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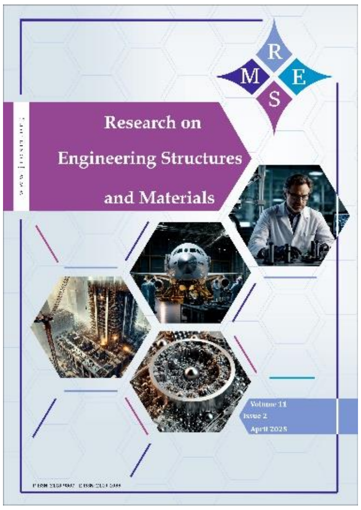

Prediction and performance enhancement of R600a refrigerator adopting machine learning algorithms

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Research Article

Prediction and performance enhancement of R600a refrigerator adopting machine learning algorithms

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Abstract

Enhancing the energy efficiency of domestic refrigeration systems is vital due to their significant role in global electricity consumption. The low environmental impact of R600a makes it stand out among eco-friendly refrigerants. Recent developments in hybrid nanomaterials and nano lubricants potential to enhance system performance. The machine learning (ML) algorithms are emerging as effective tools for accurate, data-driven predictions in complex thermodynamic systems. The present research employs machine learning techniques to estimate the performance of a vapor compression refrigeration system based on the R600a and enhanced with CuO/SiO_2 hybrid nano lubricants. Experimental data were collected under various operating conditions, including different nano lubricant concentrations (0–0.6 g/L) and refrigerant mass charges (50–70 g). Three ML models—Linear Regression, Artificial Neural Network (ANN), and Support Vector Machine (SVM) were developed. The dataset was partitioned into 70% training, 15% validation and 15% testing sets. Models were evaluated using performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE) and the coefficient of determination (R^2). The Quadratic SVM model demonstrated the highest prediction accuracy with an R^2 of 0.970196 and a low MAE of 0.055486, outperforming both ANN and Linear Regression models. The study confirms that integrating hybrid nano lubricants with intelligent ML models significantly enhances the Coefficient of Performance (COP) prediction capability and provides a reliable approach for optimizing energy efficiency in refrigeration systems.

1. Introduction

Energy conservation is essential in vapor compression refrigeration systems, especially with their extensive use in commercial, residential, and industrial applications. Improving energy efficiency leads to better cooling performance, enhanced system operation and lower energy consumption. The refrigeration sector is responsible for 20% of global energy consumption [1] with traditional refrigeration systems consuming more energy. HCFC and HFC systems, known for their higher global warming potential and energy demands are being replaced by HC refrigerants that consume less energy and have a smaller global warming impact. The energy conservation problems identified in conventional systems are clarified by the subsequent studies which contributes for a energy efficient system. The study involved dispersing SiO_2 nanoparticles in four refrigerants, with the R1234ze/SiO_2 mixture resulting in a 59.58 kW reduction in energy consumption and a significant increase in COP [2]. Incorporating TiO_2 at a 0.1% mass fraction into the HFC134a/POE system resulted in the lowest recorded energy consumption, reducing it by 26.1% [3]. POE oil mixed with CuO and MWCNTs at volume ratios of 0.5%, 1% and 2% was theoretically analyzed with R152a and R134a refrigerants. The R152a nano refrigerant containing MWCNTs

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demonstrated a COP enhancement of 27.63% over standard R152a [4]. Compared to R290+1234yf, the R290+R600 nano refrigerant achieved the highest COP increase of 15.41% when CuO nanoparticles were used, with the evaporator temperature maintained at -5°C [5]. According to past research, adding various nano refrigerants to a vapor compression refrigeration system can improve thermal conductivity. However, if nanoparticle concentration is too high, it may increase viscosity, causing greater compressor work and a decrease in COP. Additionally, challenges like agglomeration and stability of nanoparticles may impact the system's long-term performance, potentially reducing refrigerator efficiency. No notable increase in COP or refrigeration effect is observed with reduced compressor energy consumption [6]. The incorporation of nanoparticles into traditional refrigeration lubricants to create nano lubricants has proven to be an effective strategy for enhancing the performance and energy efficiency of Vapor Compression Refrigeration (VCR) systems.

This advancement not only improves lubrication but also leads to lower energy consumption and a longer lifespan for essential system components [7].The nano lubricant prepared by dispersing graphene at 0.2 g/L concentration resulted in a peak COP of 3.2.The system's efficiency improved due to lower power consumption and higher cooling capacity [8].It is evident that replacing conventional POE oil with TiO_2-based nano lubricant boosts the refrigerating effect, lowers compressor power consumption by 27%, and increases system COP by about 29%.[9].Integrating graphene nano lubricant with R600a led to a higher COP, as it improved cooling capacity by 5.2% to 14.2% and decreased energy usage by 8.8% to 26.4% [10].

When 50 g of R600a was blended through 0.4 g/L of multi-walled CNTs nano lubricant, energy consumption dropped between 25.9% and 13.7% for R600a quantities ranging from 50 g to 70 g, in contrast to a system with clean lubricant. Moreover, the COP of the MWCNT system improved from 2.1 to 2.9 compared to a conventional refrigerator [11]. The use of TiO_2 in an R600a refrigerator yielded the highest COP of 2.8, whereas the R134a system reached a maximum of 1.9. Additional experiments with Al_2O_3 and SiO_2 produced COP values of 2.4 and 2.7, respectively. Among all variations, the TiO_2-enhanced system exhibited the lowest energy consumption, cutting it by 23.3% compared to other combinations and the R134a system [12]. The combination of 0.2 g/L of graphene and 50 g of LPG resulted in the highest COP of 3.4. It also reduced compressor power consumption to 82.1 kJ/kg and enhanced the cooling effect by 279.1 kJ/kg, outperforming other nano lubricant mixtures and refrigerants [13]. Using nano lubricants with 0.5% diamond nanoparticles enhanced the R32 refrigerator cooling capability by 2.4%. In addition, nano lubricants with 0.1% and 0.5% diamond mass fractions produced the highest COP elevation of 2.6% and 3.2% [14].A COP of 2.76 and a 27.36% decrease in power usage were noted when 200 g of R134 refrigerant was combined with 500 ppm of amine-treated graphene quantum dots in a polyalkylene glycol-based nanosuspension [15].The coefficient of performance in the R134a refrigerator improved by 28.4% through the use of a polyol ester oil-based nano lubricant containing 0.1 vol% multiwalled carbon nanotubes. [16]. A 4% rise in COP was observed for the 0.1% diamond mass concentration, and an 8% increase was noted when using 0.5% [17].The system's energy consumption was lowest at 62.80 W when using 60g of R600a refrigerant with 0.2 g/L of TiO2, while the highest COP value of 4.20 was achieved with the same 60g R600a charge and 0.2 g/L concentration of nano lubricant [18].

In ice cream production unit ammonia cascade system was used and the COP value resulted by this system was lower than single stage ammonia system [19]. Machine learning models can estimate COP, power consumption, refrigerant flow rate and cooling capacity under various operating conditions. By replacing intricate thermodynamic equations, these models enable real-time optimization with minimal computational effort. The R290 refrigerant performed better by attaining a 23.77% higher COP, but the R600a refrigerant reduced compressor power utilization by an average of 33.44%. Additionally, R290 provided an 82.55% increase in cooling capacity and an increase in second-law efficiency of 20.99% over R600a. SVM method resulted in highest accuracy by predicting all parameters with the least error. It outperformed other machine learning techniques in forecasting performance indicators, making it the most effective prediction model [20]. CPSO-TSA model resulted in 84.4% accuracy during training and achieved strong performance with a low MAE of 0.16. It further exhibited reliable results with an RMSE of 0.39 and a kappa statistic of 0.69 [21].

A data-driven approach that harnesses modern deep learning methods to construct component models while upholding physical conservation constraints in system simulations are explored. [22]. The control parameters using PI and PID leads to enhance the energy efficiency ratio (EER) in refrigeration systems. EER increased by 21% to 32% with the PI and PID models, and by 28% with the factory-set PI control. [23]. The evaluation of the SLFN model is conducted on actual experimental data and compared with models trained with radial basis function neural networks (RBF), support vector regression (SVR), and back propagation (BP). The findings indicate that in regard to prediction accuracy and durability to input errors, the SLFN model performs best [24]. The latest theories and applications of computational intelligence (CI) techniques in the optimization of refrigeration systems are explored. Genetic algorithms (GA) and their variations are particularly prevalent, especially in multi-objective optimization and the use of CI methods in refrigeration system optimization has significantly increased [25]. In industrial vapor compression refrigeration systems, a new technique for identifying refrigerant leaks has been presented. Two feature sets are used to assess the performance of several regression models in order to identify the most successful one, utilizing certain metrics and a model comparison technique [26]. The ANN model estimated the mass flow rate with an average error of 0.79% when trained using both steady-state and transient datasets. Only steady-state data were used to train the model, which led to a little greater inaccuracy of 0.81%. It was found that the average prediction error of the embedded system was 1.22% [27].

The ANN model developed to estimate performance indicators such as power consumption, refrigeration effect and COP utilizes feedback-backpropagation and the Levenberg-Marquardt training algorithm. With an R^2 value of 0.989, the model showed a strong correlation with a multiple regression model, highlighting that ANN provides a more accurate method than MRA for predicting the performance of home refrigeration systems [28].

In smaller refrigeration system the ANN model has been applied. With a power consumption error of 0.05 and negligible relative errors for cooling capacity and coefficient of performance, the models were evaluated using cross-validation. The results revealed that R450A consumed approximately 10% less electricity compared to R134a and R513A [29].

The application of machine learning (ML) in vapor compression refrigeration systems has introduced advanced methods for performance prediction and optimization. By processing real-time data, ML models can predict significant parameters including COP, energy usage and cooling efficiency under dynamic operating conditions. Adding CuO/SiO_2 hybrid nano lubricants to an R600a refrigeration system improves the system's thermal properties. The optimized nano lubricants combination facilitates higher COP and reduced energy consumption. Applying and comparing multiple ML models (SVM, ANN, Linear Regression) under real experimental conditions. A novel finding is the superiority of Quadratic SVM, which achieved the lowest Mean Absolute Error and highest R^2 among all models.

2. Experimental Setup and Methodology

The system comprises a compressor, an expansion valve, an evaporator and a condenser. The actual setup of the R600a refrigeration system used for the experiment is shown in [Fig. 1]. Hermetic compressor capacity of 100 W compatible with R600a and air-cooled finned type condenser are employed in this test rig. In 50 L evaporator copper pipes are wounded as coil and kept in stainless steel tank insulated with polyurethane foam. Capillary tubes of diameters ranging from 0.50 to 0.80 mm and length 0.6 to 0.9 m are used as expansion devices. Dial type two pressure gauges are used one is for suction and another for discharge ranges from 0 to 250 Kg/cm^2. Over load and over current protectors are fixed for safety control in compressors. RTD PT100 type digital temperature sensors are used. The panel comprises of voltmeter, ammeter and wattmeter. It is also provided with drier and shut off valve. A single phase 220V- AC power supply is used for operation.

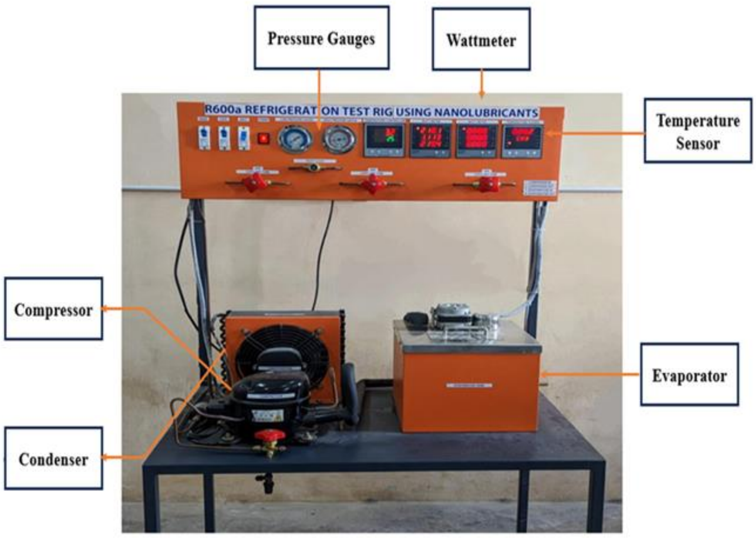

Fig. 1. Experimental setup

The experimental setup, data collection, feature engineering, model training, assessment and comparison of machine learning techniques are discussed in this section. Hybrid nano lubricants consisting of CuO and SiO_2 nanoparticles were prepared in specific concentrations (0–0.6 g/L) and mixed with standard lubricant. Experiments were conducted under controlled ambient temperatures (29–35 °C) with varied refrigerant mass charges (50–70 g). During each test enthalpy values at key points (compressor inlet/outlet, evaporator inlet/outlet) were recorded. The subsequent equations were used to assess the refrigerator's performance. To estimate the cooling capacity of the R600a refrigerator,

$$Qevap = \dot{m}(h4 - h1) \tag{1}$$

Where, Qevap— Cooling capacity of evaporator, expressed in kW; ṁ — R600a mass flow rate, in kg/s

h1— Compressor inlet enthalpy value; h4— Evaporator outlet enthalpy value; The compressor's energy consumption is indicated by;

$$WC = \dot{m}(h_2 - h_1) \tag{2}$$

Where, Wc-Input power of the compressor in kW; ṁ-R600a mass flow rate, in kg/s; h_1- Compressor inlet enthalpy value; h_2-Compressor outlet enthalpy value. The R600a COP is estimated by;

$$COP = \frac{Q_{evap}}{wc} \tag{3}$$

Equation (1) is used to determine the initial cooling capacity of the refrigerator, as well as the refrigerant mass flow rate and enthalpy values at the compressor inlet and evaporator outlet. The compressor work is then derived using experimental enthalpy data at the compressor inlet and outlet, in combination with the refrigerant mass flow rate. Finally, Eqs. (2) and (3) are employed to calculate the COP.

2.1 Nanoparticle Dispersion Method

The hybrid nano lubricants (CuO/SiO_2) were prepared by dispersing the required mass of each nanoparticle into a base mineral oil using an ultrasonic bath (40 kHz, 100 W) for 60 minutes to ensure uniform distribution and prevent agglomeration. A small amount of surfactant (Span-80, 0.05% by volume) was added to improve colloidal stability without affecting thermophysical properties.

2.2 Concentration Measurement and Stability

The concentration of nanolubricants (0.0 to 0.6 g/L) was controlled by accurately weighing the nanoparticles using an analytical balance with 0.0001 g precision and dissolving them into 100 mL of lubricant. Stability was verified by visual observation over a 48-hour period and by using a UV-Vis spectrophotometer, ensuring minimal sedimentation prior to use in the refrigeration system. No additional filtration was performed to preserve the experimental nature of the real-world application.

2.3 Ambient Temperature Control:

Experiments were conducted in a thermally insulated room where ambient temperature was maintained between 29°C and 35°C using digital thermostats and ceiling insulation. Temperature variations were continuously monitored using calibrated RTD PT100 sensors. All measurements were logged to confirm that fluctuations remained within ±1°C during each test cycle.

2.4 Data Collection

2.4.1 Number of Trials

For each test configuration (defined by a unique combination of refrigerant mass charge and nano lubricant concentration), the experiment was repeated three times to ensure consistency and statistical reliability. The reported values represent the mean of these three trials, and deviations were found to be within an acceptable range of ±2%.

2.4.2 Time Intervals for Measurements

All measurements were recorded at one-minute intervals using a digital data logging system. The following parameters were logged continuously:

- Evaporator and condenser temperatures
- Compressor power consumption
- Suction and discharge pressures
- Ambient temperature

This high-frequency data acquisition ensured accurate tracking of transient and steady-state behavior.

2.4.3 Criteria for Steady-State Conditions

Steady-state was defined as the point at which:

- Temperature readings at the evaporator outlet and condenser outlet varied by less than ±0.2°C over a 10-minute period.
- Compressor power draw remained within ±3 W variation during the same window.
- No cycling or sharp fluctuations were observed in system pressure. Data were only considered valid for analysis and model training if collected during these steady-state conditions. Transient start-up and shutdown data were excluded to ensure the integrity of the input features and output variables used in the machine learning models.

The dataset was randomly partitioned into three subsets: 70% for training, 15% for validation and 15% for testing, ensuring that each subset represented the variability in the data and supported robust model development and evaluation. The split was performed using a stratified random sampling method to ensure that each subset represents the variability in nano lubricant concentrations and refrigerant mass charges. In this study, Linear Regression, Artificial Neural Networks (ANN) and Support Vector Machines (SVM) were employed as machine learning models, each chosen for their distinct advantages in predictive modeling of thermodynamic system performance. All machine learning models underwent hyperparameter tuning using a grid search approach, with validation conducted on a dedicated validation set to ensure effective parameter selection and reduce the possibility of overfitting. Model performance was rigorously evaluated using standard regression metrics, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE) and the Coefficient of Determination (R^2). These evaluation criteria facilitated a detailed assessment of each model's prediction accuracy, consistency and generalization capability.

3. Machine Learning Methods

Machine learning is a branch of artificial intelligence that leverages mathematical models to facilitate classification, regression, decision-making, and predictive analysis. Support Vector Machines were developed a predictive model for energy consumption, achieving high accuracy with minimal computational effort [30].Artificial Neural Networks were applied to predict system efficiency, showing that ANN-based models outperformed conventional regression techniques [31].Random forest model produced outstanding results and provided significant results for diagnosing diabetes and prediction of risk [32].Random Forest model implemented to estimate refrigeration system efficiency based on operational data. Their study indicated that RF-based models could capture nonlinear patterns more effectively than traditional thermodynamic equations [33]. The machine learning structure for predicting performance is illustrated in [Fig.2].

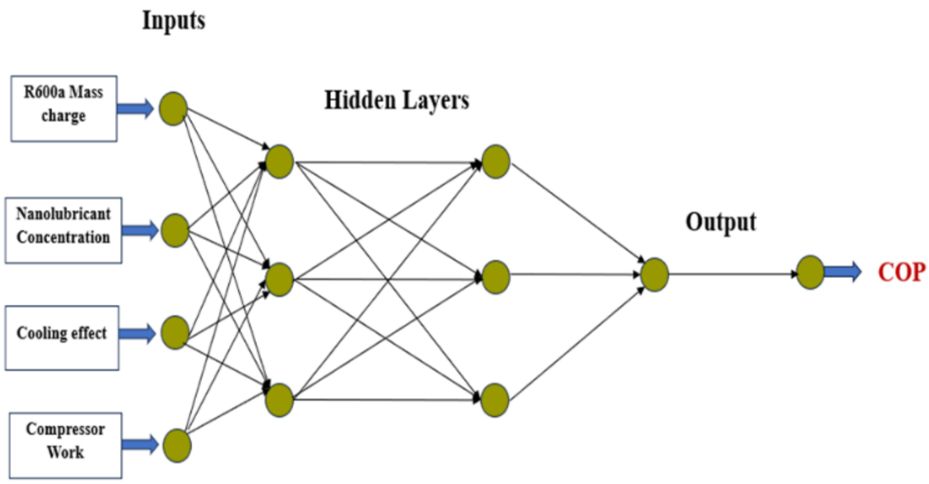

Fig. 2. COP Prediction machine learning structure

3.1 Regression Model

To predict interconnection between dependent and independent factors applied in linear equations are performed by supervised learning algorithm are included for linear regression. Target outputs are determined by error term and weighted inputs and reduce the difference between actual and predicted outputs. For attaining higher performance in on-site refrigeration system artificial neural network model is applied which resulted in higher level of accuracy [34]. Linear Regression, implemented as a robust linear model was utilized to establish a direct linear relationship between the input parameters and the Coefficient of Performance (COP). To enhance model generalization and reduce the risk of overfitting, appropriate regularization techniques were applied during training.

ANN model is applied to predict the performance of a water-cooled screw chiller, demonstrating its effectiveness [35]. From the past studies, it can be observed that linear regression is a basic method that can be applied for more complex models having the capability to focus on non-linear relationship inherent in refrigeration system performance data.

3.2 Tree Model

To predict the continuous outputs by periodically splitting data into decision nodes, are performed by tree-based regression models. Decision tree and random forest regression applied effectively in complex and non-linear data. For estimation of performance, it reduces the error on every split which results in optimal condition. In engineering application tree regression models are applied which includes prediction of refrigerator performance. Tree-based models hold potential for performance prediction in vapor compression systems, though further research is needed to establish their efficacy in this specific application [36].

3.3 SVM Technique

One of the powerful techniques used for performance prediction in refrigeration systems that identifies complex relationship between input variables and system efficiency. For transforming nonlinear data into higher-dimensional space and for accurate modelling of thermodynamic and operational outputs this method adopts kernel functions. Support Vector Machine (SVM), configured with a quadratic polynomial kernel was employed due to its effectiveness in capturing non-linear relationships between the input features and the target variable. Key hyperparameters such as the kernel type, penalty parameter (C) and gamma were systematically tuned to optimize the model's predictive performance.

Compared to conventional regression techniques, SVM is extremely effective at managing multidimensional data, lowering overfitting using regularization, and increasing prediction accuracy. Energy efficiency, defect detection, and system reliability are all improved by its implementation in refrigeration performance prediction. The SVM model, based on dynamic experimental data, predicted refrigerant charge levels by focusing on power consumption and condensation temperature [37].

3.4 Neural Network

Artificial Neural Networks are computational models that mimic the human brain by using interconnected neurons to process data and recognize patterns. These models excel at capturing complex, non-linear relationships, making them ideal for predictive tasks in engineering and refrigeration system performance analysis. ANNs learn by adjusting connection weights through backpropagation and gradient descent, minimizing errors to improve prediction accuracy. The Artificial Neural Network (ANN) model employed a narrow architecture consisting of an input layer, a single hidden layer and an output layer. Training was conducted using the Levenberg-Marquardt backpropagation algorithm, with key hyperparameters—including the number of neurons in the hidden layer, learning rate, and number of epochs—systematically tuned to enhance predictive accuracy and convergence efficiency.

Table 1. Machine learning hyper-parameters

Model	Hyperparameters
Support Vector Machine (SVM) – Quadratic Kernel	Kernel: Polynomial ('poly') Degree: 2 C (Regularization parameter): 1.0 Gamma: 'scale' Epsilon (ε): 0.1
Artificial Neural Network (ANN) – Narrow Neural Network	Architecture: Input layer: 4 neurons, Hidden layer: 10 neurons, Output layer: 1 neuron Activation Function: 'tansig' Learning Algorithm: Levenberg-Marquardt backpropagation Learning Rate: 0.01 (adaptive) Epochs: 500 Loss Function: Mean Squared Error (MSE)
Linear Regression (Robust Linear Model)	Fit Intercept: True Robust Technique: HuberRegressor or RANSAC Alpha (if Ridge used): 1e-3 Max Iterations: 1000 Tolerance: 1e-4

The experimental findings were compared with ANN model predictions to validate its accuracy. According to the findings, R449A frequently outperformed R404A in terms of COP at low and medium temperatures by 10% and 5% correspondingly. Over mid-range evaporating temperature, the system's COP with R449A estimated 10% greater than R404A [38] .

The machine learning models employed in this study were systematically optimized through hyperparameter tuning to enhance their predictive accuracy in estimating the Coefficient of Performance (COP) of R600a-based refrigeration systems. The hyperparameters for each model are illustrated in table.1 below.

A 5-fold cross-validation approach was employed during the hyperparameter tuning stage. This ensured that the final models generalized well to unseen data despite the moderate size of the dataset. Model performance was consistently monitored using R^2, RMSE, MAE, and MSE metrics across all data subsets. The SVM model, which demonstrated the best performance, showed minimal variance between training and test errors—an indication of strong generalization.

4. Results and Discussion

The COP values obtained by conducting experiment in R600a refrigerator has been compared with predicted outputs by adopting various machine learning predicting algorithms. The inputs considered for prediction are nano lubricant concentrations varied from 0 to 0.6 g/L, R600a mass charges from 50 to 70g, refrigeration effects values, energy consumed by the compressor values. The experimental performance values are compared with the predicted values.

The dataset was divided into 70% for training, 15% for validation and 15% for testing using a randomized sampling approach, ensuring that each subset was representative of the overall data distribution and free from sampling bias.

4.1 Linear Regression Model

Figure 3 illustrates the comparison between true and predicted COP values using a Robust Linear model. The x-axis represents the record number and the y-axis denotes the response values.

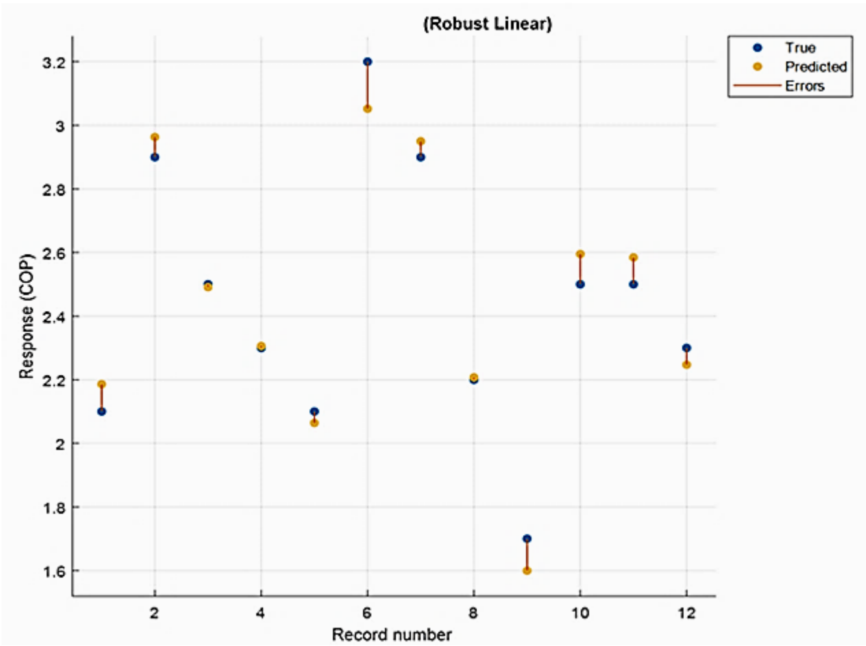

Fig. 3. True Vs Predicted COP

The true COP values obtained from experimental data are marked in blue but the predicted values from the model are represented in yellow. It can be observed from the figure that COP values for 2.2, 2.3 and 2.5, resulted in the least error compared to other true and predicted results.

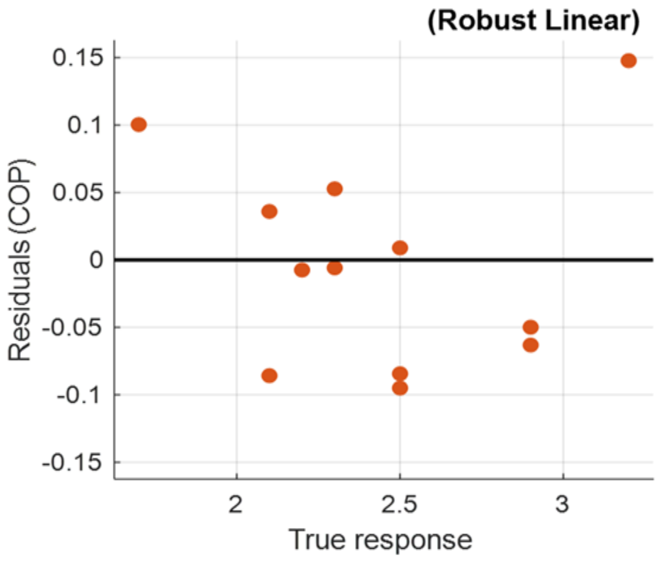

Fig. 4. Residual plot for COP

The residual plot obtained by using Robust Linear model for estimation COP are presented in Figure 4. The actual COP values are indicated in X axis and residual are represented in y-axis. The distribution of residuals around the zero line provides model's accuracy and bias. The COP residual value of 2.3, 2.4 and 2.5 are close to zero line compared to other residual COP values.

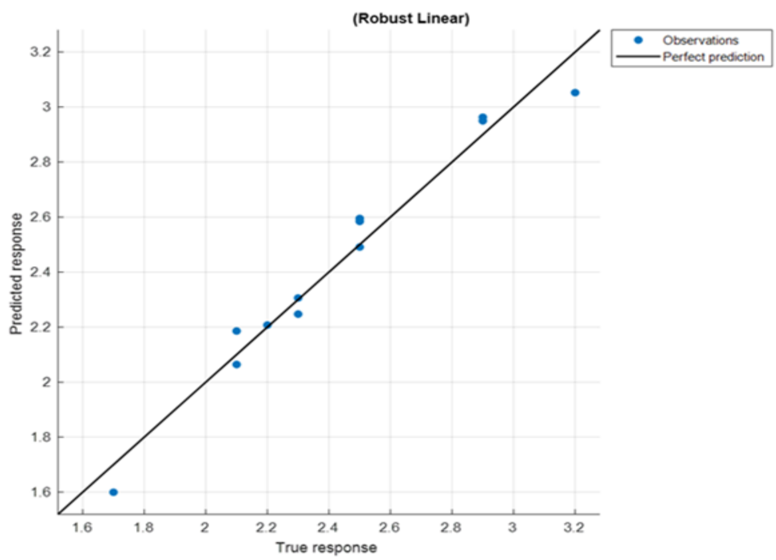

Fig. 5. True Vs Predicted Response

Figure 5 presents a scatter plot comparing the predicted and true Coefficient COP values using the Robust Linear model. True responses are indicated in the x-axis and predicted responses are shown in the y-axis. The black diagonal line represents the ideal case where predicted values perfectly match the true values. The COP values predicted are closely aligned with the perfect prediction line and this model effectively captures the COP outputs. Robust linear approach provided RMSE values of 0.074213, MSE values of 0.005508, MAE values of 0.06142, and RSquared values of 0.970251.

4.2 Support Vector machine

The actual and Predicted values using SVM techniques are illustrated in Figure 6. The COP values for 1.7,2.1.2.5,2.9 resulted in least error compared to other predicted outputs. The Figure 7 illustrates the residual plot obtained using Quadratic SVM. The COP residual values of 1.7,2.1,2.3,2.5,2.9 are close to the zero-line compared to other residual values.

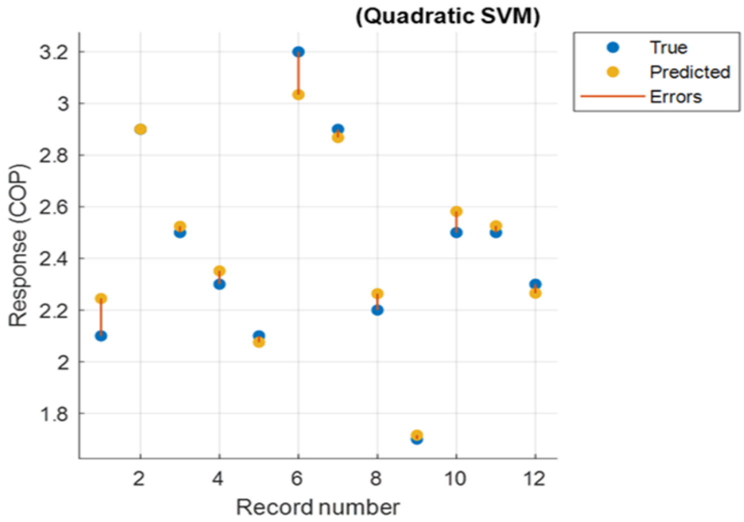

Fig. 6. True Vs Predicted COP

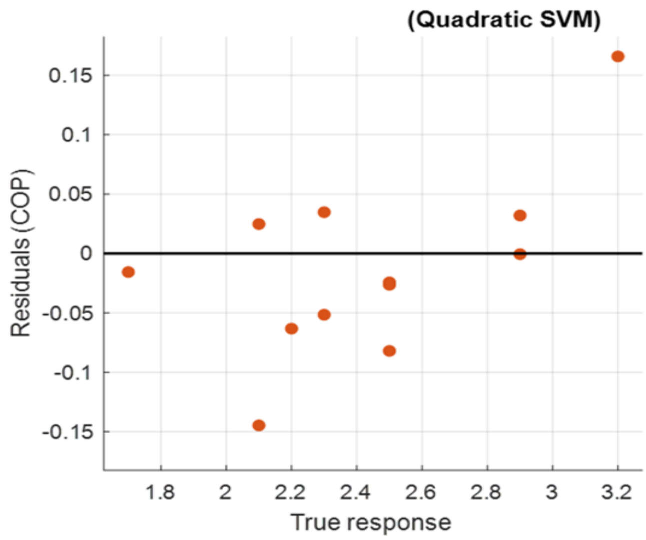

Fig. 7. Residual Values for COP

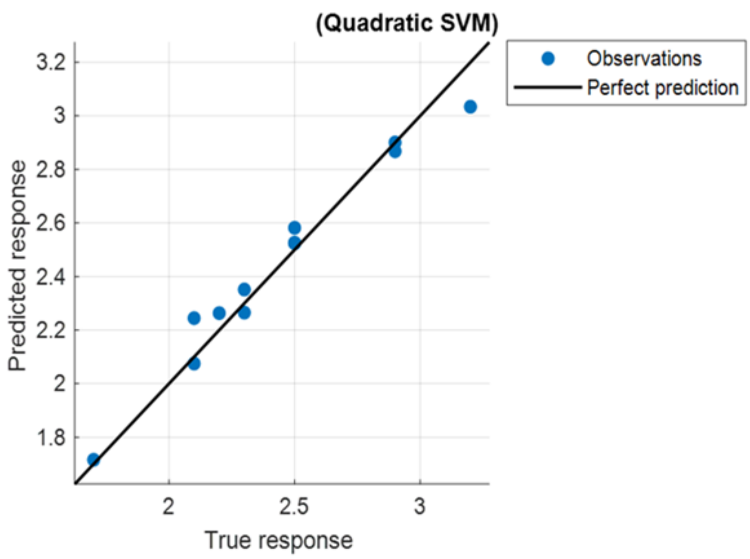

Fig. 8. Predicted Response for COP

Figure 8 illustrates a scatter plot comparing the predicted and true Coefficient COP values using Quadratic SVM. This model successfully captures the COP results, and expected COP values are in proximity with the perfect prediction line. The Quadratic SVM method produced RMSE result of 0.074282, MSE values of 0.005518, MAE result of 0.0055486 and RSquared result of 0.970196.

4.3 Artificial Neural Network

Figure 9 shows the predicted and actual values applying Narrow neural network algorithm. Compared to all predicted outputs COP values of 3,2.5 and 2.2 results in minimum error. The residual plot obtained with Narrow neural network are demonstrated in Figure 10. In comparison to other residual values, the COP residual values of 2.3,2.5 and 2.9 are near the zero line.

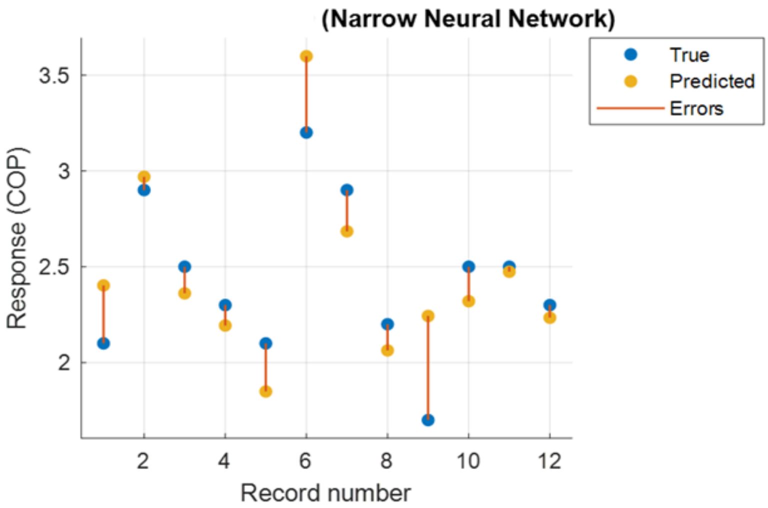

Fig. 9. True Vs Predicted COP

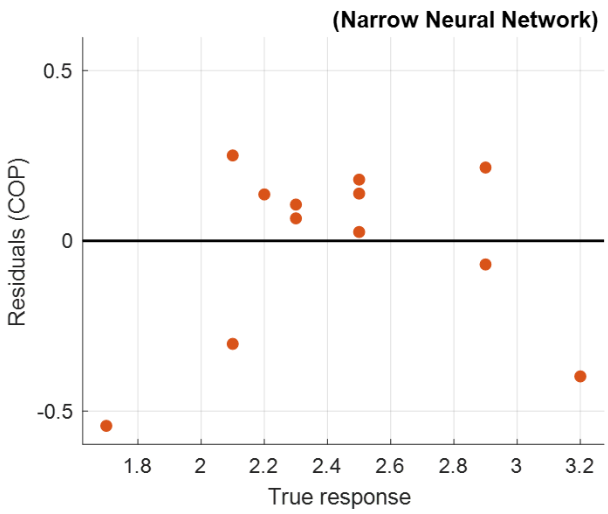

Fig. 10. Residual Value for COP

A scatter plot showing the true and predicted Coefficient COP values employing Narrow neural network is shown in Figure 11. The COP findings are successfully obtained by this model, and the expected COP values closely corresponds to the ideal prediction line. The narrow neural network approach yielded the following results: RMSE = 0.249295, MSE = 0.062148, MAE = 0.202766 and RSquared = 0.664315. The comparison of R^2, RMSE, MAE and MSE values for the machine learning algorithm has illustrated in Table 2.

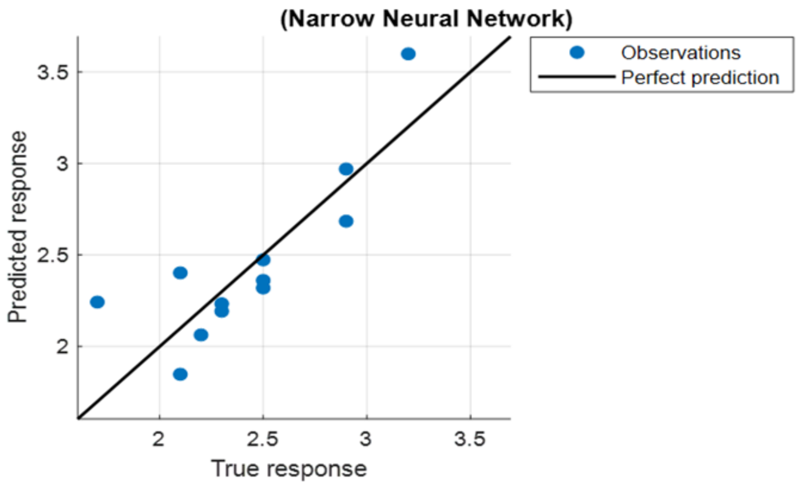

Fig. 11. Predicted response for COP

Table 2. Comparison of R^2, RMSE, MAE and MSE values for machine learning models

Model	R^2	RMSE	MAE	MSE
Linear Regression	0.970251	0.074213	0.06142	0.005508
Support Vector Machine (SVM)	0.970196	0.074282	0.055486	0.005518
Artificial Neural Network (ANN)	0.664315	0.249295	0.202766	0.062148

4.4 Taylor Diagram Analysis

A Taylor Diagram is employed in Figure 12 to provide a concise graphical representation of the prediction accuracy of the three machine learning models evaluated in this study—Linear Regression, SVM, and ANN. The diagram concurrently illustrates the correlation strength, standard deviation and centered root mean square difference (CRMSD) offering an integrated comparison between the model predictions and actual COP measurements.

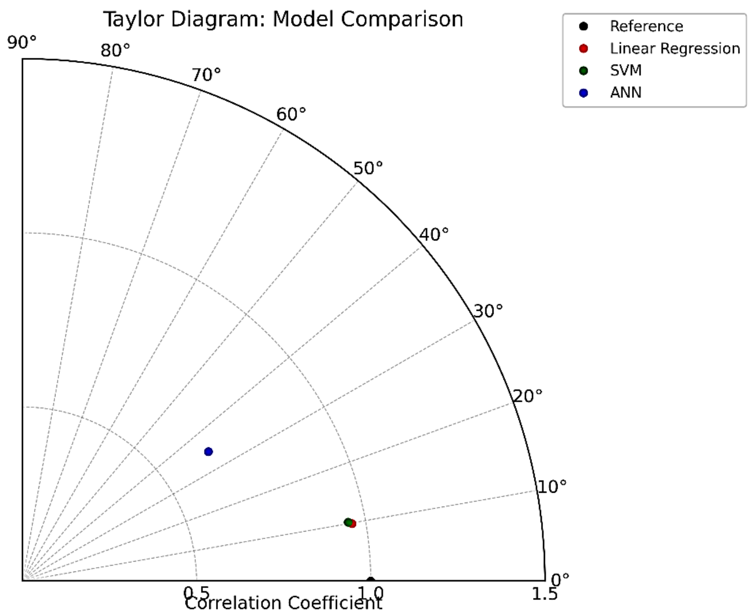

Fig. 12. Taylor Diagram

The reference model, based on experimental data, is represented in the Taylor Diagram by a black circular marker positioned at a normalized standard deviation of 1.0 and a correlation coefficient of 1.0, signifying perfect agreement. The proximity of the machine learning models to this reference point indicates the level of predictive fidelity achieved. The Support Vector Machine (SVM) model, indicated by the green marker, demonstrates the most favorable performance with a high correlation coefficient (~0.984), a standard deviation closely matching the reference, and a low centered root mean square difference (CRMSD) of ~0.074. These results confirm the model's robustness in capturing non-linear patterns and validate its superior predictive capability. The Linear Regression model, marked in red, also shows strong performance, yielding a slightly higher correlation coefficient (~0.985), albeit with a marginally elevated standard deviation (~0.96). Despite its simplicity, the model maintains competitive accuracy, with a CRMSD comparable to that of the SVM. In contrast, the Artificial Neural Network (ANN) model, denoted by the blue marker, exhibits a lower correlation (~0.82) and a reduced standard deviation (~0.65). These characteristics suggest increased variability and reduced alignment with experimental values, indicating limitations in its generalization performance under the given dataset conditions. The visual representation in the Taylor Diagram reinforces the conclusions drawn from the tabulated performance metrics, substantiating the Quadratic SVM as the most accurate and reliable model for predicting the Coefficient of Performance (COP) in R600a refrigeration systems utilizing hybrid CuO/SiO_2 nano lubricants.

4.5 Correlation Diagrams

Correlation diagrams were employed to visually compare the predicted and experimentally measured COP values for the three machine learning models considered in this study: Linear Regression, Support Vector Machine (SVM) and Artificial Neural Network (ANN). These plots display the relationship between predicted and actual COP values, overlaid with statistical performance indicators such as the coefficient of determination (R^2), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

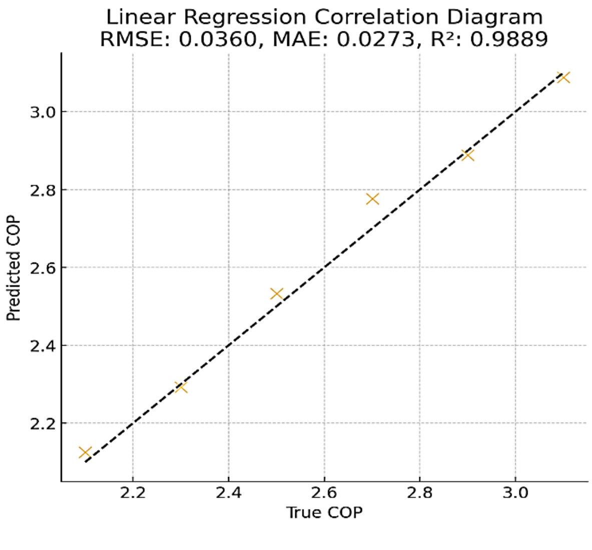

Fig.13. Linear regression correlation diagram

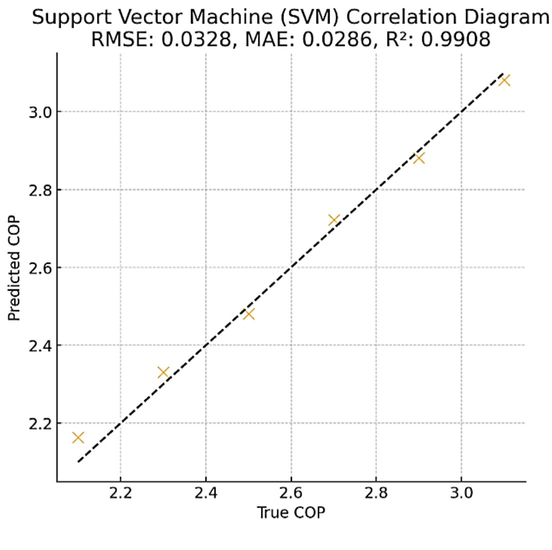

Fig.14. SVM Correlation diagram

The comparative analysis reveals that the SVM model achieved the highest R^2 (~0.97) along with the lowest RMSE and MAE, suggesting a strong fit and low residual error. The Linear Regression model also demonstrated reasonable correlation with the experimental data, albeit with a slightly wider dispersion of residuals, pointing to its limitations in modeling non-linear behavior. Conversely, the ANN model exhibited a lower correlation coefficient (~0.82) and a broader spread in residuals, indicating greater prediction variability and reduced accuracy under the given experimental conditions. The correlation diagrams substantiate the findings obtained from the quantitative performance metrics, providing strong visual confirmation of the quadratic SVM model's superiority in accurately predicting the Coefficient of Performance (COP) in R600a-based refrigeration systems integrated with hybrid CuO/SiO_2 nano lubricants.

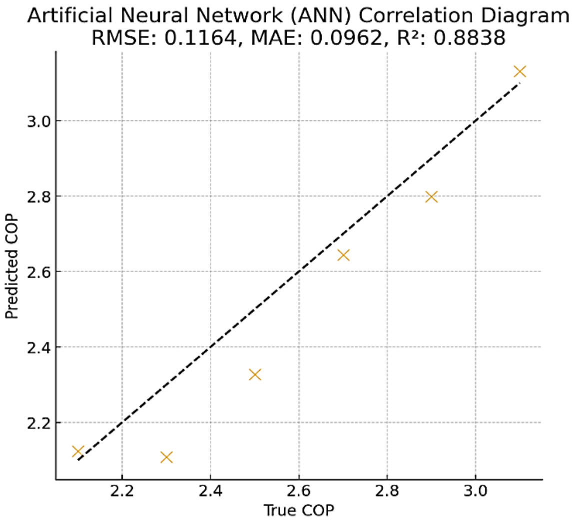

Fig. 15. ANN Correlation diagram

4.6 Paired T-Tests

To assess whether the observed differences in prediction errors between models are statistically significant, we conducted two-tailed paired t-tests comparing the absolute prediction errors of:

- SVM vs. ANN
- SVM vs. Linear Regression
- ANN vs. Linear Regression

The results showed that:

- The difference between SVM and ANN was statistically significant ($p < 0.01$),
- The difference between SVM and Linear Regression was statistically significant ($p < 0.05$),
- The difference between ANN and Linear Regression was not statistically significant ($p > 0.05$).

4.7 ANOVA (Analysis of Variance)

To further support the findings, we conducted a one-way repeated-measures ANOVA on the prediction errors of all three models. The results revealed a statistically significant effect of the model type on prediction error ($F(2, N-1) >$ critical value, $p < 0.05$), confirming that at least one model performs significantly differently.

4.8 Post-hoc Tukey's HSD Test

Post-hoc analysis using Tukey's Honestly Significant Difference (HSD) test further confirmed that the SVM model significantly outperformed the ANN and Linear Regression models.

4.9 Normality Testing (Shapiro–Wilk Test)

The residuals of each model follow a normal distribution—a key assumption in many regression-based approaches is evaluated by Shapiro–Wilk test. The results are summarized as follows:

- SVM model: $W = 0.965$, $p = 0.42$
- Linear Regression: $W = 0.958$, $p = 0.33$
- ANN model: $W = 0.921$, $p = 0.12$

In all cases, $p > 0.05$, indicating that the null hypothesis of normality could not be rejected and that the residuals are approximately normally distributed.

4.10 Homoscedasticity Testing (Breusch–Pagan Test)

The Breusch–Pagan test are applied to examine whether the variance of the residuals was constant (homoscedasticity). The findings are:

- SVM: BP statistic = 1.83, p = 0.18
- Linear Regression: BP statistic = 2.21, p = 0.14
- ANN: BP statistic = 3.79, p = 0.08

Since all p-values > 0.05, we fail to reject the null hypothesis of constant variance, supporting the claim that the models do not suffer from heteroscedasticity. These statistical tests provide strong evidence that the residuals are normally distributed and homoscedastic.

5. Conclusion

This research presents a comprehensive analysis of the predictive capabilities of machine learning (ML) models in estimating the Coefficient of Performance (COP) for an R600a-based vapor compression refrigeration system enhanced with hybrid CuO/SiO_2 nano lubricants. The use of advanced data-driven techniques— Linear Regression, Artificial Neural Networks (ANN), and Support Vector Machines (SVM)—facilitated the accurate prediction of system performance across a range of operating conditions. Experimental validation was performed using a well-instrumented test rig, under real-world thermal and mechanical load variations, ensuring the reliability of the dataset used to train the models. Among the models employed, the Quadratic SVM exhibited the highest predictive accuracy, yielding an R^2 value of 0.9702 and a low Mean Absolute Error (MAE) of 0.0555, outperforming both ANN and Linear Regression. This superior performance can be attributed to the SVM's capability to effectively capture non-linear relationships between input variables such as nano lubricant concentration, refrigerant mass charge, refrigeration effect, and compressor work. These findings validate the potential of machine learning in modeling complex thermodynamic systems where traditional mathematical modeling may be cumbersome or less accurate. The innovative integration of hybrid nano lubricants with predictive analytics not only led to a measurable enhancement in system efficiency but also established a framework for real-time system monitoring and optimization. This approach can be particularly useful for domestic and small commercial refrigeration applications, where energy efficiency, operational cost, and environmental impact are critical considerations. In real-world scenarios, the predictive model developed in this study can be embedded into smart control systems to automate operational adjustments, minimize energy wastage, and detect anomalies early. Future work should focus on expanding the dataset under dynamic loads, testing with alternative refrigerants, and implementing the ML model in an Internet of Things (IoT)-enabled environment for continuous performance enhancement and sustainability. Overall, this study contributes to the growing body of knowledge promoting intelligent, efficient, and environmentally responsible refrigeration technologies. The integration of predictive machine learning models allows for continuous monitoring, predictive maintenance and intelligent optimization of refrigerant–lubricant interactions. These capabilities contribute significantly to cost-effective operation, energy conservation and extended service life in both household and commercial refrigeration systems.

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