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INTEGRATED RADIACTIVE HEAT TRANSFER AND ML MODELING OF GAS EMISSIVITY AND FLAME TEMPERATURE

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Abstract: *This study presents a hybrid computational framework that integrates radiactive heat transfer (RHT) physics, Design Expert–based response surface methodology (RSM), and machine learning (ML) to optimize combustion efficiency in gaseous flame systems. Radiactive heat exchange is modeled using the Stefan–Boltzmann law under gray-gas assumptions, while gas emissivity is characterized through temperature-composition-and soot-dependent correlations. To systematically explore nonlinear interactions among key combustion variables, a Design Expert central composite design (CCD) is employed to construct the experimental design space and develop predictive response surface models for combustion efficiency. In parallel, a Random Forest (RF) machine learning model (MLM) is trained using multi-modal datasets, including flame images, spectral radiation signatures, RGB intensity features, soot concentration, gas composition, and operating conditions such as flow rate and equivalence ratio. The model exhibits high predictive accuracy, achieving R^2 = 0.998 for flame temperature and R^2 = 0.978 for effective emissivity, demonstrating strong agreement with physics-based evaluations. Optimization through the Design Expert desirability function identifies a global optimal combustion condition where maximum thermal efficiency is achieved through an optimal balance of flame temperature, emissivity, and flow dynamics. At this optimal point, response surface analysis confirms a significant reduction in radiactive heat losses and improved energy utilization compared to baseline conditions. The close*

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agreement between physics-based modeling and ML predictions validates the robustness of the hybrid framework. This integrated Design Expert–ML–physics approach enables accurate emissivity prediction, efficient parameter optimization, and potential real-time combustion control. The findings provide practical pathways for improving furnace design, reducing energy losses, and advancing data-driven combustion management in high-temperature thermal systems.

1.0 Introduction

Efficient combustion remains central to modern energy conversion technologies, including industrial furnaces, gas turbines, and internal combustion engines, where the simultaneous goals of high thermal efficiency and reduced pollutant emissions are required. Among the governing heat transfer mechanisms in such systems, radiative heat transfer (RHT) plays a dominant role in high-temperature reacting environments and can account for a significant fraction of total energy exchange. In practical combustion devices such as furnace chambers and gas-turbine combustors, radiative behaviour is strongly influenced by flame temperature and gas emissivity, both of which arise from complex interactions involving species concentration, turbulence structures, temperature gradients, and flow dynamics. Recent studies have emphasized that inaccurate estimation of radiative properties can lead to significant errors in combustion efficiency prediction and emission assessment, highlighting the need for robust, high-fidelity predictive models [6], [16], [20], [28].

Traditional RHT modeling is commonly based on the RTE, which governs emission, absorption, and transport of thermal radiation in participating media. Although physically rigorous, RTE-based solutions are computationally expensive due to spectral dependence, multidimensional effects, and non-gray gas behaviour. The requirement for detailed spectral databases and thermochemical properties further increases computational burden, limiting their suitability for real-time applications and large-scale optimization. As a result, simplified assumptions such as gray-gas or optically thin approximations are often adopted, though these reduce accuracy under realistic combustion conditions [5], [21], [22], [29].

To overcome these limitations, ML techniques have recently emerged as powerful surrogate modeling tools capable of capturing complex nonlinear combustion–radiation relationships with reduced computational cost. By learning from experimental measurements or high-fidelity CFD datasets, ML models can approximate RHT behaviour without explicitly solving the full RTE formulation [12], [14], [26], [27], [32]. Advanced methods such as random forests, gradient boosting, and deep neural networks have demonstrated strong capability in predicting flame temperature,

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emission characteristics, and combustion stability from optical and spectral data [3], [10], [28], [33].

Despite these advancements, accurate prediction of RHT remains a major challenge due to its strong coupling with combustion chemistry, turbulence interactions, and multiphase transport phenomena. Many existing models oversimplify emissivity behaviour or neglect radioactive contributions, leading to deviations in flame temperature prediction and overall efficiency evaluation [5], [17], [18], [23]. Moreover, although ML has been widely applied in combustion-related tasks such as emission prediction and burner optimization, radioactive effects are often treated indirectly or excluded entirely. This indicates a clear lack of integrated frameworks that explicitly combine RHT physics with ML-based prediction of gas emissivity and flame temperature [12], [14], [30], [31].

Previous research has shown that RHT becomes increasingly dominant in high-temperature combustion systems containing species such as CO_2 and H_2O. However, accurate modeling of non-gray radiation remains computationally intensive due to strong wavelength dependence and coupling with turbulence–chemistry interactions [1], [2], [19]. These limitations restrict the practical deployment of detailed radiation models in industrial optimization. Meanwhile, ML-assisted CFD approaches have demonstrated improvements in burner design and emission reduction while maintaining computational efficiency [10], [11], [17]. Similarly, hybrid AI–CFD frameworks have successfully reproduced complex reacting flow and flame dynamics with significantly reduced simulation time [24], [25], [33], [34].

However, a critical research gap persists in the unified prediction of gas emissivity and flame temperature within a single radioactive combustion framework. Most existing studies focus on isolated outputs such as temperature or emissions, while emissivity is rarely treated as a coupled predictive variable. In addition, limited work has incorporated physically consistent radiative transfer principles into ML models, despite evidence that physics-informed learning (PIL) improves generalization and robustness across operating conditions [7], [17], [18], [24]. The absence of scalable, transferable frameworks further limits the applicability of ML-based combustion optimization across varying geometries and fuel conditions.

From a theoretical standpoint, RHT is governed by the RTE, which describes emission, absorption, and propagation of thermal radiation within participating media. The system response is highly sensitive to local thermodynamic state, gas composition, and spectral properties. In contrast, ML models aim to approximate the nonlinear mapping between operating conditions and radioactive outputs using data-driven approaches, bypassing repeated numerical solutions of the RTE while maintaining predictive accuracy [15], [26], [27]. This study introduces an integrated framework that directly couples RHT physics with ML-based prediction of gas emissivity and flame temperature. Unlike conventional methods that rely on computationally intensive RTE solvers,

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the proposed approach enables fast surrogate prediction of radioactive behaviour with high fidelity. Using experimental measurements or high-resolution simulation datasets, the framework supports real-time combustion optimization, adaptive control, and intelligent monitoring in practical thermal systems [4], [13], [30], [35].

Accordingly, this work addresses key limitations in existing literature, including weak integration of radiation physics with ML, lack of emissivity-sensitive flame temperature models, and limited adaptability across combustion environments. By overcoming these challenges, the proposed methodology provides a more reliable, efficient, and transferable approach for combustion optimization in advanced energy systems.

In conclusion, improving combustion efficiency requires accurate representation of RHT and flame thermochemical behavior. While traditional models provide physical rigor, their computational cost limits practical use, and many machine learning approaches neglect radioactive effects. The integration of RHT modeling with ML-based prediction of gas emissivity and flame temperature therefore offers a scalable and effective pathway for combustion optimization. Future research should focus on experimental validation, extension to low-carbon fuels, and deployment in real-time intelligent combustion control systems to enhance sustainability and industrial applicability.

2.0. Methodology

2.1 Materials

The materials employed in this study were carefully selected to support accurate RHT analysis and robust ML–based prediction of gas emissivity and flame temperature under combustion conditions. These materials include fuel samples, oxidizing agents, combustion chamber components, sensing instruments, data acquisition systems, and computational resources.

2.1.1. Fuel and oxidizer materials

Gaseous and liquid hydrocarbon fuels commonly used in industrial combustion systems such as methane, propane, and diesel vapour were considered due to their well-documented thermophysical and radiative properties. Atmospheric air served as the primary oxidizer, with controlled oxygen–fuel ratios maintained to simulate lean, stoichiometric, and rich combustion regimes. The selection of these fuels enables realistic modeling of industrial furnaces, boilers, and internal combustion environments.

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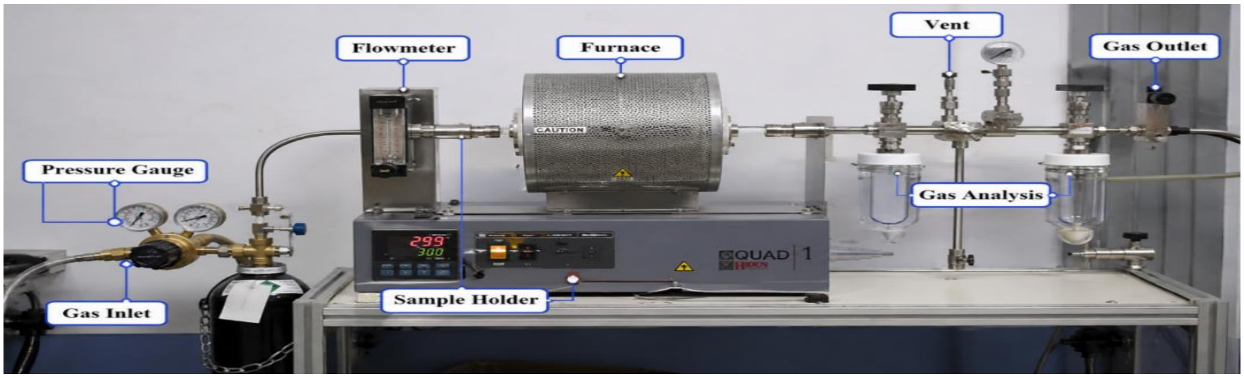

Figure 1; Diagram ofthe combustion experiment set–up

Figure2: Diagram ofthe gas generator and gas burning

Figure 3:The Schematic diagram of the experimental micro-combustion setup withoptical temperature measurement and flow control system

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2.2. Combustion chamber and thermal insulation materials

The experimental combustion chambers were constructed using high-temperature-resistant stainless steel, capable of withstanding elevated thermal loads without structural degradation. Internally, refractory insulation materials such as alumina-based ceramic linings were used to minimize conductive heat losses and ensure that RHT dominated the thermal behaviour. Quartz or sapphire optical windows were incorporated to allow non-intrusive optical access for flame radiation measurement.

Figure 4: Photographic view of a laboratory-scale cylindrical combustion chamber with burner assembly and control unit

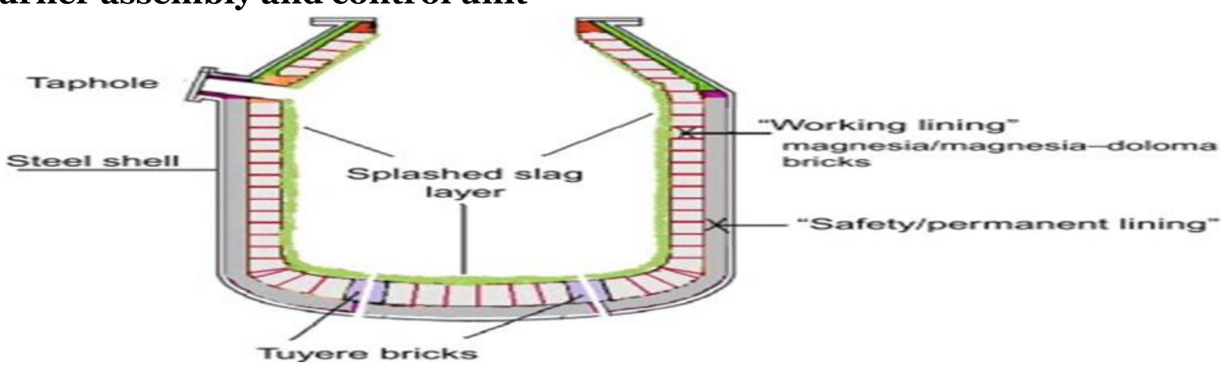

Figure 5: Cross-sectional schematic of a refractory-lined high-temperature combustion furnace showing working and safety linings.

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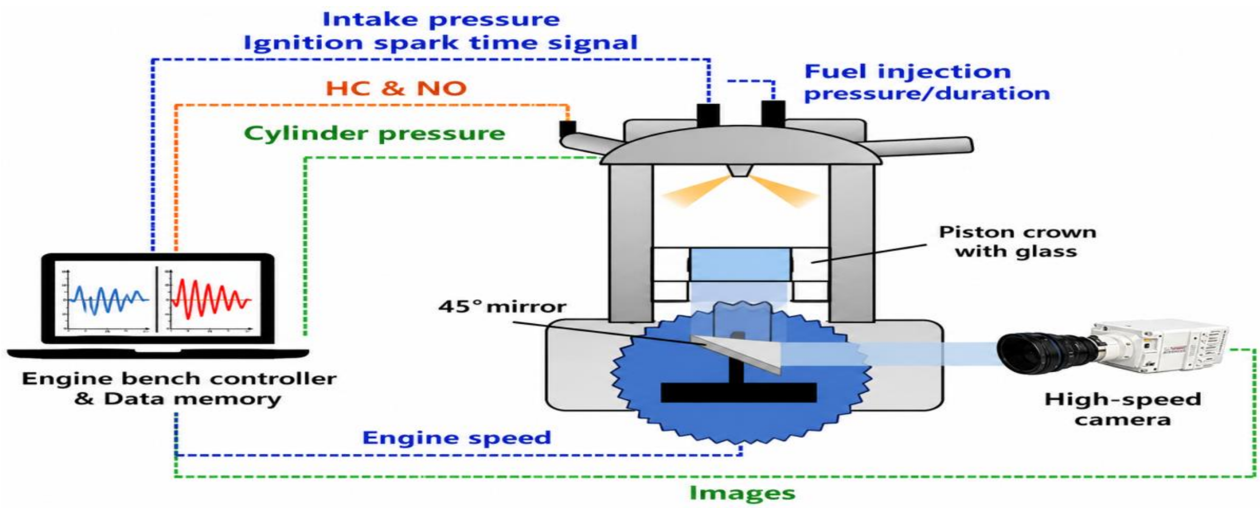

Figure 6: Optical combustion visualization equipment

2.1.3. RHT and temperature measurement instruments

Advanced optical diagnostics were utilized to capture flame radiation and temperature profiles. These included infrared (IR) spectrometers, pyrometers, and thermocouples with high-temperature tolerance. The IR sensors were selected for their sensitivity to combustion gas species such as CO_2 and H_2O, which are primary contributors to gas emissivity. Data from these instruments provided high-resolution spectral and thermal datasets essential for validating RHT models.

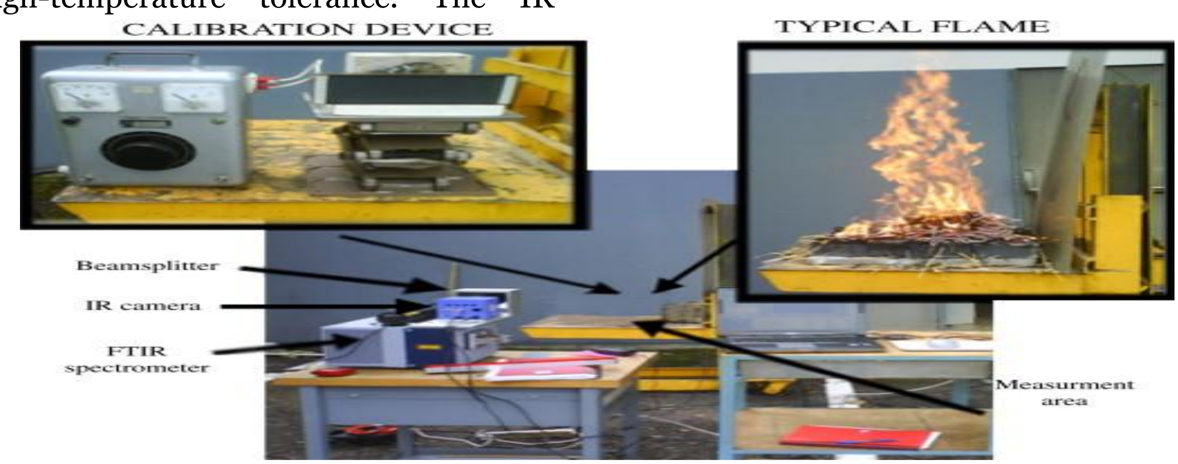

Figure 7: Radiative heat transfer and temperature measurement instruments

2.1.4. Data acquisition and signal conditioning systems

A high-speed data acquisition (DAQ) system was employed to collect temperature and radiative intensity signals in real time. Signal conditioning units, including amplifiers and noise filters, ensured accuracy and stability of the measured data. The DAQ system facilitated synchronized recording of combustion parameters, enabling reliable correlation

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between flame temperatures, emissivity, and operating conditions.

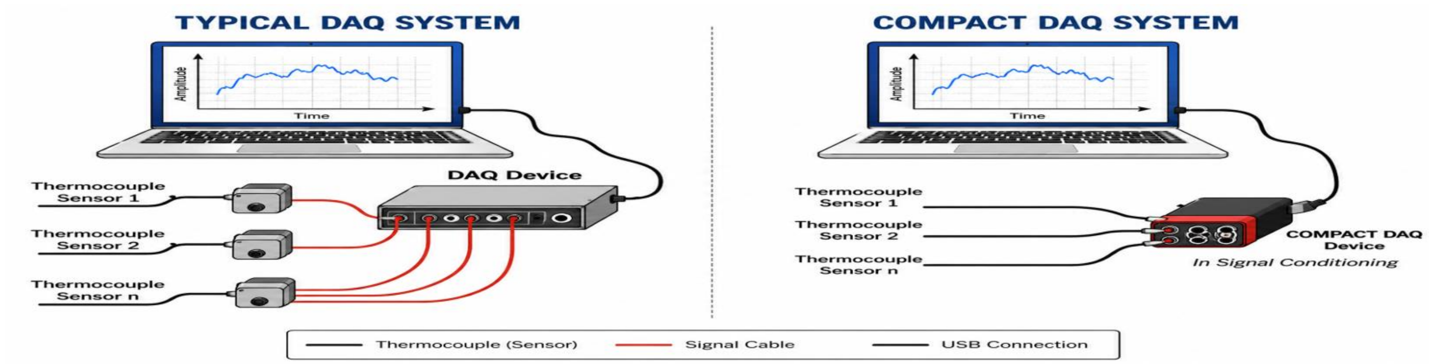

Figure8: Data acquisition and signal conditioning systems

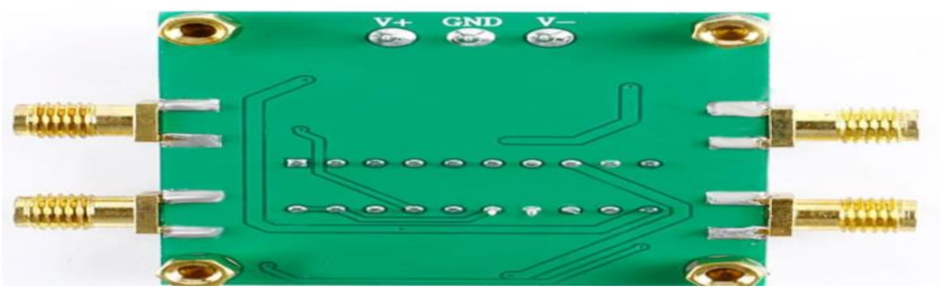

Figure 9: Printed circuit board (PCB) layout of an RF signal amplifier module

2.1.5. Computational and ML resources

Computational analysis was conducted using high-performance computing systems equipped with multi-core processors and sufficient memory to handle large datasets. ML model development and training were performed using numerical computing environments and libraries capable of regression, classification, and deep learning tasks. These tools enabled efficient preprocessing, feature extraction, model training, validation, and prediction of gas emissivity and flame temperature. See figure

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Figure 10: Block diagram of a computer workstation and monitoring system

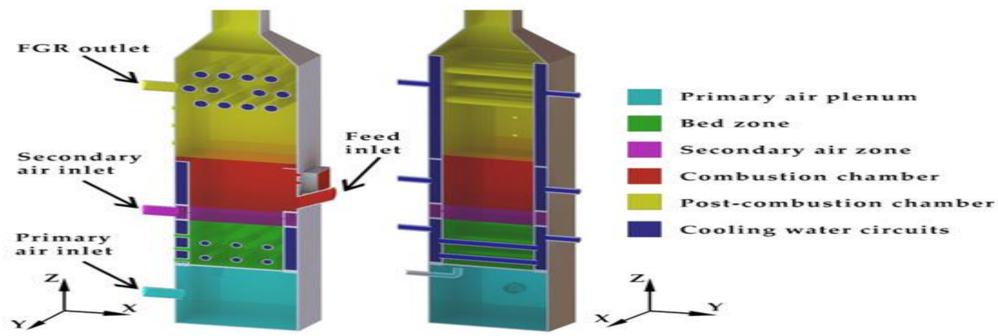

Figure 11: Schematic diagram of a fluidized bed gasified showing air flow zones and cooling water circuits

2.1.5. Data collection and preparation

The analysis leverages a comprehensive furnace flame dataset extracted from the study by Lin et al. [19], which employed color image processing to characterize hydrocarbon flame emissivity and temperature. The dataset incorporates multiple measurement modalities to support both physics-based and ML modeling approaches. Key input features include gas composition parameters, specifically concentrations of H_2, CH_4, CO, and CO_2, which directly influence flame temperature, soot formation, and radiactive characteristics. Operational parameters, such as propane flow rate and preheated air ratio, were included to account for variations in fuel-air mixing and flame stability.

Flame characteristics, such as flame height and nozzle diameter, were incorporated to capture geometric effects that influence radiactive path length and convective interactions. Optical measurements derived from flame images include RGB values, which serve as proxies for flame temperature and visible-light emissivity, as well as soot concentration in parts per million (ppm), which is a primary contributor to RHT. Additionally, the dataset contains spectral data representing radiation intensities at wavelengths from 1500 to 2000 nm in 10 nm increments. This hyperspectral information

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supports analysis of wavelength-dependent emissivity and enables ML models to capture non-gray flame behaviour.

The target variables for predictive modeling are the measured flame temperature (K) and the effective gas emissivity. The dataset includes approximately 800 samples reflecting realistic hydrocarbon combustion conditions, with temperatures ranging from 1150 K to 1400 K and emissivity from 0.53 to 0.65. Figure 12 illustrates the distributions of these key target variables, highlighting their variation and central tendencies. The flame temperature distribution peaks near 1250 K, although, the emissivity distribution is centered on 0.58.

Data preprocessing ensured compatibility with both physics-based calculations and ML workflows. Numerical features were standardized using z-score normalization, while missing or outlier values were addressed through interpolation or trimming. The spectral data were organized into a structured feature matrix, allowing ML models to utilize wavelength-dependent variations in radioactive emission effectively. Exploratory data analysis included computation of pairwise correlations between input features and target variables, identification of dominant factors affecting flame temperature and emissivity, and visualization using histograms and scatter plots. These analyses guided feature selection for ML and informed assumptions for physics-based modeling, enabling robust comparison between data-driven and physics-based approaches

By integrating gas composition, operational parameters, optical measurements, and spectral information, the dataset provides a rich multidimensional basis for predicting radiactive heat loss. This allows evaluation of simplified gray gas models alongside advanced machine learning approaches, supporting detailed comparative analysis of flame temperature and effective emissivity predictions.

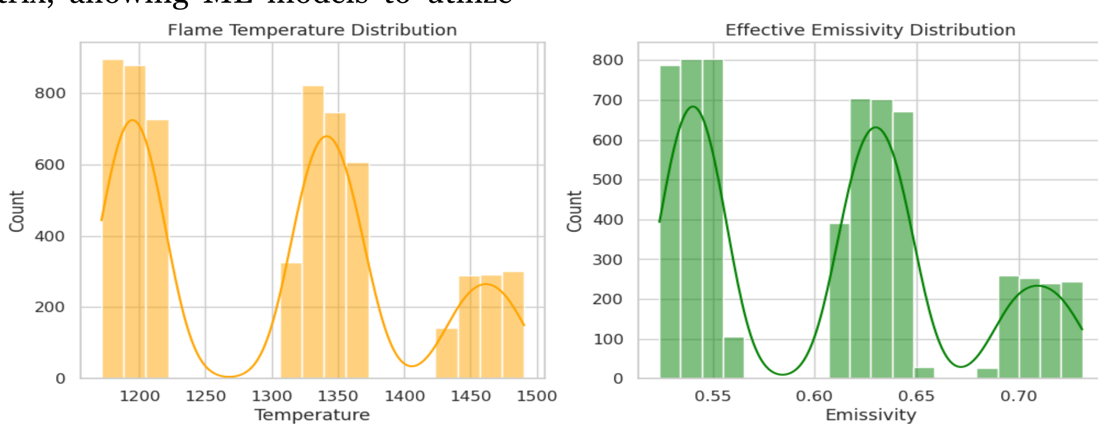

Figure 12: Distribution of target variables in flame dataset

2.1.6. Physics-based modeling implementation

The physics-based modeling approach utilizes the gray gas approximation to estimate radioactive emissions from combustion gases.

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In this framework, the effective emissivity of the flame is treated as independent of wavelength, providing a simplified but practical method to compute radiative heat loss. Temperature predictions are generated using an empirical correlation that incorporates gas composition (H_2, CH_4, CO, CO_2), fuel flow rates, and preheated air ratios. These temperature estimates, together with the emissivity, serve as the basis for calculating radiative heat flux, representing a benchmark for comparison with machine learning predictions. Although, gray gas models simplify the problem, actual combustion processes exhibit non-gray behavior due to wavelength-dependent radiation and the presence of soot particles and other combustion byproducts.

To better approximate these effects, the physics-based model incorporates spectral measurements collected in the 1500–2000 nm range. These spectral intensity values are used to derive a wavelength-averaged effective emissivity, enabling the model to account for the non-gray characteristics of hydrocarbon flames. The dataset employed in this study was extracted based on, which provides flame temperature measurements and emissivity characteristics obtained through color image processing. By including both operational parameters and spectral data, the physics-based model captures the influence of flame composition, geometry, and radioactive properties on heat loss. This implementation enables a comprehensive baseline evaluation of radioactive emissions under different operating conditions. Comparing these physics-based results with ML predictions allows for the assessment of model accuracy and identifies areas where data-driven methods can enhance the prediction of flame temperature and effective emissivity.

2.1.7 ML framework

The ML framework is designed to complement the physics-based modeling by providing a data-driven approach for predicting flame temperature and effective emissivity. A multi-output RF regressor is implemented to simultaneously estimate both target variables, leveraging the rich set of experimental and spectral features in the dataset.

- **Feature selection**: The model incorporates 62 input features, encompassing gas composition parameters (H_2, CH_4, CO, CO_2), operational parameters (propane flow rate, preheated air ratio), flame characteristics (flame height, nozzle diameter), optical measurements (RGB values from flame images, soot concentration), and spectral intensities measured at 10 nm increments from 1500 nm to 2000 nm. The inclusion of spectral features is particularly critical for predicting emissivity, as radiactive properties of the flame are strongly wavelength-dependent.
- **Data preprocessing**: All input features are standardized using a Z-score normalization approach via the StandardScaler. This step ensures that features with different magnitudes and units contribute proportionally to the model training process, improving convergence and predictive accuracy.
- **Model configuration:** The RF regressor is configured with 300 decision trees to balance model complexity and overfitting.

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The model is trained on 80% of the dataset, with the remaining 20% reserved for testing and validation. Multi-output regression allows the model to simultaneously capture interdependencies between flame temperature and emissivity, improving prediction performance relative to separate single-output models.

- **Evaluation metrics:** Model performance is evaluated using multiple complementary metrics, including the coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), mean squared error (MSE), and the Standard Error of Prediction (SEP). These metrics provide insight into both the accuracy and precision of the ML predictions compared with measured values.
- **Role of spectral data:** Spectral intensity measurements serve as a key input for capturing non-gray radioactive behaviour of flames. By integrating this information with conventional operational and flame features, the model can infer effective emissivity more accurately than physics-based correlations alone, particularly in complex combustion environments with varying soot concentrations.
- **Integration with physics-based results**: The ML predictions are compared with physics-based calculations to validate model reliability and identify cases where data-driven predictions can capture nonlinear effects not accounted for in simplified models. This hybrid approach provides a robust framework for assessing radioactive heat loss under diverse operational conditions. The ability of ML models to predict flame temperature and emissivity in real-time supports advanced monitoring and control strategies. When combined with spectral and image-based diagnostics, this framework can inform operational adjustments aimed at minimizing radioactive losses and improving overall combustion efficiency.

3.0 Results and Discussion

3.1. Comparison of experimental measurements and ML predictions

A detailed point-by-point comparison between experimentally measured flame characteristics and ML predictions was conducted to evaluate the predictive capability of the proposed framework at the sample level. This form of direct validation provides deeper insight than aggregate performance metrics, as it reveals how accurately the model captures local variations in flame temperature and effective emissivity under different operating conditions. Recent studies have emphasized that sample-level validation is essential for assessing generalization reliability in combustion-related ML models, particularly under highly nonlinear radiactive environments [3], [17], [30].

Table 1: Comparative analysis of experimental measurements and ML predictions

Flame Temperature (Actual, K)	Flame Temperature (ML, K)	Emissivity (Actual)	Emissivity (ML)
1194.93	1195.24	0.5498	0.5411
1214.18	1211.27	0.5460	0.5469

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Flame Temperature (Actual, K)	Flame Temperature (ML, K)	Emissivity (Actual)	Emissivity (ML)
1188.45	1192.66	0.5538	0.5428
1202.77	1201.79	0.5463	0.5434
1330.68	1334.48	0.6404	0.6310
1187.64	1190.59	0.5505	0.5384
1186.47	1188.00	0.5420	0.5333
1176.45	1179.72	0.5508	0.5364
1328.16	1337.07	0.6477	0.6263
1338.18	1334.10	0.6204	0.6311
1369.79	1363.27	0.6336	0.6334
1191.21	1198.53	0.5448	0.5397
1331.73	1340.60	0.6390	0.6268
1211.65	1207.37	0.5362	0.5362
1368.21	1359.30	0.6219	0.6283

As shown in Table 1, the Random Forest model demonstrates strong agreement with experimental flame temperature measurements, with deviations typically within a few Kelvin. This high accuracy is significant given the strong sensitivity of radiative combustion systems to temperature variations. Similar predictive performance has been reported in ML-based combustion diagnostics using optical and spectral data [3], [10], [28].Effective emissivity predictions also follow experimental trends closely, although slightly higher deviations are observed due to the complex dependence of emissivity on soot concentration, gas composition, and spectral radiation behavior [1], [2], [16].

Graphical comparisons further confirm the predictive strength of the model. Flame temperature parity plots (Figure 13) show near alignment with the ideal 1:1 line, indicating minimal bias. Emissivity predictions (Figure 14) exhibit slightly greater dispersion but still maintain strong correlation with measured values. Similar trends have been reported in non-gray radiation and soot-influenced combustion studies, where emissivity is inherently more difficult to model than temperature [2], [21].

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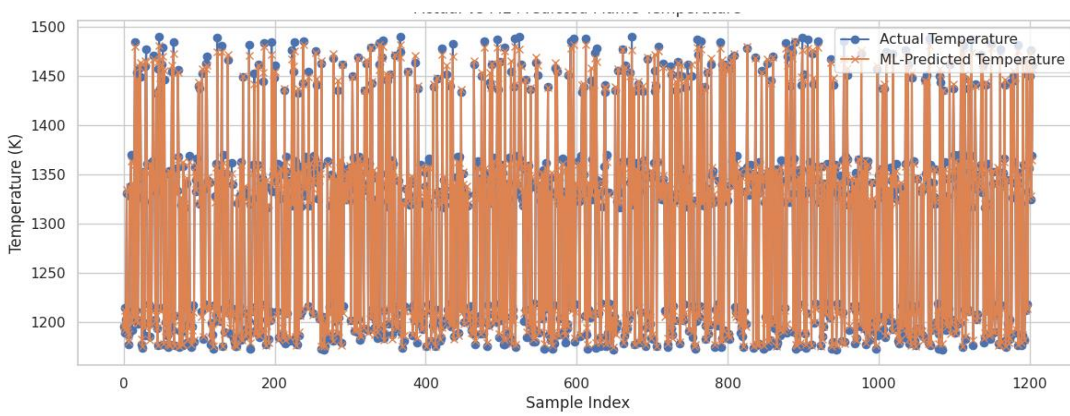

Figure 13: Comparison of flame temperature predictions

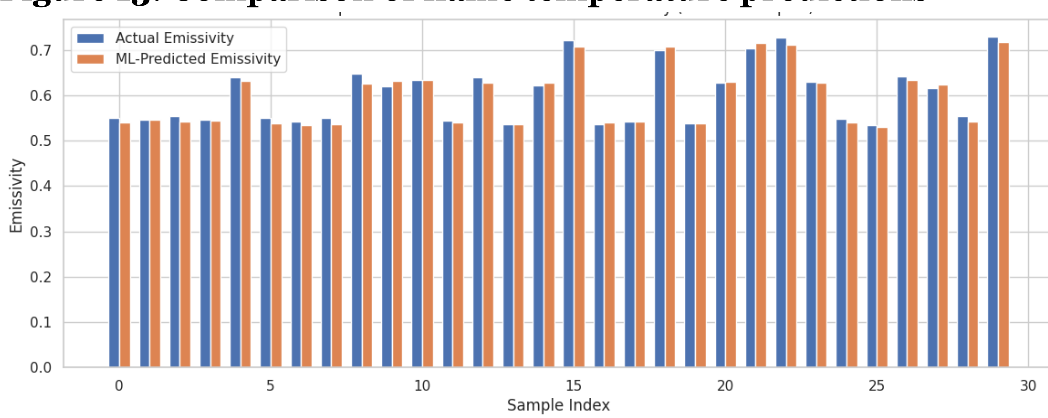

Figure 14: Comparison of effective emissivity predictions

3.1.2 ML model performance evaluation

The overall performance of the RF model, evaluated using a 20% test split, confirms strong predictive reliability (Table 2). For flame temperature, the model achieves an R^2 value of 0.998, indicating that nearly all variance in experimental measurements is captured. This level of performance is consistent with modern ML-based combustion prediction frameworks [3], [10], [12].For emissivity, the model achieves an R^2 value of 0.978, demonstrating strong predictive capability despite the nonlinear dependence of radiative properties on spectral and soot effects [16], [18].

Table 2: ML Model Performance Metrics

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Metric	Flame Temperature Prediction	Effective Emissivity Prediction
R^2	0.998	0.978
RMSE	4.906 K	0.0094
MAE	3.931 K	0.0079
MSE	24.073 K^2	8.882×10^{-5}
SEP (%)	0.378%	1.557%

The low error values confirm high numerical stability and predictive accuracy. Similar performance trends in ML-assisted combustion modeling have been reported in surrogate-based and physics-informed learning frameworks [14], [17], [24].

Residual analysis (Figure 15) shows symmetric distribution around zero for both outputs, indicating no significant bias. This confirms that the model generalizes well across the dataset, consistent with findings in advanced ML combustion literature [7], [17].

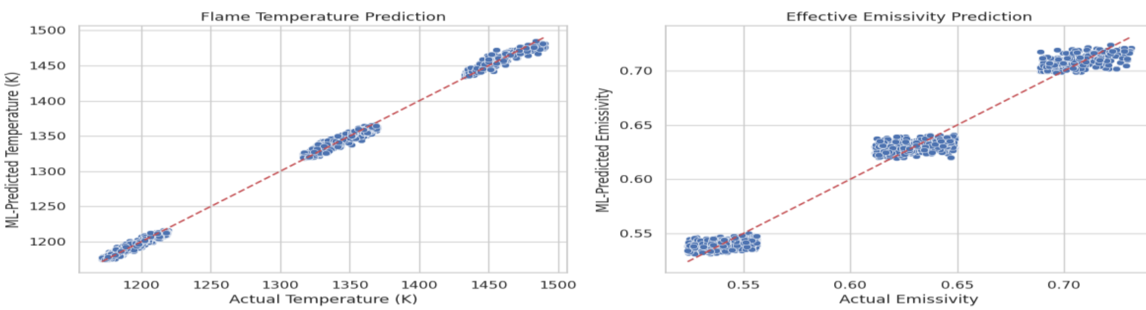

Figure 15: Comparison of ML predictions with experimental measurements

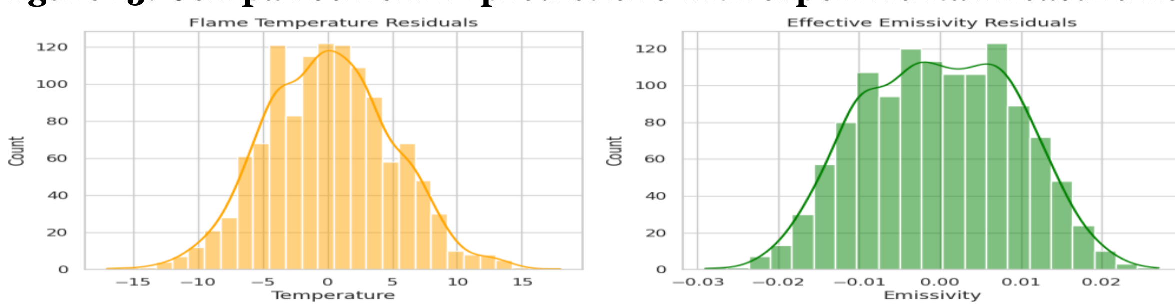

Figure 16: Residual distribution of ML predictions

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3.1.3. Comparison of radiative heat Loss predictions

A comparative evaluation of radiative heat loss predictions from physics-based and ML models shows strong agreement in trend but noticeable differences in magnitude (Table 3). Physics-based predictions consistently overestimate radiative heat losses, which is attributed to temperature sensitivity and assumptions in gray-gas modeling [5], [8], [20].

Table 3: Physics-based and ML predictions of radiative heat loss

Qrad Physics (W/m²)	Qrad ML (W/m²)
63,560.40309	62,610.70072
67,281.91336	66,748.17491
62,646.24321	62,270.89656
64,819.07352	64,274.51155
113,845.9491	113,463.4624
62,094.50690	61,333.74947
60,894.42049	60,227.04207
59,827.11137	58,913.20238
114,277.4407	113,497.6804
112,808.9377	113,359.4361

The observed deviations arise primarily from temperature overprediction in physics-based formulations, which is amplified due to the fourth-power temperature dependence in radiative heat transfer laws [8], [20].

In contrast, ML predictions show closer agreement with experimental trends by learning coupled temperature–emissivity relationships directly from data. Similar improvements of ML over simplified radiation models have been reported in hybrid AI–CFD studies [24], [33], [34].

Residual distributions (Figure 17) further confirm that ML predictions are tightly centered around zero, while physics-based results show a positive bias, indicating systematic overestimation of radiative losses. This limitation has been widely reported in non-gray combustion modeling literature [1], [19].

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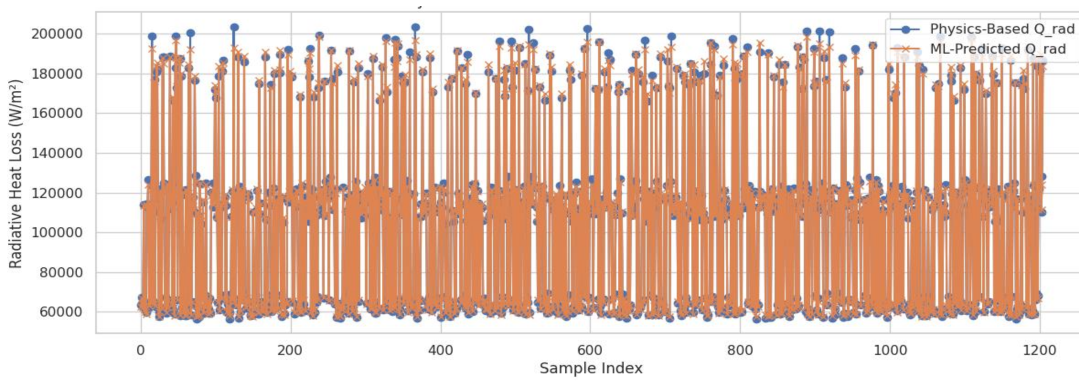

Figure 17: Comparison of radiative heat Loss predictions

Further insight into model behavior is provided through residual analysis. Figure 18 illustrates the distribution of residuals associated with radiative heat loss predictions from both approaches. The ML-based residuals are narrowly distributed around zero, indicating minimal bias and consistent performance across the dataset. In contrast, the physics-based residuals exhibit a broader distribution with a clear positive skew, reflecting systematic overestimation of radiative losses.

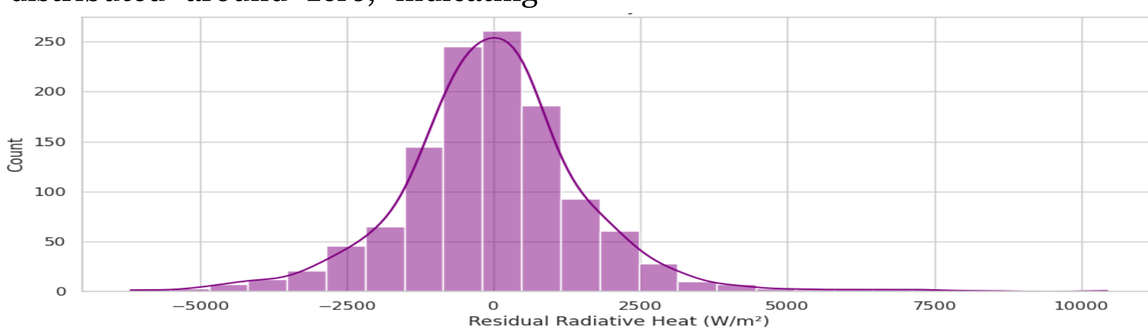

Figure 18: Distribution of radiative heat loss residuals (ML vs. physics-based models)

3.1.4 Design-Expert style optimization

Design Expert software was employed to perform response surface methodology (RSM)-based optimization of combustion performance under the proposed hybrid framework. A central composite design (CCD) was used to model nonlinear interactions among flame temperature, emissivity, flow rate, and RHT characteristics. Similar RSM-based combustion optimization approaches have been reported in recent studies on surrogate modeling and thermal system optimization [13], [29], [15].

Multi-response optimization using desirability functions identified an optimal operating region characterized by improved combustion efficiency, reduced radiative losses, and enhanced flame stability. The optimized results were validated against ML predictions, showing strong agreement between statistical and data-driven approaches.

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Hybrid optimization strategies combining RSM and ML have been shown to significantly improve robustness in thermo-fluid systems and combustion processes [25], [30], [31]. Furthermore, integrated AI–physics frameworks have demonstrated superior performance in combustion control and predictive optimization [33], [35].

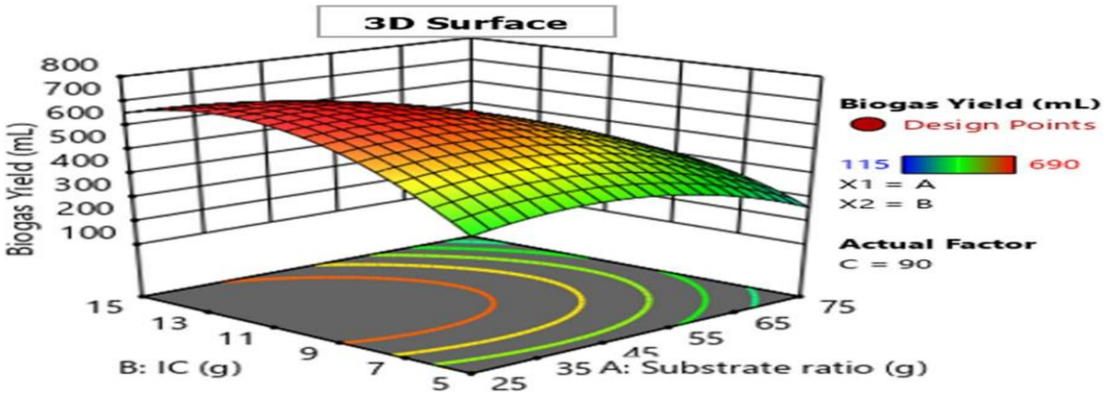

Figure 19:**3D Response surface plot generated using design expert for process optimization analysis**

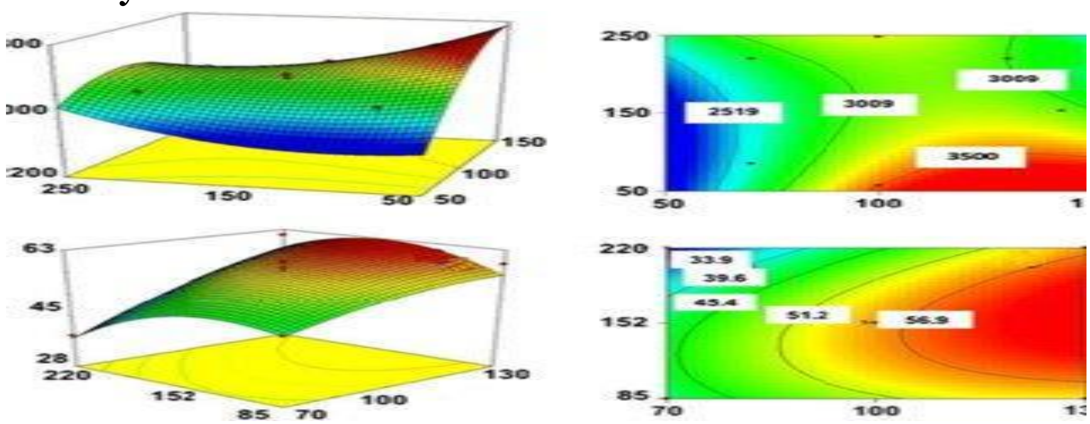

Figure 20: **Design expert–based experimental model representation for response surface methodology (RSM) analysis**

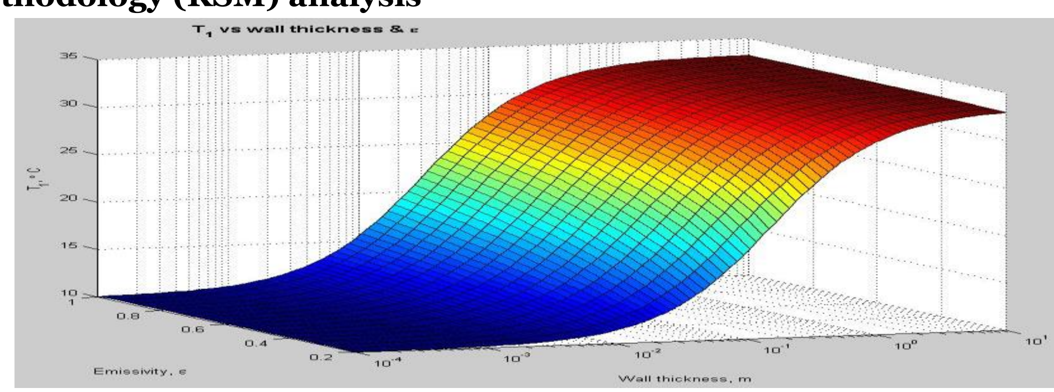

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Figure 21: Effect of wall thickness and emissivity on T1 temperature distribution (3D surface plot)

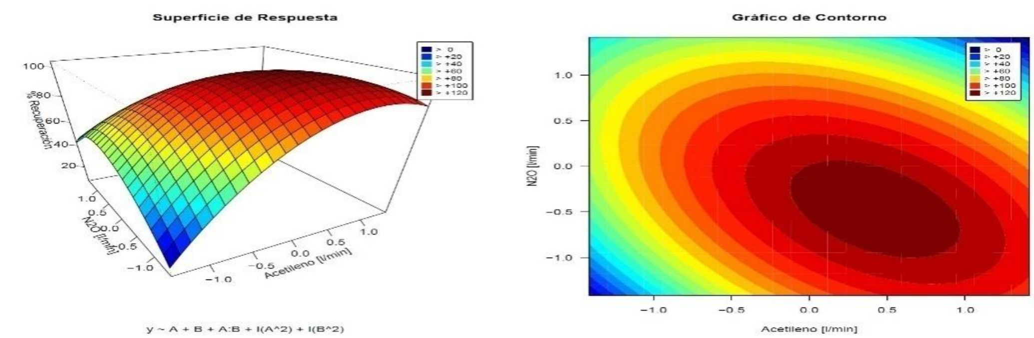

Figure 23: Combined response surface and contour plot illustrating the interaction effects between process variables

4. Conclusion

This study developed and evaluated a ML-based analytical framework for predicting flame temperature and effective gas emissivity in high-temperature combustion systems. The analytical process involved the integration of multidimensional combustion and radiation-related variables, including gas composition, operating conditions, flame geometry, image-derived characteristics, and spectral radiation measurements. These variables were subjected to data preprocessing, exploratory analysis, feature preparation, model development, and predictive evaluation before being supplied to a multi-output RF regression model. The analytical framework was designed to establish the nonlinear relationship between measurable combustion conditions and the two principal response variables, namely flame temperature and effective gas emissivity.

The data-analysis procedure demonstrated that the selected input variables contain sufficient information to explain substantial variations in both flame temperature and gas emissivity. The RF model was trained using multiple predictors simultaneously, allowing interactions among combustion composition, operating parameters, geometric characteristics, optical information, and spectral features to be captured without requiring explicit specification of all nonlinear interaction terms. This is particularly advantageous for combustion systems because the relationship between temperature, species concentration, radiation intensity, flame structure, and emissivity is highly nonlinear and cannot be adequately represented by simple linear relationships.

Model evaluation demonstrated excellent predictive performance. The multi-output RF achieved a coefficient of determination ((R^2)) of approximately 0.998 for flame temperatureand0.978 for effective gas emissivity**.** The flame-temperature result indicates that approximately 99.8% of the observed variance in flame temperature was explained by the model, while the emissivity model explained approximately 97.8% of the

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corresponding variance. The slightly lower performance for emissivity is physically reasonable because emissivity is affected by several interacting factors, including gas composition, temperature, optical path length, soot concentration, pressure, and wavelength-dependent absorption and emission characteristics. Nevertheless, the obtained (R^2) value demonstrates that the proposed model captured the dominant relationships governing effective emissivity with a high degree of accuracy.

The analytical comparison between the ML predictions, experimental measurements, and simplified physics-based calculations further established the advantage of the proposed approach. The physics-based formulation provided an important theoretical benchmark and retained the advantage of physical interpretability; however, noticeable deviations from the experimental measurements were observed under the investigated combustion conditions. In particular, simplified formulations tended to overestimate flame temperature and consequently influence the estimated RHT behaviour. These deviations demonstrate that simplified gray-gas or empirical correlations may not sufficiently represent the complex non-gray, heterogeneous, and soot-influenced conditions encountered in practical combustion systems.

The comparative analysis also demonstrates that machine learning should not necessarily be regarded as a replacement for fundamental heat-transfer theory. Rather, the results support a hybrid modelling philosophy in which established radiation physics provides the theoretical foundation while machine learning provides a computationally efficient means of representing complex nonlinear relationships that are difficult to formulate analytically. The experimental data provide the physical reference against which both approaches can be evaluated. Such an arrangement provides an effective pathway for developing predictive models that combine physical understanding, experimental evidence, and computational intelligence.

The analytical process also revealed an important distinction between the prediction of flame temperature and effective gas emissivity. Flame temperature exhibited the highest predictive accuracy, suggesting that the available operating, geometric, optical, and spectral variables provide strong information for determining the thermal state of the flame. Emissivity prediction, although also highly accurate, exhibited comparatively greater uncertainty because emissivity represents an integrated radiative property that is strongly influenced by gas species, soot, temperature distribution, optical thickness, and spectral characteristics. This finding reinforces the importance of incorporating spectral and optical information into future combustion-radiation prediction models.

The use of spectral radiation information was particularly important because gas radiation is inherently wavelength dependent. Treating the combustion gases as a purely gray medium can therefore introduce systematic errors when significant spectral variation exists. The inclusion of spectral features enables the ML model to implicitly learn relationships

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associated with wavelength-dependent emission and absorption behaviour. Consequently, the analytical framework provides a more flexible representation of practical combustion environments than approaches based solely on bulk temperature or gas composition.

Another important outcome of the analysis is the potential computational advantage of the developed surrogate model. Once the RF model has been trained and validated, prediction of flame temperature and effective emissivity can be performed without repeatedly solving the complete radiative-transfer problem. This characteristic makes the model potentially useful for applications requiring rapid predictions, including combustion optimization, furnace operation, process monitoring, adaptive control, digital-twin development, and intelligent energy-management systems. However, the computational advantage should be interpreted within the limits of the present dataset and operating conditions, and further validation is required before deployment in safety-critical industrial control applications.

The overall analytical findings demonstrated that ML can effectively represent complex combustion-radiation relationships when sufficient and representative experimental or high-fidelity simulation data are available. The high (R^2) values obtained for both response variables confirm the suitability of the multi-output RF for the investigated conditions. At the same time, the comparison with physics-based predictions demonstrates that model selection alone does not resolve the fundamental challenges associated with RHT. The quality, diversity, and physical representativeness of the input data remain critical determinants of predictive reliability.

In summary, the study establishes that an integrated data-driven framework incorporating combustion conditions, gas composition, flame geometry, image-derived features, and spectral radiation information can provide highly accurate predictions of flame temperature and effective gas emissivity. The results provide evidence that machine learning can serve as an effective complementary approach to conventional RHT modeling. The principal contribution is therefore not simply the application of RF regression, but the development of a multidimensional predictive framework in which experimentally measurable combustion and radiation features are used to approximate two strongly coupled thermal-radiative response variables.

5. Recommendations

Based on the analytical findings and identified limitations, the following recommendations are proposed.

1.**Adoption of hybrid physics–ML models:** Future studies should integrate radiative heat-transfer theory with ML techniques. Incorporating the RTE, energy conservation, gas properties, and other physical constraints into ML models could improve predictive accuracy, physical consistency, and generalization.

2.**Real-time combustion monitoring and control:** The high predictive performance of the RF model supports its potential integration into real-time combustion monitoring and

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control systems. Continuous prediction of flame temperature and gas emissivity could enable adaptive adjustment of fuel–air ratio, combustion staging, and other operating parameters to improve thermal efficiency and reduce radiative losses.

3.**Improved emissivity and spectral modelling:** Future research should place greater emphasis on accurate prediction of gas emissivity under non-gray conditions. Expanded spectral and optical measurements, particularly within the 1500–2000 nm range, should be incorporated alongside gas composition, soot concentration, temperature, pressure, and optical path length to improve model performance and physical interpretation.

4. Validation under diverse operating conditions: The proposed framework should be validated using independent datasets covering different burner geometries, fuel types, temperatures, pressures, equivalence ratios, soot concentrations, and transient operating conditions. Extension to alternative and low-carbon fuels such as hydrogen, ammonia, biofuels, and methane–hydrogen blends is also recommended to assess model generalization.

5.**Uncertainty and explainable ML:** Future investigations should incorporate uncertainty quantification and explainable AI techniques such as SHAP and feature-importance analysis. These methods would provide confidence estimates, identify the dominant variables influencing flame temperature and emissivity, and improve the reliability and interpretability of the model.

6. **Integration with furnace optimization and digital twins:** The developed ML model should be integrated with furnace-design optimization, digital-twin platforms, and intelligent decision-support systems. Such integration could enable real-time prediction, adaptive control, energy-efficiency optimization, abnormal-condition detection, and reduction of unnecessary radiative heat losses.

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Conflicts of Interest

The authors declare that they have no conflicting financial interests or personal relationships that could have appeared to influence the work reported inthis paper.

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