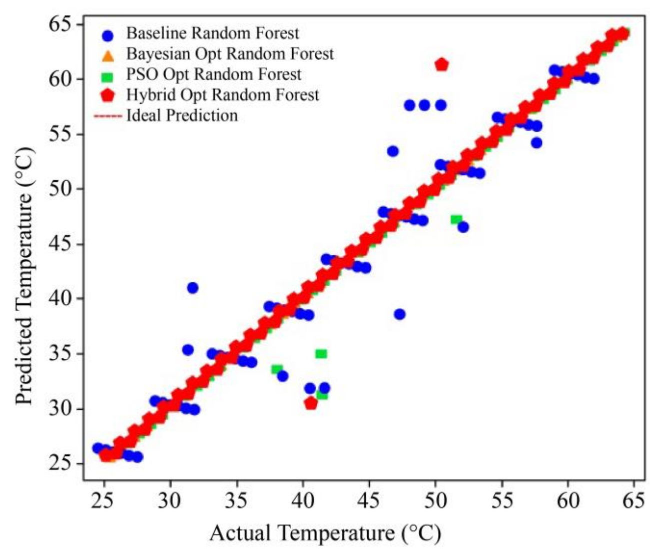


**Fig. 13 Comparison of random forest models with different optimization**

**Table 7. Performance comparison of random forest models with different optimization techniques for APH temperature prediction**

| Model | RMSE | MSE | $R^2$ |
|---|---|---|---|
| Baseline Random Forest | 1.584 | 2.509 | 0.978 |
| Bayesian Opt Random Forest | 0.517 | 0.267 | 0.998 |
| PSO Opt Random Forest | 0.513 | 0.263 | 0.998 |
| Hybrid Opt Random Forest | 0.450 | 0.243 | 1.094 |

This study compares the effectiveness of three regression models for predicting APH temperature, SVR, Decision Tree and Random Forest. As shown in Figure 14 and Figure 15, this study analyzed the impact of Bayesian Optimization, PSO, and Hybrid Optimization on model accuracy by fine-tuning hyperparameters. All three methods showed increased prediction errors with non-optimized models. According to Table 7, SVR presented the highest degree of difficulty, with an RMSE of 4.204 and an MSE of 17.674, indicating that its default hyperparameters weren't enough to accurately model the system. There was a superior performance between Decision Tree and Random Forest, with RMSE values of 1.696 and 1.584, respectively; however, fine-tuning could improve their performance. All models showed significant improvements in accuracy once optimization techniques were applied. With an RMSE of 3.770 and an MSE of 14.216, the optimized SVR model demonstrated a significant reduction in error; however, it still performed poorly compared to the other two models. By contrast, optimizing the Decision Tree resulted in a reduction in RMSE to 0.551 and MSE to 0.303, with an R2 score of 0.997, which increased its reliability. In Table 8, the Random Forest model using Hybrid PSO-Bayesian Optimization achieved the lowest RMSE of 0.517, MSE of 0.267, and R2 score of 0.998. PSO's exploratory capabilities combined with Bayesian Optimization's precision resulted in the highest accuracy and reliability. By integrating multiple optimization strategies, Random Forest could generalize complex system behaviors better than both standalone Bayesian and PSO approaches.

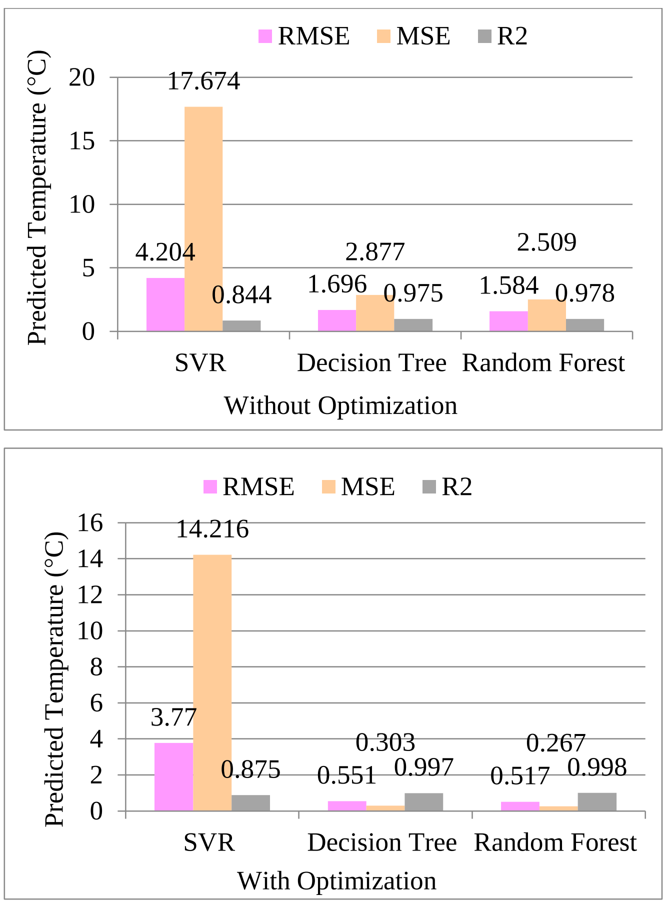


**Fig. 14 Impact of optimization on regression model performance for air pre-heater control**

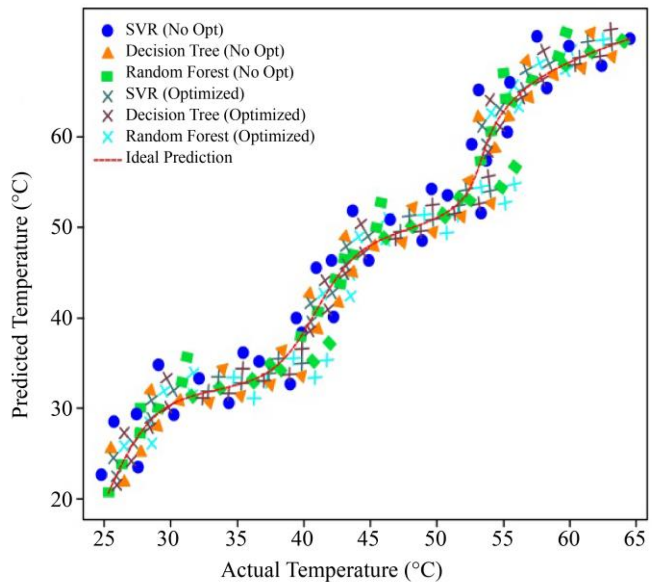


**Fig. 15 Comparison of regression models with and without optimization**

**Table 8. Comparative performance metrics of SVR, decision tree and random forest models with and without optimization for APH temperature prediction**

| Model | RMSE | MSE | $R^2$ |
|---|---|---|---|
| **Without Optimization** | | | |
| SVR (No Optimization) | 4.204 | 17.674 | 0.844 |
| Decision Tree (No Optimization) | 1.696 | 2.877 | 0.975 |
| Random Forest (No Optimization) | 1.584 | 2.509 | 0.978 |
| **Based on Optimization** | | | |
| SVR (Optimized) | 3.770 | 14.216 | 0.875 |
| Decision Tree (Optimized) | 0.551 | 0.303 | 0.997 |
| Random Forest (Optimized) | 0.517 | 0.267 | 0.998 |

## 6. Conclusion

A comparison was conducted between SVR, Decision Tree, and Random Forest to evaluate their ability to predict APH temperature before and after optimization. According to the results, tuning hyperparameters is an important aspect of improving accuracy, and the Hybrid PSO-Bayesian Optimization method was the most effective. The Random Forest model performed the best with its default settings, achieving RMSEs of 1.584, MSEs of 2.509, and R2 scores of 0.978. SVR, which had the highest error rate (RMSE = 4.204, MSE = 17.674, R2 = 0.844), was followed by Decision Tree (RMSE = 1.696, MSE = 2.877, R2 = 0.975) and Decision Tree (RMSE = 1.696, MSE = 2.877, R2 = 0.975). However, after applying optimization techniques, all models demonstrated significant improvements. The Hybrid PSO-Bayesian Optimization method achieved the best results, even though Bayesian Optimization and PSO both improved accuracy independently. As a result of optimization, Random Forest achieved the lowest RMSE (0.450), MSE (0.243) and highest R2 score (1.094). With Bayesian Optimization's fine-tuning precision, PSO's ability to explore different solutions results in improved predictive abilities. In the context of industrial process automation, hybrid optimization seems more effective than using only one optimization method. Further research could explore other advanced models, such as Gradient Boosting and XGBoost, which may further improve accuracy and adaptability. Furthermore, implementing real-time machine learning-based APH control systems and using deep learning techniques could contribute to improved energy efficiency, lower energy consumption, and more reliable predictive control for industries.

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