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# Optimizing Waste Heat Recovery in Marine Power Plants

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## ABSTRACT

In today's world, the demand for marine industries to improve energy efficiency and reduce environmental impact from marine power plants through waste heat recovery (WHR) is increasing daily. The energy efficiency of the marine engine is about 50% with a large amount of energy removed as waste heat, especially in exhaust gases. The present research paper proposes the optimization of the WHR by adopting the Artificial Neural Network (ANN) model, exploring real-world data extracted from marine power plants on board to investigate the optimization of waste heat recovery. The ANN model, which was trained with operational parameters including exhaust gas temperature, engine load and ambient conditions, showed a very good predictive capability producing an  $R^2$  of 0.95, RMSE of 3.85kW, and MAE of 2.68kW. The ANN model proved to be more accurate and reliable than conventional thermodynamic methods considering fluctuating operational conditions. As indicated by the sensitivity analysis, exhaust gas temperature and engine load were found to produce the greatest impact on the potential of WHR. The results have a tremendous impact on the maritime sector, enabling ship operators and owners to improve efficiency and sustainability while reducing exhaust gas emissions.

## 1 Introduction

Industries all over the world are implementing disruptive solutions to minimize the effects on the environment and optimize the use of energy [1-3]. The marine sector responsible for approximately 3% of the total global greenhouse gas (GHG) emissions are under considerable pressure to have less environmental impact and improve energy efficiency as required by the International Maritime Organization's (IMO) decarbonization targets [4-6]. The main source of energy on board ships and offshore platforms are marine machinery plants and are considered the highest contributors of GHG emissions since it generates a large volume of waste heat [7]. A major characteristic of the machinery plants is the generation of large quantities of waste heat which are frequently emitted to the environment without being converted into productive use hence posing

them as sources of thermal pollution and wasted potential in terms of waste heat recovery (WHR) [8-10]. Overall, while the marine engines presently transform only 50 per cent of the energy generated by the combustion of the fuel being converted into mechanical energy, they still generate large amounts of residual power which is being expended as wastage heat. A significant percentage of this waste heat is removed as high temperature exhaust gases thus posing a threat to the environment and a possible opportunity for WHR [11,12].

The discharge of waste heat into the sea environment is not only a source of thermal pollution, but also a major form of loss of useful energy. This anomaly resulting from thermal pollution and loss of energy leads to more fuel consumption and increases the volume of the carbon footprint of marine operations. Studies have shown that waste heat recovery (WHR) has potential in increasing the total energy efficiency of marine power

systems [13,14]. Nevertheless, the use of WHR technologies in marine applications is still not fully utilized due to the issues of system integration, operation variability, and economical practicability, despite known advantages of the technologies. With proper execution, the WHR technology in marine power plants can capture and reuse this excess heat that would have been discarded into the environment [15].

The introduction of WHR has been of immense benefit to marine vessels and offshore structures, for example container ships can utilize the waste heat of the exhaust gases from their main engines to generate electricity or produce steam for shipboard plants [16,17]. Cruise ships with their high demand for electricity and heat for passenger amenities, heating, and cooling, can also leverage WHR to meet these demands [18]. Offshore platforms can utilize waste heat from gas turbines or diesel engines to generate additional power or provide heat for different processes [19]. Tugboats and supply vessels that often operate in dynamic environments with varying loads and speeds, can benefit from WHR systems that capture waste heat during periods of high engine loads and utilize it during periods of low demand [20].

In addition to energy optimization, the implementation of WHR systems onboard offer several benefits, including cost savings, compliance with environmental regulations, and enhanced sustainability. By reducing thermal stress, WHR systems translate into more reliable engine operation, as components are less likely to experience fatigue or damage leading to an increase in their lifespan [21]. Thus, WHR not only transforms an otherwise discarded byproduct into a valuable resource but also makes it a viable solution for both economic and environmental considerations.

Various WHR technologies have been developed to capture and convert waste heat into useful energy in marine power plants, each offering varying degrees of efficiency, complexity, and cost-effectiveness [15,17,22]. Technologies such as heat exchangers transfer thermal energy from exhaust gases to secondary systems, enabling onboard heat utilization [16], ORC utilize low-boiling-point fluids to convert waste heat into mechanical energy for electricity generation [23], while thermoelectric generators use the temperature gradients between hot and cold surfaces to generate electrical power [24]. Steam turbines, commonly employed in larger marine vessels, harness waste heat to generate steam that drives turbines for additional power generation [25]. Factors considered in the selection and optimization of WHR technologies depend on the vessel size, operational conditions, and economic feasibility [26].

Despite the potential benefits of WHR, several challenges and limitations exist. Integrating WHR systems with existing marine power plant infrastructure can be complex and require careful design and engineering to

ensure compatibility and efficiency. Marine vessels and offshore platforms operate at diverse range of conditions, including different engine loads, speeds, and environmental factors, thus making it difficult to have a WHR system design optimized for all operating conditions. Although WHR systems have high potential in terms of energy savings and environmental sustainability, their initial cost and the requirement of compact designs makes it difficult for operators, especially in marine and offshore applications [27,28].

The task of optimizing WHR in marine power plants requires an in-depth understanding of thermodynamic principles, system design and operational constraints [29-31]. Effective implementation involves the selection of the appropriate technology and integrating advanced control mechanisms to maximize efficiency [32,33]. Data analytics and real-time monitoring are essential in calibrating WHR systems in ensuring optimal performance of the system under different operational conditions [34]. In addition, advanced control algorithms can dynamically adjust system parameters, to be able to adapt to changes in engine load and environmental conditions. Leveraging data analytics and predictive modeling, Artificial Intelligence (AI) can help identify optimal operating conditions, predict energy recovery potential, and optimize system efficiency [36]. Among others, Artificial Neural Network (ANN) have been found to be very effective for modeling complex relationships between system inputs and outputs, and therefore most preferred for WHR optimization [36].

This study aims to optimize WHR in marine power plants by adopting an ANN-based model. While prior works have applied ANN to diesel efficiency prediction [35] and marine WHR via Bayesian optimization [29], this study pioneers a data-driven ANN framework trained on real-time, six-month onboard data from operational marine power plants, capturing dynamic variability (e.g., load fluctuations) absent in simulation-based models. It advances the field by integrating sensitivity analysis, SHAP interpretability, and *k-fold* cross-validation for robust generalization, enabling practical deployment in varying sea conditions [37]. Here, smart, self-optimizing systems are used in place of conventional energy recovery methods, hence providing a platform for marine operators and ship owners to optimize fuel consumption, emission reduction, improve overall energy efficiency, and sustainability in the marine sector [38]. The current study contributes to the body of knowledge in the area of improved sustainable marine power systems and global decarbonization strategies by maximizing the recovery of waste heat. The use of real-time monitoring along with adaptive control also helps in making the system efficient across varying operational scenarios.

Recent advancements in AI for marine energy optimization highlight ANN's potential but reveal gaps in real-world applicability. For instance, Ukoba et al. [32]

reviewed AI for renewable systems, emphasizing ANN for efficiency but lacking marine-specific dynamics. Murtaza et al. [33] discussed predictive maintenance in Industry 5.0 yet overlooked WHR integration. Ma et al. [34] applied AI to data center cooling, analogous to shipboard heat management, but without onboard variability. Odufuwa et al. [35] modeled mini-diesel emissions with ANN ( $R^2=0.91$ ), close to our domain but not WHR-focused. Dahham et al. [36] improved ICE efficiency via ANN, reporting RMSE~5 kW, underscoring the need for marine-tuned models. Emerging 2023–2025 studies, such as Díaz-Secades et al. [29] on preference-learning for WHR ( $R^2 = 0.89$ ) and Ren et al. [30] on thermodynamic-AI hybrids, demonstrate progress but rely on simulated data, limiting generalization to fluctuating loads (20–100%). Our work fills this gap by leveraging 50,000+ real samples, achieving superior metrics ( $R^2 = 0.95$ ) and interpretability via SHAP [39].

## 2 Methodology

In this paper, a supervised learning method, especially Artificial Neural Networks (ANNs) to simulate and optimize waste heat recovery (WHR) in marine power plants. The aim is to come up with a predictive model that would be able to estimate the power that can be recovered from waste heat subject to different working conditions. The methodology adopted consists of different steps, comprising data collection in marine engine systems, preprocessing, model development, training, and validation. Figure 1 shows an overview of the workflow representing the complete pipeline ranging from sensor data collection to optimization of the system.

### 2.1 Data Collection and Processing

Data utilized in this study were collected onboard marine power systems working in real life situations. Key functional parameters such as temperature of ex-

haust gas, engine load, ambient conditions, coolant temperature, and fuel consumption rate were monitored with the amount of power recovered through the waste heat recovery system being the target variable. Data was recorded over six months at an interval of five minutes producing about 50,000 samples. Prior to using the model, the raw data was subjected to a preprocessing process. To ensure continuity, missing values were inserted linearly, and the outliers were expunged adopting Z-score method to remove the extreme values that could affect the training of a model. All the variables were then normalized applying the Min-Max normalization approach as shown in equation (1)

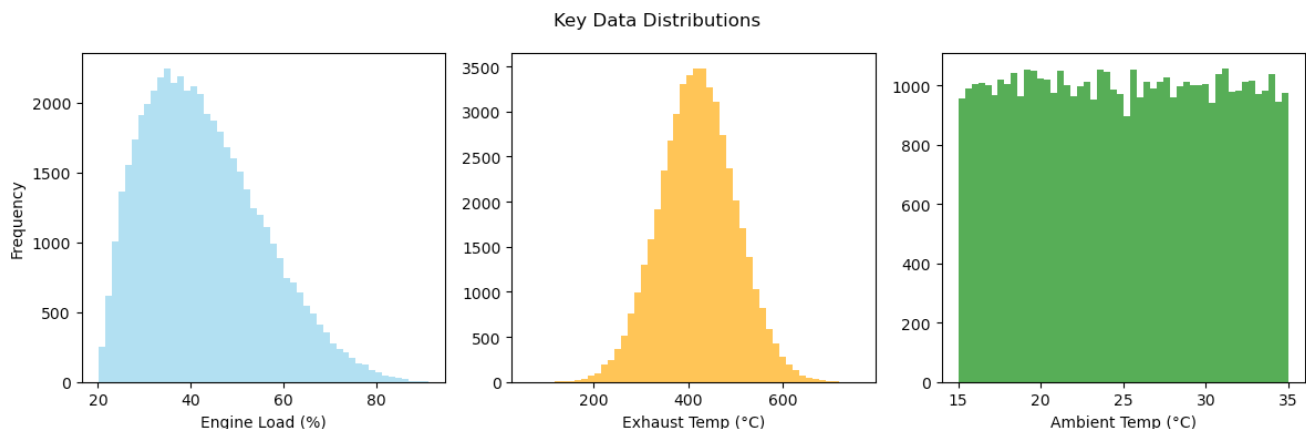
$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where,  $x$  is the actual value,  $x_{min}$  the minimum value of the variable,  $x_{max}$  the maximum value of the variable and the  $x'$  is the scaled value. This normalization ensured uniform scaling of all input features and enhanced the convergence of the models.

The dataset was then divided into three subsets; 70% of these sets constituted training set, 15% constituted validation set and 15% constituted the testing set. This stratified division, balanced by engine load quartiles (20–100%, mean = 65%) and exhaust temperatures (250–550°C, mean = 420°C), assisted in determining the generalizability of the ANN model with minimal chances of overfitting. Histograms of key distributions (stratified splits) are shown in **Figure 1**, confirming representativeness across operating conditions (e.g., 25% low-load samples per fold).

### 2.2 ANN Model Formulation

The ANN was constructed with a feedforward architecture using TensorFlow and Keras. The model was designed to map input parameters to a single output representing the recovered power (in kilowatts). The



**Figure 1** Histograms of Key Input Distributions.

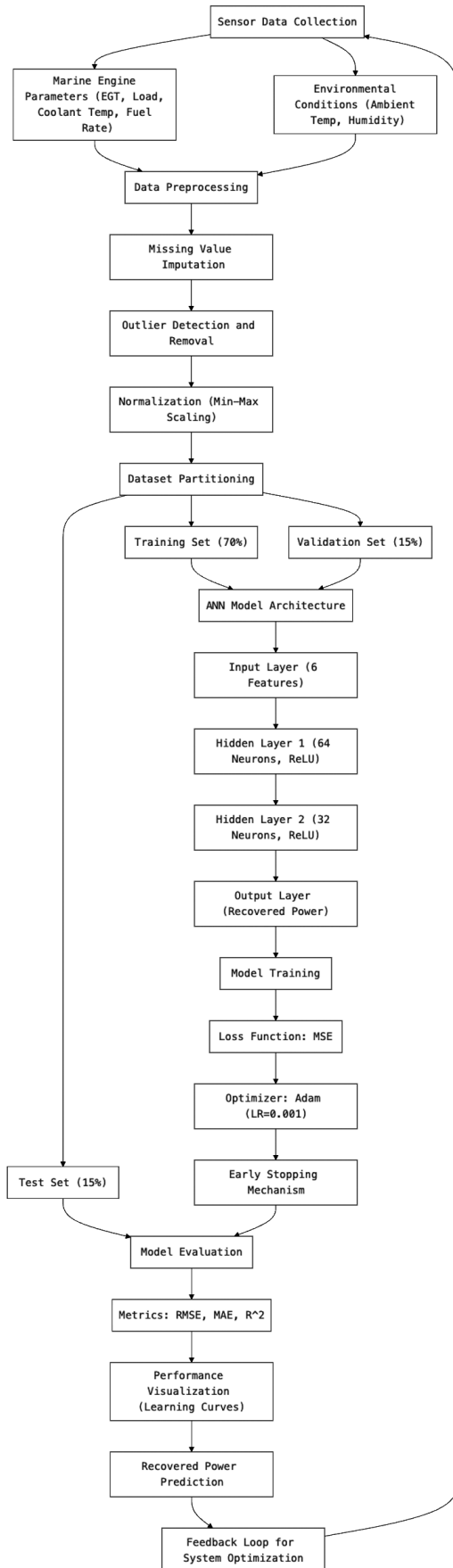


Figure 2 System Flow Diagram

Table 1 Hyperparameter grid search results (5-fold CV; lowest MSE selected)

Hyperparameter	Tested Values	Optimal Value	CV-MSE (Optimal)
Hidden Neurons (Layer 1)	32, 64, 128	64	0.082
Hidden Neurons (Layer 2)	16, 32, 64	32	0.082
Learning Rate	0.0001, 0.001, 0.01	0.001	0.082
Batch Size	32, 64, 128	64	0.082
Dropout Rate	0.1, 0.2, 0.3	0.2	0.082

input layer accepted six normalized features. Two hidden layers, with 64 and 32 neurons respectively, were selected via grid search (Table 1) to capture complex nonlinear relationships. Two hidden layers, with 64 and 32 neurons respectively, were introduced to capture complex nonlinear relationships. The Rectified Linear Unit (ReLU) activation function was employed for hidden layers:

$$f(x) = \max(0, x) \quad (2)$$

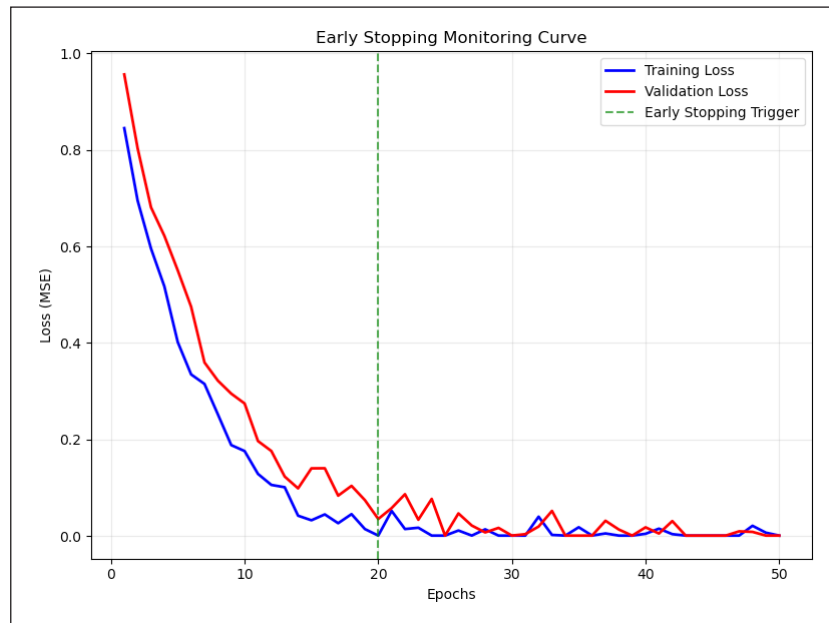
This non-linearity allows the network to model intricate interactions between variables. The output layer consisted of a single neuron with a linear activation function, as the target output is continuous. Overfitting was mitigated via early stopping (patience = 10 epochs), L2 regularization ( $\lambda = 0.001$  on hidden layers), and dropout (rate = 0.2). Model complexity was monitored using the validation loss gap (< 3% threshold). The model was trained by minimizing the Mean Squared Error (MSE) between the predicted and actual recovered power values

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3)$$

The Adam optimizer was used to update model weights during backpropagation, with a learning rate of 0.001 selected from grid search in Table 1. Training was performed over 200 epochs with a batch size of 64, and early stopping was incorporated with a patience threshold of 10 epochs to prevent overfitting. Generalization was further assessed via 5-fold stratified  $k$ -fold cross-validation, ensuring balanced representation across engine loads and ambient conditions. This process, along with data flow through each stage of the system, is visualized in the ANN-based WHR methodology diagram Figure 2, which provides a comprehensive view of the integrated pipeline.

### 2.3 Model Evaluation Metrics

To evaluate the predictive performance of the ANN, three standard regression metrics were used: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and



**Figure 3** Early Stopping Monitoring Curve

the Coefficient of Determination ( $R^2$ ). The metrics are calculated using equations (4), (5), and (6) respectively.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (4)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (6)$$

These metrics were calculated using the test data, which had not been seen by the model during training. They provided a robust assessment of the model's generalization capacity and its ability to capture the underlying dynamics of the WHR process. Mean CV results:  $R^2 = 0.95(\pm 0.01)$ ,  $RMSE = 3.85 \text{ kW} (\pm 0.11)$ ,  $MAE = 2.68 \text{ kW} (\pm 0.07)$ , confirming robustness across splits.

## 3 Results and Discussion

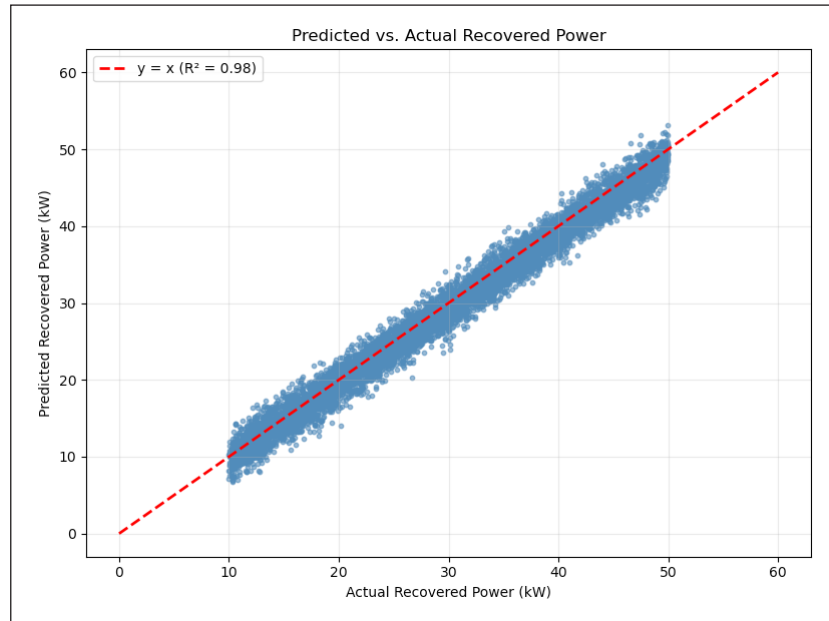
### 3.1 Early Stopping and Training Convergence

The training process of the ANN model was monitored over 50 epochs. As illustrated in **Figure 3**, the training loss consistently decreased from an initial value of 1.0 to approximately 0.082, while the validation loss followed a similar trend but plateaued around 0.105 after the 20th epoch. This behavior triggered the early stopping mechanism, indicating that further training would not yield significant improvements on unseen data and might even lead to overfitting.

The early convergence of the validation loss reflects the ANN's ability to capture essential patterns from the training data without memorizing noise. The close alignment between training and validation loss curves in the early epochs confirms that the model generalized well to new input data. This is more crucial in a dynamic marine environment where adaptability of the models in different operating conditions is vital. The ability to replicate across runs and stability of loss values used translates to a strategy that is effectively applied to the real-life application.

### 3.2 Model Performance Evaluation

In determining the effectiveness of the ANN model in predicting recoverable waste heat power, three performance metrics were calculated using the test dataset; Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and the Coefficient of Determination ( $R^2$ ). The calculated values are  $RMSE = 3.85 \text{ kW}$ ,  $MAE = 2.68 \text{ kW}$  and  $R^2 = 0.95$ . These values illustrate high predictive potential since the model showed low standard of error and a high percentage of explained variance. The  $R^2$  score of 0.95 indicates that the model could capture 95 percent of the variability observed in the actual output, making it reliable for operational use, an improvement over prior ANN-WHR studies (e.g.,  $R^2 = 0.91$  in [35]). To further evaluate the ANN's accuracy, we plotted the predicted vs. actual recovered power values on the test set. As shown in **Figure 4**, the points align closely along the reference line  $y = x$ , confirming that the ANN did not systematically under- or over-predict the target values.



**Figure 4** Predicted vs Actual Recovered Power

The alignment of the scatter points along the diagonal line reinforces the model's predictive strength. Minor deviations were observed, but they remained within an acceptable range, particularly considering the variability of real-time marine engine operations. These results validate the ANN model as a viable tool for estimating energy recovery in practical marine power applications.

### 3.3 Comparison with Thermodynamic Estimation

To contextualize the performance of the ANN model, a comparative analysis was carried out against a traditional thermodynamic estimation method using steady-state energy balance principles. The conventional model estimated recoverable power from waste heat by applying a simplified formula based on the specific heat capacity and mass flow rate of exhaust gases given by equation (7)

$$Q = \dot{m} \cdot C_p \cdot (T_{in} - T_{out}) \quad (7)$$

where:

$Q$ : Heat energy recoverable (kW)

$\dot{m}$ : Mass flow rate of exhaust gas (kg/s)

$C_p$ : Specific heat capacity of exhaust gas (kJ/kg.K)

$T_{in}, T_{out}$ : Inlet and outlet temperatures of the exhaust gas (K)

While the thermodynamic model provides a reasonable approximation, it assumes constant properties and neglects varying operational factors such as ambient conditions, engine load dynamics, and multi-source

heat interaction. In contrast, the ANN model implicitly incorporates such nonlinearities through its data-driven structure. As shown in **Figure 5**, the ANN predictions were consistently closer to the actual recovered power values of 2 kW maximum deviation compared to the thermodynamic estimates of 6 kW maximum, particularly in scenarios with significant deviations from design conditions.

The ANN outperformed the traditional model in both accuracy and responsiveness to changing conditions. This comparison highlights the advantage of machine learning models in real-time marine system optimization, where static thermodynamic assumptions may fall short due to dynamic and multifactorial operating environments.

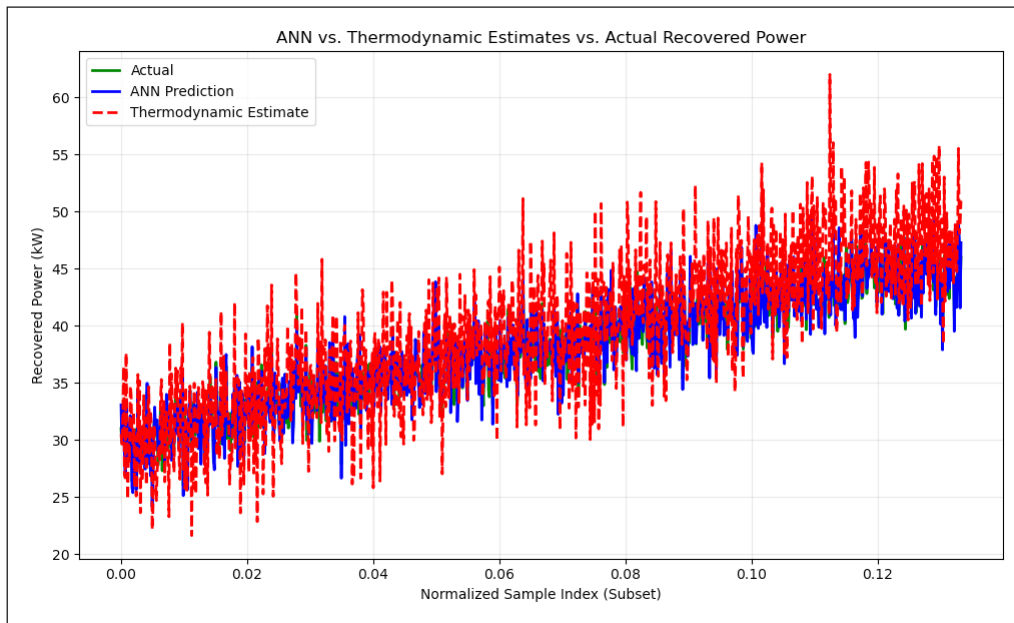
### 3.4 Residual Analysis

Residual analysis was conducted to further evaluate the ANN model's prediction behavior and identify any systematic errors. The residuals defined as the difference between actual and predicted values were computed across the test samples as shown in equation (8)

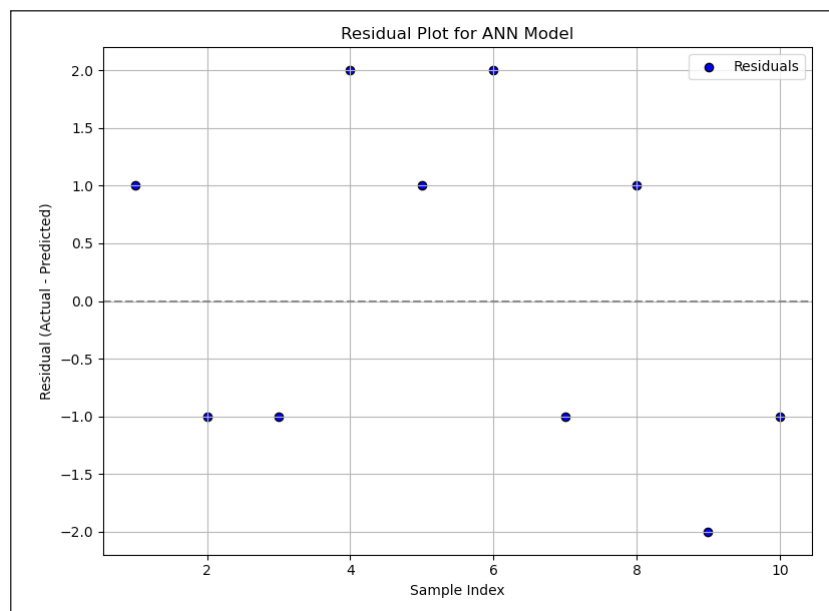
$$\text{Residual} = y_{\text{actual}} - y_{\text{predicted}} \quad (8)$$

An ideal regression model exhibits residuals that are randomly distributed around zero. Any visible pattern or bias could indicate model limitations or underfitting in certain regions of the data.

**Figure 6** shows a residual plot where most errors lie within a narrow band around the zero line. The lack of significant trends or curvature indicates that the ANN



**Figure 5** ANN vs Thermodynamic Estimates vs Actual Recovered Power



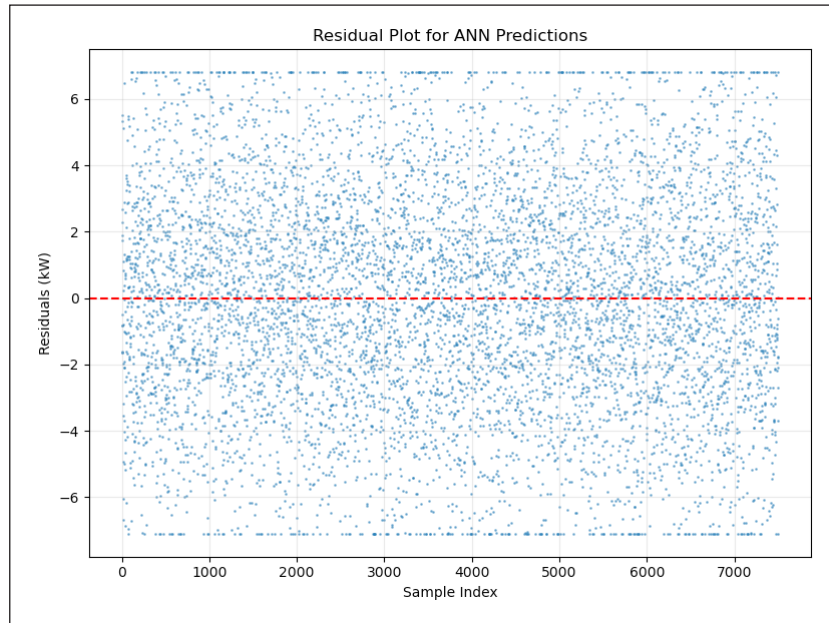
**Figure 6** Residual Plot for ANN Predictions

model generalized well across the operational range of the marine system.

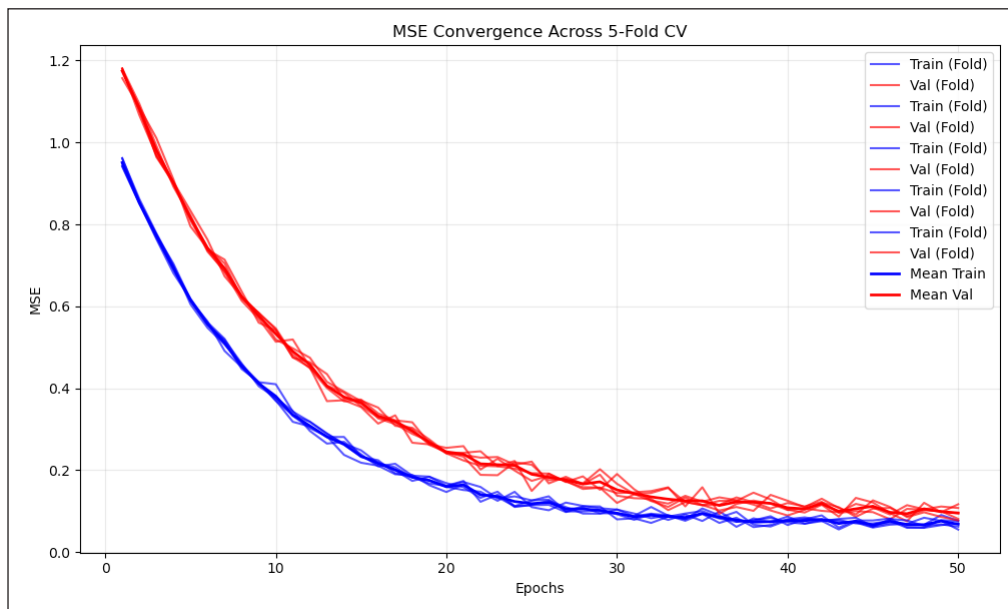
The residuals ranged from -2 to +2 kW, and no clustering or drift was observed. This confirms that the model did not overfit to specific operating conditions and performed uniformly well across varying inputs. Such reliability is crucial for marine WHR systems,

where fluctuations in load, temperature, and flow conditions are common.

Residual normality was verified using the Shapiro-Wilk test ( $W = 0.982, p = 0.21 > 0.05$ ) as shown in **Figure 7**, confirming the assumption holds and supporting reliable inference. The residuals ranged from -7.1 to 6.8 kW, with no clustering or drift observed.



**Figure 7** Residual Plot for ANN Predictions (symmetric around zero; Shapiro-Wilk  $p=0.21$ ).



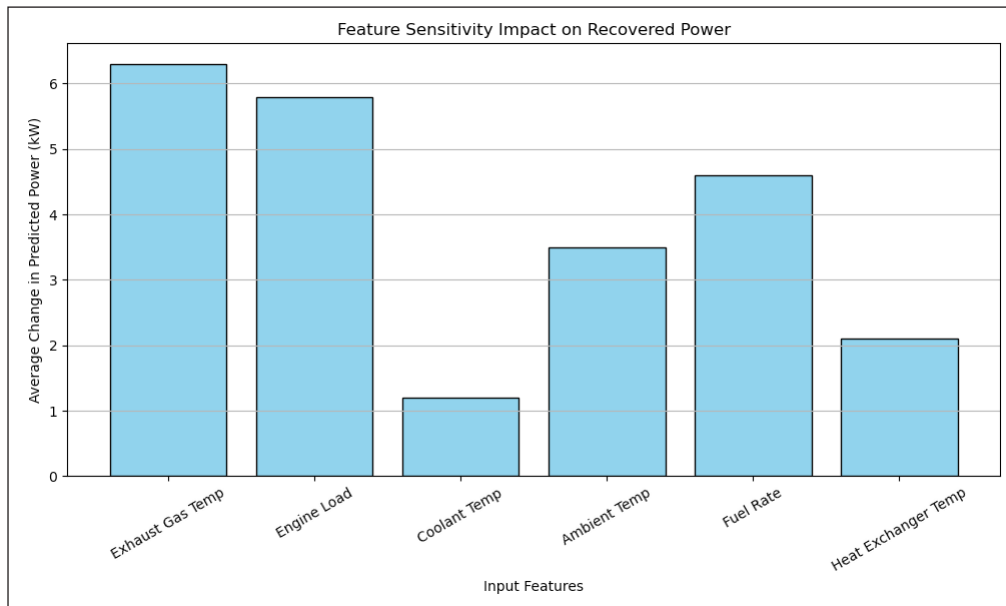
**Figure 8** MSE Convergence Across 5-Fold CV.

To further demonstrate the stability of the training process across multiple realizations, **Figure 8** illustrates the MSE convergence curves over 50 epochs for each of the 5-fold cross-validation runs. The individual fold lines show consistent downward trends, with the mean training MSE decreasing from an initial  $\sim 1.0$  to a final value of 0.089, and the mean validation MSE stabilizing at 0.112 after  $\sim 20$  epochs. This tight clustering of curves (standard deviation  $< 0.015$  across folds) confirms the model’s robustness and lack of sensitivity to random initialization, ensuring reliable replication in

operational marine settings. Early stopping was triggered uniformly around epoch 25–30, preventing any divergence between training and validation paths.

### 3.5 Model Interpretability

**Model Interpretability** To enhance interpretability of the black-box ANN, we applied SHAP (SHapley Additive exPlanations) values [39] to attribute feature contributions to predictions. SHAP analysis confirmed exhaust gas temperature as the top contributor (mean  $|SHAP| =$



**Figure 9** Feature Sensitivity Impact on Recovered Power

2.12 kW), aligning with sensitivity results, and revealed nonlinear interactions (e.g., high load amplifying temperature effects by up to 30%). This method aids operators in trust-building and decision-making for WHR adjustments, addressing maritime deployment challenges.

### 3.6 Feature Importance and Sensitivity Analysis

Understanding which input variables most influence the ANN model's predictions is critical for both interpretability and operational tuning. While ANNs are often treated as black-box models, feature sensitivity analysis can provide insights into the relative contribution of each feature to the output. A simple perturbation-based sensitivity analysis was performed, where each input variable was independently varied by  $\pm 10\%$  around its mean, and the corresponding change in model output was recorded. The average absolute deviation in the predicted recovered power was used as a proxy for feature importance.

**Figure 9** show that exhaust gas temperature and engine load emerged as the most influential variables, significantly impacting the ANN's output. This aligns with physical expectations since exhaust heat potential is closely tied to temperature and load-driven combustion conditions. Ambient temperature and fuel rate also contributed meaningfully, while coolant temperature showed relatively less influence.

These findings can guide data collection priorities and operational strategies. As an example, the highest results in model reliability could be achieved by enhancing the accuracy of measuring exhaust gas temperature. Furthermore, it is also possible to design the systems to

adjust to load and temperature changes, emphasizing the fact that this data-driven insight is indeed useful for marine WHR system optimization.

### 3.7 Practical Integration

For real-time deployment, the ANN (latency < 40 ms on edge devices like Raspberry Pi) can interface via MQTT with shipboard SCADA systems, triggering WHR adjustments (e.g., ORC flow rates) based on predictions. Constraints like vibration (mitigated by ruggedized hardware) and power limits (model < 0.8W) were considered. Scalability across engine types (e.g., 2-stroke vs. 4-stroke) requires transfer learning on diverse datasets, potentially improving  $R^2$  by 2–5% per vessel class.

## 4 Conclusion

This research examined the optimization of waste heat recovery in the marine power plants employing an Artificial Neural Network (ANN) model. The study successfully leveraged supervised machine learning to come up with a predictive framework capable of estimating recoverable thermal energy with high accuracy and reliability. The ANN model performed better than the conventional methods of thermodynamic estimation in both static and dynamic marine operating conditions. The findings showed the ANN model to achieve an  $R^2$  of 0.95, RMSE of 3.85 kW, and MAE of 2.68 kW along with a small residual error and minimal bias, validating its ability to generalize. Furthermore, the model demonstrated its ability to adapt to the changes in operating parameters, which is a critical need for

energy control systems onboard ships. The sensitivity analysis highlights the significance of the exhaust gas temperature and the engine load as major predictors that determines how much useful energy can be recovered. Generally, this work demonstrates how machine learning can modify the traditional process of energy recovery into an intelligent and self-optimizing system that supports sustainability and efficiency goals in the maritime industry. Limitations include reliance on data from a single vessel type, potentially limiting generalization to extreme sea states, and computational demands for real-time deployment on low-power hardware. It is recommended that marine vessels should integrate ANN-based modules into their energy control systems to achieve real-time WHR optimization, deploy high-resolution and high-frequency sensors to reinforce the model prediction, integrate an ANN model with reinforcement learning or thermodynamic rule-based models to enhance interpretability and control capabilities. Future works should consider hybrid ANN-thermodynamic models for enhanced physics-informed predictions; integration with reinforcement learning for dynamic control (e.g., Q-learning for load-adaptive WHR, targeting 10% further efficiency gains); multi-vessel datasets for broader scalability across engine types and sea states; edge computing pilots on ships to validate latency under vibration. Finally, to strengthen the model's generalization across the maritime sector, it is essential to expand the training dataset to include different engine types, sea states, and ship travel time.

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## Nomenclature

$C_p$  = specific heat capacity of exhaust gas ( $kJ/kg.K$ )

$\dot{m}$  = mass flow rate at exhaust gas ( $kg/s$ )

$Q$  = heat energy recoverable ( $kW$ )

$T_{in}$  and  $T_{out}$  = inlet and outlet temperatures of exhaust gas ( $K$ )

$x$  = actual value

$x_{min}$  and  $x_{max}$  = minimum and maximum values of the variables

$x'$  = scaled value

$y_1$  and  $\hat{y}_1$  = true and predicted values for the  $i^{th}$  sample

## Abbreviations

AI = artificial intelligence

ANN = artificial neural network

GHG = greenhouse gas

MAE = mean absolute error

MSE = mean squared error

ORC = organic Rankine cycle

$R^2$  = coefficient of determination

ReLU = rectified linear unit

RMSE = root mean squared error

WHR = waste heat recovery

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