Artificial Neural Network and Response Surface Methodology-Based Analysis of Ammonia-biodiesel Dual-Fuel Combustion for Marine Applications

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As the global energy landscape shifts toward sustainability, optimizing **internal combustion (IC) engines** for **low-carbon and zero-carbon fuels** has become increasingly important. With the gradual phase-out of fossil fuels, alternative energy sources such as **ammonia, biodiesel, and hydrogen** are being explored to reduce emissions and improve efficiency. But Hydrogen has several challenges such as backfires, high laminar flame propagation (2.9 m/s), knocking, emissions and material constraints that have restricted the application of hydrogen energy in internal combustion (IC) engines, However, several research has been going on in this area. Among these, **ammonia emerges as a promising zero-carbon fuel**, but its practical application faces challenges due to **poor ignitability, slow flame speed, and high ignition temperature**, necessitating advanced combustion strategies. However, achieving pure ammonia compression ignition remains challenging due to its low ignitability, slow flame speed, unfavourable combustion characteristics, and high ignition temperature. Consequently, most modern research on ammonia as a fuel involves blending it with diesel or biodiesel, which serves as a supplementary ignition source. Additionally, ammonia has a higher hydrogen density and is relatively cost-effective to produce compared to other alternative fuels. We have performed an experimental study and calculated various parameters such as **Brake Thermal Efficiency (BTE), Brake Specific Fuel Consumption (BSFC), Cylinder Pressure (CP), Net Heat Release (NHR), and Emission Parameters**. All these parameters were optimized using **Artificial Neural Networks (ANNs) and Response Surface Methodology (RSM)** techniques. However Machine learning techniques, particularly **Artificial Neural Networks (ANNs)**, are increasingly being applied to **engine performance prediction and optimization**. These models help in **reducing experimental time and cost** while improving accuracy in calibration and control strategies. ANN-based models can capture **complex nonlinear relationships** between engine parameters and combustion characteristics, offering a reliable alternative to conventional empirical models. To address these challenges, **Response Surface Methodology (RSM)** has been widely used to **optimize injection parameters, and compression ratio (CR) and improve engine performance**. RSM helps in developing empirical models that **establish relationships between input variables and combustion responses**, thereby aiding in the calibration of ammonia-based dual-fuel engines for **higher efficiency and lower emissions**. Additionally, ammonia's **high hydrogen density and cost-effective production** make it a promising candidate for sustainable energy applications. **Response Surface Methodology (RSM)** is a statistical and mathematical approach used for **modelling, analyzing, and optimizing complex systems** where multiple interacting variables influence the outcome. Originally developed for industrial process optimization, RSM has found extensive applications in **combustion engine research**, particularly in improving **fuel injection strategies, performance optimization, and emissions reduction**.

In internal combustion (IC) engine studies, **RSM is used to develop empirical models that describe the relationship between key input parameters (such as injection timing, fuel ratio, and compression ratio) and performance indicators (such as Brake Thermal Efficiency (BTE), Brake Specific Energy Consumption (BSEC), and emission levels)**. This method enables researchers to **predict, refine, and optimize engine behaviour** without conducting a large number of costly and time-consuming experiments. The **RSM process** involves the following steps:

1. **Design of Experiments (DoE)** – A systematic approach is used to select key variables and their levels, ensuring that the experimental runs capture the full range of possible interactions.
2. **Developing a Regression Model** – Based on experimental data, RSM constructs a polynomial equation (usually quadratic) that describes the system's response to different input conditions.
3. **Optimization & Validation** – Using response surfaces, contour plots, and desirability functions, RSM identifies optimal conditions, which are then validated experimentally.

Ammonia, despite being a promising zero-carbon fuel, faces challenges such as **low ignitability, slow flame speed, and high ignition temperature**. To overcome these limitations, researchers use **biodiesel as a supplementary ignition source** and employ RSM to **optimize the injection parameters for efficient combustion**. RSM reduces the dependence on traditional trial-and-error methods by providing a **systematic and efficient approach to engine calibration and optimization**. When combined with **Artificial Neural Networks (ANNs)**, RSM further enhances prediction accuracy and enables the **development of advanced engine control strategies** for alternative fuels like ammonia. In this study, I developed an **Artificial Neural Network (ANN) model** to predict **Net Heat Release (NHR), and Critical Pressure** from combustion data. The workflow involved **data preprocessing, model development, hyperparameter tuning, and evaluation** to ensure accurate and reliable predictions. To enhance data quality, I performed **data cleaning**, which included:

- **Handling missing values** using imputation techniques or removing incomplete records.
- **Identifying and removing outliers** using statistical methods like the **IQR method** and **Z-score analysis**.
- **Standardizing the dataset** using **StandardScaler** to normalize feature values and improve model convergence. **Cross-validation & Model Optimization**

To **prevent overfitting** and improve model generalization, I implemented **cross-validation** during model training. I used:

- **K-Fold Cross-Validation (K=5 or 10)** to split the dataset into multiple training and validation subsets, ensuring the model performed well on unseen data.
- **Hyperparameter tuning** by adjusting the number of hidden layers, neurons, learning rate, and batch size for optimal performance.

ANN Model & Training

The final ANN architecture included multiple **dense layers** with **ReLU activation**, an **Adam optimizer**, and a **Mean Squared Error (MSE) loss function**. The model was trained using **early stopping** and **learning rate scheduling** to enhance efficiency.

Evaluation & Results

The trained model was evaluated using:

- **Mean Squared Error (MSE)** and **R^2 Score** to measure prediction accuracy.
- **Residual analysis** to assess model bias and variance.
- **Scatter plots of true vs. predicted values** to visualize model performance.

The approach successfully improved prediction accuracy, demonstrating the ANN model's potential in combustion data analysis.

The efficiency in **Random forest** is less than the **ANN** model That is **98%** in the Ann and **87%**