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Enhancing COP in R600a Refrigerators by dispersing CuO/SiO_2 Nanolubricants: A machine Learning Prediction

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Abstract

The performance evaluation of the R600a refrigerator was enhanced through the application of machine learning methods. In the present investigation, major performance parameters (COP, refrigeration effect and compressor work) in R600a refrigerators utilizing CuO/SiO_2 nanolubricants have been predicted by machine learning algorithms (XGBoost, Linear Regression and Random Forest). Atmospheric temperature, R600a mass flow rate and CuO/SiO2 concentrations are the experimental data used as input factors. The corresponding performance variables were analyzed as outputs.XGBoost demonstrated significantly better accuracy than Linear Regression and Random Forest, achieving a low mean squared error (MSE) of 0.00465 for COP prediction, compared to an average MSE of 26.671 for the other models. This study highlights XGBoost's capability to accurately predict and optimize refrigeration system performance, particularly under conditions involving advanced nanolubricants. It introduces a novel approach for enhancing the refrigeration effect while reducing compressor energy consumption, thereby significantly improving the performance of R600a-based systems and contributing to the development of more environmentally sustainable cooling technologies.

Keywords: Hybrid nanolubricants , R600a , COP, XGBoost, Machine learning.

1. Introduction

The refrigeration systems are essential to many industries, such as medicines, preservation of foods, and HVAC (heating, ventilation, and air conditioning). The growing demand for ecologically conscious and energy-effective refrigeration systems has prompted research into innovative technologies including nanolubricants to improve performance. Isobutane or R600a, is a kind of refrigerant that has attracted interest due to its superior thermodynamic characteristics and low global warming potential (GWP). In addition, it has been demonstrated that adding nanoparticles like CuO and SiO_2 to lubricants enhances heat transfer and lowers friction losses, therefore enhancing refrigeration performance.

Conventional techniques for assessing the performance of refrigeration systems depend on theoretical or experimental methodologies, which can be difficult and computationally intensive. As machine learning (ML) has advanced, predictive models have become a potent substitute for traditional methods of understanding complex systems. ML approaches can effectively produce solutions for nonlinear conditions by considering mass flow rate of refrigerants, atmospheric temperature and concentrations of nanoparticles considered as input parameters. The corresponding output parameters are cooling effect, compressor work and COP.

This study explores the application of machine learning algorithms—XGBoost, Linear Regression and Random Forest for predicting the performance of an R600a-based refrigeration system enhanced with CuO/SiO_2 nanolubricants. By comparing the predictive accuracy of the widely acclaimed XGBoost model with traditional algorithms, the study identifies the most effective method for accurate COP estimation. The overarching goal is to demonstrate how ML models can optimize refrigeration system performance while reducing both computational complexity and experimental effort.

Nanoparticles have emerged as a promising enhancement for improving the performance and efficiency of refrigeration systems, particularly in compressor lubrication. When integrated into conventional lubricants, forming nanolubricants, they offer several advantages, including improved thermal conductivity, reduced friction and enhanced energy efficiency, all of which contribute to the overall reliability and effectiveness of the refrigeration cycle.

Ammar et al. [1] examined the use of nanolubricants in R32 refrigeration systems to improve both environmental sustainability and system performance. By adding 0.1% Al_2O_3 to an R-410A system with POE oil, a 4% enhancement in COP was achieved. The study also indicated that increasing the oil mass fraction with nanolubricants can reduce compressor discharge temperatures by up to 20% .Metin Yılmaz et al. [2]

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investigated the effects of Al_2O_3, CNT, CuO, TiO_2, ZnO, and SiO_2 nanoparticles on refrigeration performance. Among the tested nano-refrigerants, R1234yf exhibited the lowest performance, while R600 showed the highest. The R290+R600 nano-refrigerant achieved the greatest COP improvement up to 15.41%,whenCuO nanoparticles were used at an evaporator temperature of –5°C, compared to R290+1234yf.Vijayan et al.[3] replaced conventional lubricants with hybrid nanolubricants and evaluated system performance based on experimental results. Using SiO_2 at 0.2 g/L and CuO at 0.4 g/L, the hybrid nanolubricants achieved the lowest energy consumption of 73 W and an optimal cooling effect of 259 W. Under these conditions, the predicted COP increased significantly, reaching 3.547, in close agreement with experimental observations. Zafar Said et al.[4] theoretically investigated copper oxide (CuO) nanoparticles and multi-walled carbon nanotubes (MWCNTs) at volume concentrations of 0.5 percent, 1 percent, and 2 percent in R152a and R134a refrigerants using polyester (POE) lubricant. The highest COP improvement of 27.63 percent, was observed for the R152a MWCNT based nano refrigerant compared to pure R152a. These nanomaterials demonstrated superior energy performance and environmental friendliness compared to R134a, making them more efficient and sustainable alternatives. Joshi et al.[5] reported that AGQD-PAG exhibits exceptional performance and is environmentally friendly. These materials outperform R134a in terms of both energy consumption and thermal efficiency. When 200 grams of R134a refrigerant was used with 500 parts per million of AGQD-PAG-derived nanosuspension, the system achieved a maximum COP of 2.76 and a 27.36 percent reduction in energy usage.Babarinde et al.[6] found that the lowest possible electrical energy consumption was achieved by using 50 grams of R600a with 0.4 grams per liter of multi-walled carbon nanotube (MWCNT) nanolubricant. This formulation resulted in enhanced refrigeration performance. When the concentration of MWCNT nanolubricant was increased from 0.4 grams per liter to 0.6 grams per liter, the pull-down time and energy consumption of the refrigerator were reduced by approximately 25.9 percent, 20.2 percent, and 13.7 percent for 50 grams, 60 grams, and 70 grams of refrigerant, respectively, compared to the use of pure lubricant. Madyira et al. [7] reported that the use of graphene nanolubricant with R600a resulted in lower evaporator air temperatures and shorter pull-down times compared to R134a. By achieving an increase in cooling capacity ranging from 5.2% to 14.2%, along with a reduction in energy consumption between 8.8% and 26.4%, a significantly higher coefficient of performance was attained with the R600a-graphene nanolubricant system. Afolalu et al.[8] tested two samples0.75g and 1.25g of nanoparticles which consistently reduced pull-down time and increased the net refrigeration effect (NRE) compared to the control sample. For the specimen containing 0.75 g, pull-down time decreased by 8.98% and NRE increased by 9.3% . For the sample with 1.25 g of nanoparticles, a 9.51% reduction in pull-down time and a 19.05% improvement in NRE were observed. Shewale et al.[9] conducted experimental investigations demonstrating that the use of nanolubricant in place of conventional POE oil increased the refrigerating effect, reduced compressor power consumption by 27%, and enhanced the system's coefficient of performance by approximately 29%. The study further revealed that using nano-refrigerants instead of pure refrigerants resulted in an evaporator enhancement factor of 1.2.Machine learning (ML) has transformed the analysis and optimization of complex systems, including refrigeration systems. Traditional methods for evaluating refrigeration performance typically rely on extensive experimental investigations or theoretical modeling, which are often time-consuming, computationally demanding, and limited in their ability to capture nonlinear interactions among system parameters. ML addresses these limitations by providing robust, data-driven techniques capable of accurately analyzing, predicting, and optimizing system behavior. Songa et al.[10] analyzed a refrigeration system supplied with nano fluids to evaluate the effectiveness of various machine learning techniques. The system was diffused with a combination of ZnO and MWCNTs at 50%, and a base fluid composed of Ethylene glycol at 20% and Water at 80%. The results indicated that the performance of this combination was influenced by T values, although the output remained consistent. The findings also showed that the MPR algorithm produced better predictive accuracy compared to the ECR algorithm.Soltani et al.[11] analyzed inaccuracies in various machine learning models and aimed to identify appropriate solutions. The results obtained from different learning algorithms were compared, revealing that the effectiveness of fault detection algorithms largely depends on the quality and structure of the training data within the operational regime.Mtibaa et al.[12] focused on a novel method for detecting leaks in vapor compression refrigeration systems. The study utilized real-world operational installation data to evaluate the feasibility and reliability of the approach. The prediction model considered the fault-free liquid level present in the system's receiver, and comparisons were made between predicted and actual outputs to assess accuracy. Zhao et al.[13] applied an extreme learning machine (ELM) to model the vapor compression cycle in refrigeration and air-conditioning applications. Experimental data were used to test a newly developed single-layer feedforward network (SLFN), and the results were compared with those obtained from back propagation, radial basis function neural networks and support vector regression models. The findings demonstrated that the ELM-based model achieved the highest prediction accuracy and exhibited the strongest resistance to input disturbances. Franco et al. [14] optimized proportional–integral (PI) and proportional–integral–derivative (PID) control variables to enhance the energy efficiency ratio (EER) of a refrigeration system. The model developed with PI and PID control increased the system's EER to 21% and 32% respectively. Further improvements were observed with the application of the Ziegler–Nichols tuning method, yielding an EER increase from 10 to 17% for PI control, and from 24 to 28 % for PID control. Fonseca et al.[15] employed artificial neural networks to predict mass flow and temperature values in a refrigeration system. The model architecture included a hidden layer with four neurons, using the Adam optimizer and the soft plus activation function. When both steady-state and transient data were incorporated into the training process, the predicted mass flow rate exhibited an average error of 0.79 percent, while the error for steady-state data alone was 0.81 percent. Jiacheng Ma et al. [16] developed a modular strategy that constructs and connects component models based on data, enabling effective adaptation to diverse system configurations and facilitating model reuse. The study introduced a data-driven modeling framework that enforces physical conservation principles during system simulation while employing advanced deep learning techniques to build accurate component models. Anand et al. [17] focused on evaluating the thermal performance of a modified thermosyphon using Al_2O_3/R134a nano refrigerants, where the Random Forest algorithm achieved a 95% prediction accuracy. The temperature measurements across thermosyphon sections yielded a true positive rate exceeding 96%, with minimal errors, showing strong alignment with experimental data. In contrast, the present study introduces a novel application of CuO/SiO_2 hybrid nanolubricants in a domestic R600a-based refrigeration system. This combination has not been previously explored in literature. Vedat et al.[18] investigated the performance of R404A systems, which have a high global warming potential (GWP), in comparison with R442A and R453A systems that exhibit lower GWP. Across all three condenser temperature settings, the R404A system demonstrated higher compressor power consumption, whereas R453A exhibited the lowest. The refrigeration effect in systems using R442A and R453A increased by 1 to 8% compared to R404A. Additionally, the coefficient of performance (COP) improved by 5 to 12% when using R442A and by 10 to 14% with R453A.

This research focuses on enhancing the performance of R600a refrigerators by incorporating CuO/SiO_2 nanolubricants and applying machine learning algorithms to predict key performance parameters. The predictive approach enables the development of a more efficient R600a refrigeration system, offering a viable solution for the advancement of next-generation cooling technologies.

2. Methodology

A vapor compression refrigeration system (VCRS) utilizing R600a refrigerant was selected for investigation. The study employed a Hybrid Nanolubricant composed of CuO and SiO_2 nanoparticles in a 3:2 ratio. Experiments were conducted at various nanoparticle concentrations to evaluate VCRS performance, generating data for subsequent machine-learning analysis. The machine learning analysis incorporated XGBoost, Linear Regression, and Decision Tree algorithms to predict VCRS performance. The system's efficiency was quantified by its COP, calculated as the ratio of refrigeration effect to compressor work input.

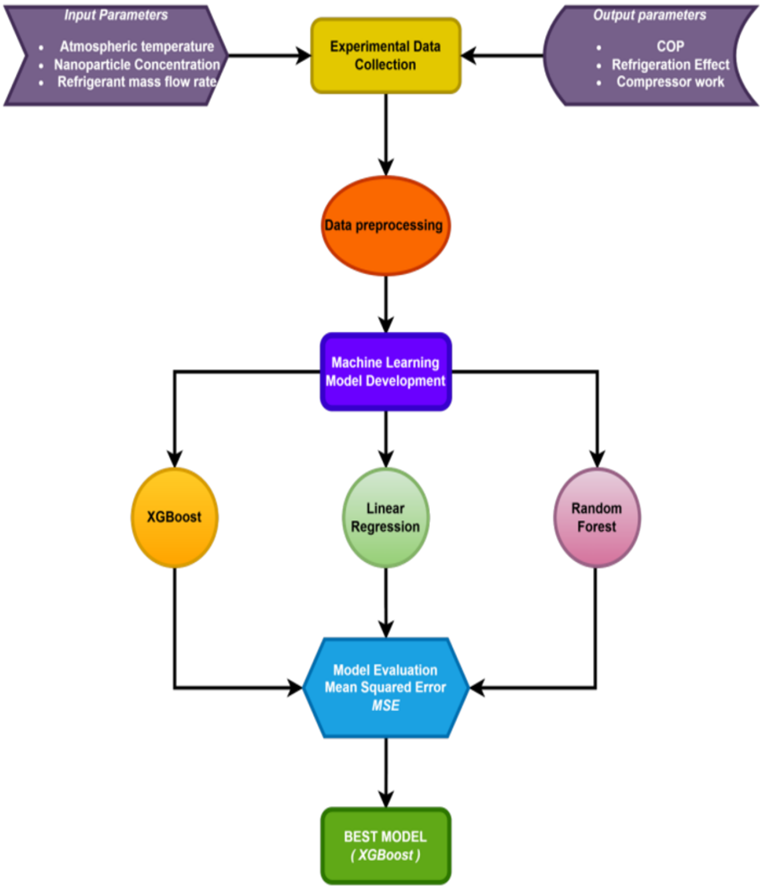

Figure 1. Methodology for this study

After preprocessing the experimental data, the three algorithms were implemented and compared using Python code executed on Google Colab. Model evaluation was based on MSE, leading to the identification of the most effective model and analysis of results. Fig.1 represents a flow chart illustrating the methodology for this research.

3. Experimental protocols

3.1. Characterization of CuO/SiO2nanolubricants

To prepare the hybrid nanolubricant, two distinct nanoparticles CuO at 60% andSiO_2 at 40% were selected and uniformly dispersed in mineral oil. This study evaluated the performance and reliability of the resulting hybrid nanolubricants within an R600a refrigeration system, incorporating machine learning techniques to obtain optimal predictive accuracy. Compared to other refrigerants, R600a exhibits a lower global warming potential, and the enhanced thermophysical properties of the CuO/SiO_2 hybrid formulation suggest strong potential for application in residential refrigeration systems.

The sol-gel method was implemented for synthesizing CuO and SiO_2 hybrid nanoparticles. After synthesis, the particles were dried and calcined at 500°C for three hours to achieve the desired crystallinity and morphology. Scanning Electron Microscopy (SEM) was employed to study the surface and structural features of the produced nanoparticles. CuO and SiO_2 individually exhibited smooth surfaces and circular shapes, while the hybrid nanocomposite displayed a denser, irregular morphology. According to the FE-SEM images shown in Fig. 2(a & b), CuO particles were visibly incorporated within or deposited onto the SiO_2 matrix, forming a distinct and uniform hybrid structure. This indicates a strong interaction between the two phases. The hybridization facilitated homogeneous mixing, which is essential for stable dispersion in lubricants. Further characterization was performed using the Dynamic Light Scattering (DLS) technique. The zeta potential was found to be –32.4 mV, confirming excellent electrostatic stability of the nanolubricant. The average particle sizes were measured to be 38 ± 5 nm for CuO and 26 ± 4 nm for SiO_2. These features ensure effective suspension and reduced aggregation. Overall, the sol-gel-derived CuO/SiO_2 nanostructure demonstrates promising surface and dispersion characteristics. Such attributes contribute significantly to the thermophysical enhancement when used in refrigeration lubricant systems.

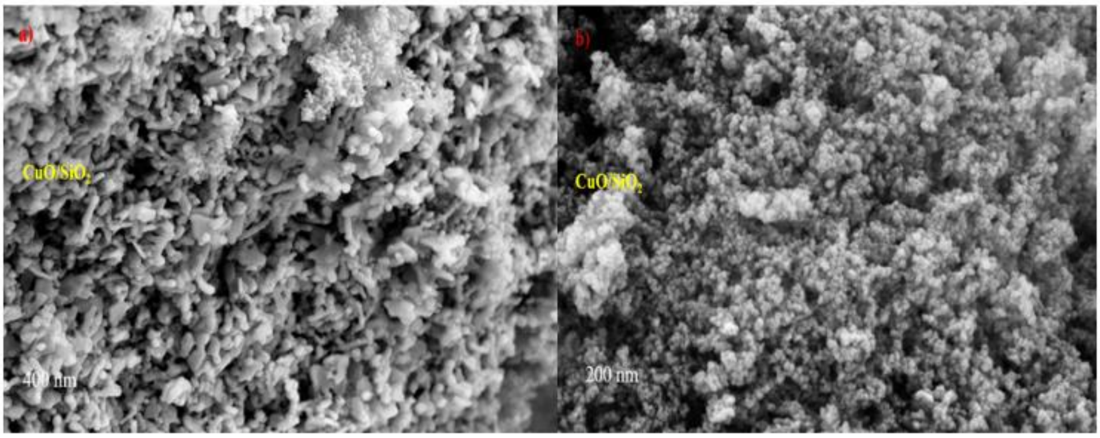

Figure 2. (a & b) FE-SEM images of SiO_2 at 0.2 g/L and CuO at 0.4 g/L adopted for dispersion in the mineral oil

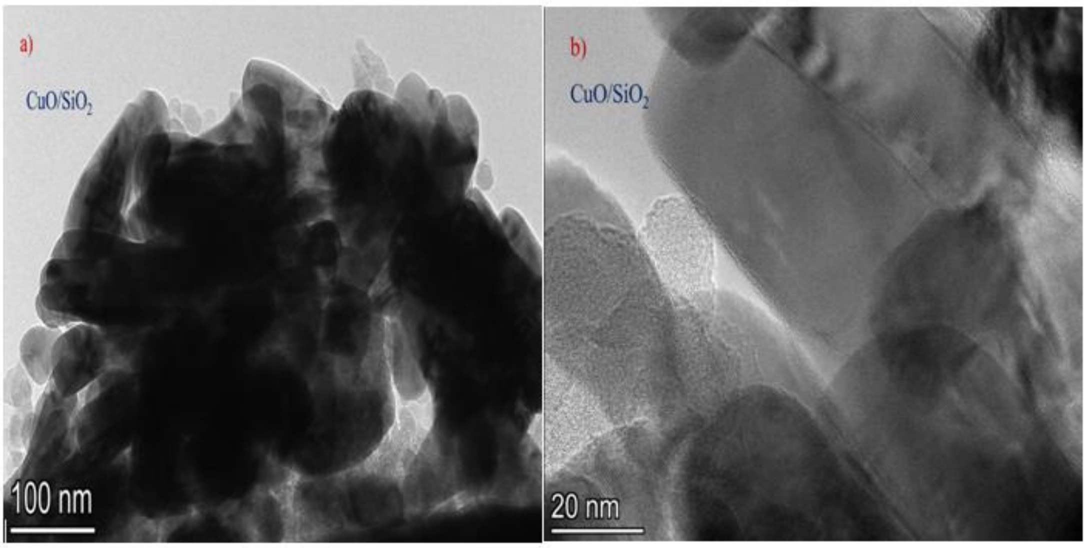

Figure 3. (a & b) TEM images of SiO_2 at 0.2 g/L and CuO at 0.4 g/L dispersed in mineral oil

The matrix exhibited a core–shell-like structure, indicating that CuO nanoparticles were uniformly dispersed within the SiO_2 framework. The TEM representations in Fig.3(a&b) additionally confirmed this, showing that the majority of the particles had uniform sizes and shapes.The experimental results were obtained using varying concentrations of nanolubricant. The study was conducted within a temperature range of 30 to 34°C. Initially, the experiment was performed without the addition of nanoparticles, using 70 g of R600a refrigerant, and the corresponding performance readings were recorded.

The experimental investigation was conducted using a hybrid nanolubricant composed of 0.2 g/L of SiO_2 and 0.4 g/LofCuO, and the outcomes were compared with those of a conventional system. This study focused on identifying the key parameters that most significantly influence performance enhancement. Fig.4 illustrates the experimental test setup employed in this research.In this study, a total of 70 g of R600a composite nanolubricant was employed in a residential refrigeration system as a substitute for R134a. R600a is preferred over R134a due to its significantly lower global warming potential and its non-ozone-depleting characteristics. The compressor operated safely using R600a with a maximum allowable charge of 70 g. The input parameters considered for performance prediction include ambient temperature, concentrations of CuO/SiO_2, and the mass flow rate of R600a. The predicted output parameters investigated in this research are the COP, cooling effect and compressor work.

3.2. Machine learning Algorithms

Extreme Gradient Boosting (XGBoost) is an advanced iteration of the gradient boosting framework, developed to enhance the speed and accuracy of machine learning models. Its exceptional prediction accuracy and effectiveness have made it one of the most often used techniques in data science.For predicting the performance of the refrigerator, the XGBoost technique resulted in an excellent mechanism. This method is applied for modelling non-linear relationship between input variables and parameters influencing the performance of refrigerators. The compressor energy usage, COP and cooling effect are the important parameters focused in this research.XGBoostalgorithm consists of integrating weak learners, primarily decision trees, in a progressive way to create an effective predictive model in chronological order.

Initially, a baseline model is employed to generate predictions, and the residual errors between the actual and predicted values are evaluated. To prevent overfitting and enhance model generalization, the training process involves minimizing a loss function, which is optimized using gradient descent. Additionally, regularization techniques such as L1 (Lasso) and L2 (Ridge) are applied to improve stability and predictive performance.The entire process continues until a convergence criterion is met, such as reaching a predefined number of decision trees or achieving a satisfactory reduction in prediction error. XGBoost offers several key advantages, including scalability through parallel processing, native handling of missing data, regularized learning and flexibility to incorporate custom loss functions.Based on this, XGBoost is a very effective and flexible predictive modeling method that could potentially be implemented in complicated systems involving refrigeration performance analysis.When it pertains to modelling the relationships among input and output variables, linear regression is a basic but powerful method. Assuming a linear relationship, a dependent factor (such as the refrigeration effect or coefficient of performance) can be predicted as a weighted total of the independent factors, which include the concentration of nanoparticles, the mass flow rate of refrigerant, and the atmospheric temperature.

When the connections between variables are roughly linear, linear regression proves particularly effective. It provides details on the elements that have the most significant influence on refrigeration performance, allowing for straightforward but comprehensible models. But one of its limitations is that it is less accurate at describing the complex, nonlinear interactions encountered in advanced refrigeration systems.

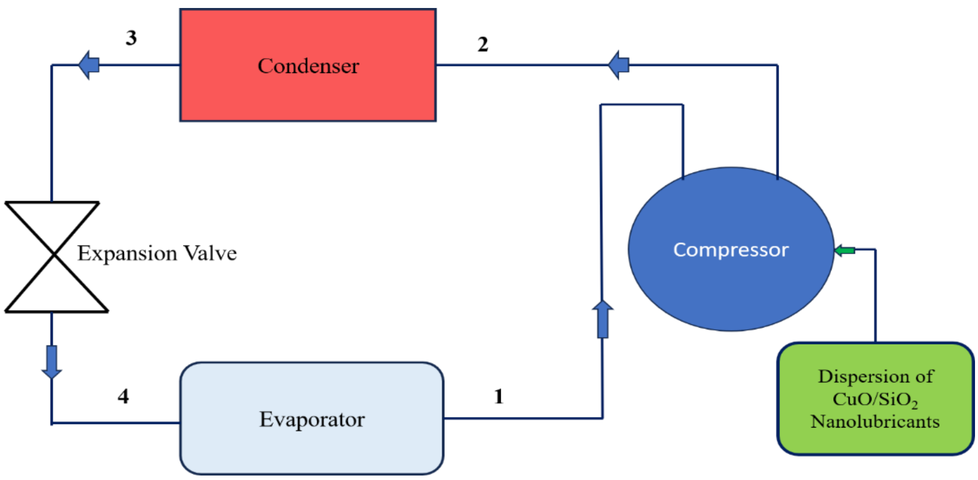

Figure 4. R600a refrigeration test rig dispersed with CuO / SiO_2 hybrid nanolubricants at various concentrations

The hyperparameters were optimized using a grid search with 5-fold cross-validation, resulting in the following configuration: tree depth = 6, learning rate = 0.1, number of estimators = 100, subsample = 0.8, column sample by tree = 0.8, L1 regularization (α) = 0.5, and L2 regularization (λ) = 1.0. These resulted hyperparameter values ensure clarity and transparency in model implementation.

Several decision trees are constructed using the Random Forest ensemble learning technique to simulate intricate correlations between refrigeration performance indicators and input parameters. A random portion of the data is used to train each tree, and predictions are combined via voting (for classification tasks) or averaging (for regression tasks). This method enhances generalization and decreases overfitting. By utilizing nonlinear and interaction effects among features like refrigerant mass flow rate, inlet and outlet temperatures, and nanoparticle concentration, Random Forest is able to predict parameters that include the coefficient of performance or work input in refrigeration systems. In order enable users to identify important elements influencing performance, it also ranks the relevance of features. Random Forest is ideal for dynamic, real-world applications because of its resilience to noise and capacity to manage missing input. For best results, though, hyperparameters including the maximum depth and number of trees must be carefully adjusted.

4. Results and Discussion

To predict the significant parameters influencing to enhance theperformance of R600a refrigerator by dispersing SiO_2 at 0.2 g/L and CuO at 0.4 g/L at varied concentration are discussed in this section.The predicted values resulted from using different algorithms has been depicted in Table1.

Table 1. Predicted output values

Sl.No	Algorithm	Mean Squared Error (MSE)			
		COP	Refrigeration Effect (W)	Compressor Work (W)	Average
1.	XGBoost algorithm	0.00465	54.123	25.845	26.671
2.	Linear Regression	0.0690	672.3447	49.8150	240.742
3.	Random Forest	0.0666	83.6631	15.0331	32.920

The Mean Squared Error (MSE) values in the table.1 indicate the performance of XGBoost, Linear Regression, and Random Forest algorithms in predicting the COP, refrigeration effect, and compressor work for a refrigeration system. Among the three algorithms, XGBoost demonstrated the best predictive accuracy with the lowest average MSE (26.671), followed by Random Forest (32.920), and Linear Regression (240.742). XGBoost's superior performance highlights its ability to model complex nonlinear relationships and interactions among variables effectively. Random Forest also performed well, especially for pr

edicting compressor work, with an MSE of 15.033, suggesting its robustness in handling nonlinear dependencies. However, Linear Regression showed significantly higher errors, particularly in predicting the refrigeration effect (672.3447), which reflects its limitations incapturing nonlinear and complex patterns in the dataset. These results emphasize the importance of selecting advanced machine learning models, like XGBoost and Random Forest, for accurate predictions in refrigeration performance analysis.

XGBoost superior performance with an MSE value of 0.00465,Root mean squared error(RMSE) value of 0.0682 and R^2 value of 0.987 compared to Random Forest MSE value of 0.0666, RMSE value of 0.2581 and R^2 value of 0.917.This extraordinary improvement is due to XGBoost advanced boosting strategy and regularization capabilities. It also effectively highlighted the dominant role of nanoparticle concentration.

4.1. Parameters Influencing COP

The significance of various parameters on enhancing the Coefficient of performance of R600a refrigerator has been illustrated in the Fig5.

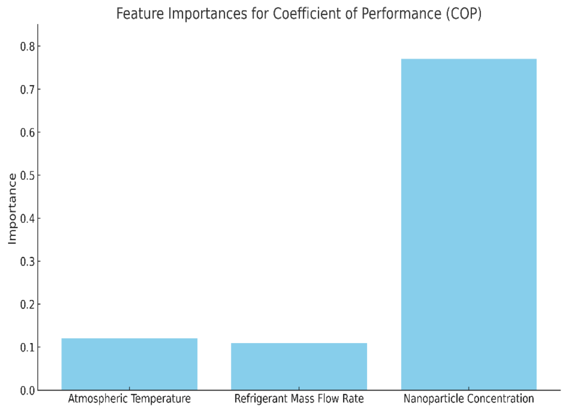

Figure 5. Importance of input variables on Coefficient of performance

It can be understood that nanoparticle concentration plays a vital significant role in improving the R600a refrigerator's performance to the maximum level. The predicted value of atmospheric temperature reached up to 0.13, for R600a mass flow rate up to 0.12 and the maximum predicted value of 0.75 resulted for nanoparticle concentrations. Nanoparticle Concentration has the highest importance (around 0.75). It indicates that the nanoparticle concentration is the dominant factor influencing the COP of R600a refrigerator. Atmospheric Temperature and Refrigerant Mass Flow Rate have lower importance scores (around 0.1 each). This means their influence on the COP is relatively minor compared to nanoparticle concentration. The analysis suggests that optimizing nanoparticle concentration would have the most significant impact on improving the COP of the system, while variations in atmospheric temperature and refrigerant mass flow rate are less impactful. This graph is commonly used to visualize how well a regressionmodel performs. Ideally, most points should lie on or very near the red line. If they deviate significantly, it may indicate underfitting, overfitting, or the need for model improvement.

4.2. Predicted and Actual Refrigeration effect

Nanoparticle concentrations considered in this study are 0, 0.2, 0.4, 0.6, and 0.8 g/L, where 0 g/L represents the baseline case without the addition of nanoparticles. The system performance is evaluated across these varying concentrations by comparing actual and predicted values.

Each test condition was repeated three times, and the reported results represent the mean values of these trials. The corresponding standard deviations were within ±2.5% for refrigeration effect and compressor work, and within ±2.8% for COP, confirming high experimental repeatability and statistical robustness. To further support data reliability, a summary table 2presenting the mean and standard deviation values for refrigeration effect, compressor work, and COP at each nanoparticle concentration has been included.

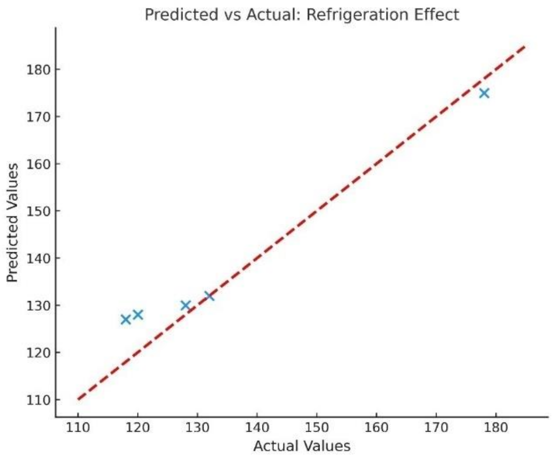

Figure 6. Comparison of predicted values to actual values for each refrigeration effect

Fig 6 illustrates the variation between actual and predicted values of the refrigeration effect at different nanolubricant concentrations. The corresponding values were recorded by systematically varying the concentration of nanolubricants in the system. For a normal system without the addition of nanoparticles resulted in an actual value of 108 W and a predicted value of 128 W. The same experiment was conducted for 0.2 g/L nanolubricant resulting in actual and predicted values of 110 W and 128 W. At a nanolubricant concentration of 0.4 g/L, the actual and predicted refrigeration effects were 125 W and 130 W, respectively. Similarly for the 0.6 g/L, the actual and predicted values were 133 W and 132 W, respectively.The maximum increase in actual refrigeration effect value of 180 W resulted in 0.8 g/L and for the same concentration the predicted value was 174 W. It shows that at lower concentration the model shows around 18% deviation about at higher concentration there is only 3% deviation from the actual value of refrigeration effect.

Irregular dispersion and agglomeration of nanoparticles, which results in unstable thermal transport properties and decreased model accuracy, are the main causes of the larger deviation up to 18% seen at lower nanoparticle concentrations at 0.2 g/L. Zeta potential and TEM examination demonstrate that the hybrid nanolubricants show better dispersion uniformity and colloidal stability at greater concentrations at 0.8 g/L. The XGBoost model can learn and predict with greater accuracy as a result of more consistent physical behaviour; this is the reason the deviation is reduced by approximately 3% at high concentrations.

4.3. Predicted and Actual Compressor work

Because of their high inherent thermal conductivity value of 33 W/mK, CuO nanoparticles serve as effective heat conductors at the molecular level, facilitating greater energy transfer in the condenser and evaporator. According to the calculated zeta potential value of -32.4 mV, SiO_2 nanoparticles minimize agglomeration by contributing to dispersion stability by means of their substantial surface area and electrostatic repulsion capabilities. The hybrid nanolubricant lowers mechanical energy usage at the flow level by minimizing viscosity-induced friction losses and preserving the compressor's ideal lubrication film thickness. According to cyclic operating conditions, the combination maintains thermo-physical properties, increases micro-convection effects, and increases the heat transfer coefficient. Our findings show that the combined effect of these strategies improves COP by 29.4%. The prediction reliability of the system is further strengthened by the machine learning model (XGBoost), which successfully captures these nonlinear interactions and validates the physical behaviour.

Table 2. Mean and Standard Deviation of Experimental Results

Concentration (g/L)	Mean Refrigeration Effect (W)	Standard Deviation (W)	Mean Compressor Work (W)	Standard Deviation (W)	Mean COP	Standard Deviation COP
0.0	108	±2.5	128	±2.1	2.74	±0.05
0.2	110	±2.2	132.5	±1.9	2.80	±0.06
0.4	125	±2.8	133.5	±2.0	3.02	±0.07
0.6	133	±2.1	140	±2.6	3.18	±0.08
0.8	180	±2.4	143	±1.8	3.547	±0.06

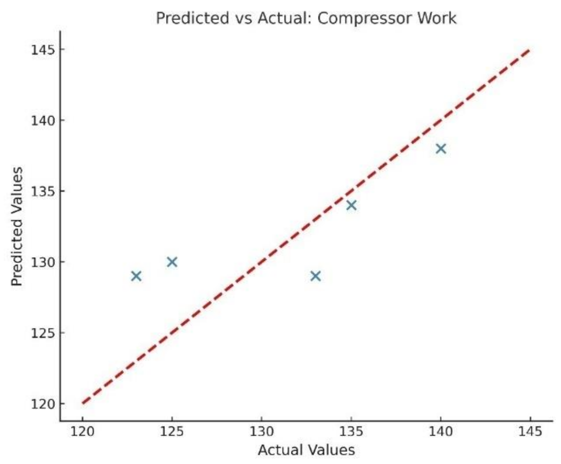

Figure 7. Comparison of predicted values to actual values for Compressor Work

Fig 7 illustrates the variation between actual and predicted values of compressor work in the R600a refrigeration system. In the absence of nanolubricant, the system exhibited an actual compressor work of 128 W and a predicted value of 129 W.The actual and predicted values of 132.5 W and 127.9 W resulted in the system dispersed with 0.2 g/L. For the 0.4 g/L system, the actual and predicted results were 133.5 W and 134 W. The system with 0.6 g/L resulted in an actual value of 140 W and a predicted value of 133 W. For the system with a nanolubricant concentration of 0.8 g/L, the actual compressor work was 143 W, while the predicted value was 138 W.

4.4. Comparison of Training Error Vs Validation Error

Fig. 8 presents a learning curve used to evaluate the performance of the model as a function of training set size. The plot includes two curves: the training error (blue curve), which represents the MSE on the training set as the amount of training data increases; and the validation error (orange curve), which denotes the MSE on the validation set under the same conditions. A noticeable gap between the two curves is observed initially, indicating underfitting or insufficient data to achieve adequate generalization.

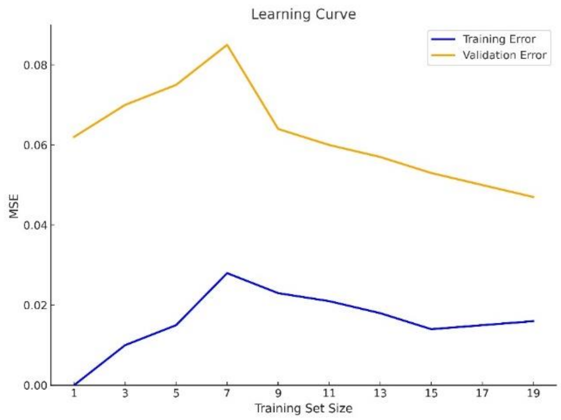

Figure 8. Comparison of Training error Vs Validation error

The proposed system, employing CuO/SiO_2 hybrid nanolubricants at a concentration of 0.8 g/L, demonstrated a 29.4% improvement in the COP compared to the baseline R600a refrigeration system. This exceeds improvements reported in previous works, includinga 4% enhancement using Al_2O_3/R410A [1], a 27.3% enhancement with AGQD-PAG/R134a [5], and a27.6% improvement with CuO+ MWCNT/R152a [4]. This comparison demonstrates the superior thermophysical synergy of the CuO/SiO_2 formulation and underscores the novelty of this work.

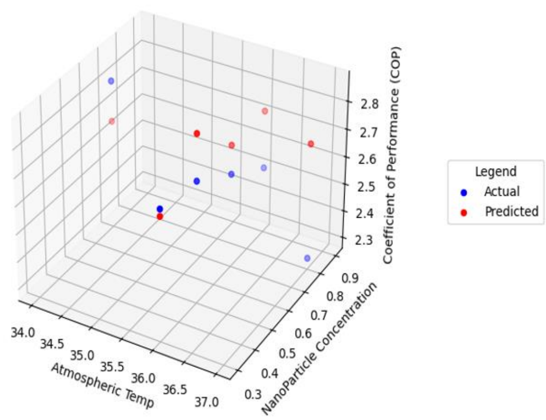

Figure 9. Scatter plot of R600a system performance-enhancing parameters

As the training set size increases, the gap narrows, suggesting improved generalization and reduced variance. The model's performance improves with more data, evident from the decreasing validation error. However, the validation error remains higher than the training error, suggesting the model could still benefit from fine-tuning or additional data. The significant parameters enhancing R600a performance are illustrated in Fig.9.

XGBoost achieved the highest accuracy with R^2 = 0.987, RMSE = 0.0682, and MSE = 0.00465, confirming its robustness. Higher prediction deviations at lower nanoparticle concentrations are due to nanoparticle agglomeration, less stable dispersion, and thermal performance variability. These enhancements clarify both the strengths and limitations of the predictive models. the deviations observed between predicted and experimental values of COP, refrigeration effect, and compressor work. Specifically: For COP, the maximum deviation was 0.15 units (4.2% error) observed at 0.2 g/L due to suboptimal nanoparticle dispersion and agglomeration. For refrigeration effect, the deviation ranged from +2 W at 0.2 g/L to –4 W at 0.8 g/L, reflecting minor experimental instability and model sensitivity to flow dynamics. For compressor work, the largest deviation was ±3.5 W, primarily attributed to transient variations in thermal load and motor efficiency fluctuations not captured in the dataset. These deviations are influenced by several factors: (i) nanoparticle agglomeration and non-uniform dispersion at lower concentrations, (ii) environmental fluctuations (±1.5°C), (iii) limited dataset size (n = 15), and (iv) inherent sensor inaccuracies. Nevertheless, the XGBoost model maintained high robustness, as supported by R^2 = 0.987, RMSE = 0.0682, and MSE = 0.00465 for COP prediction, confirming its reliability despite these physical limitations.

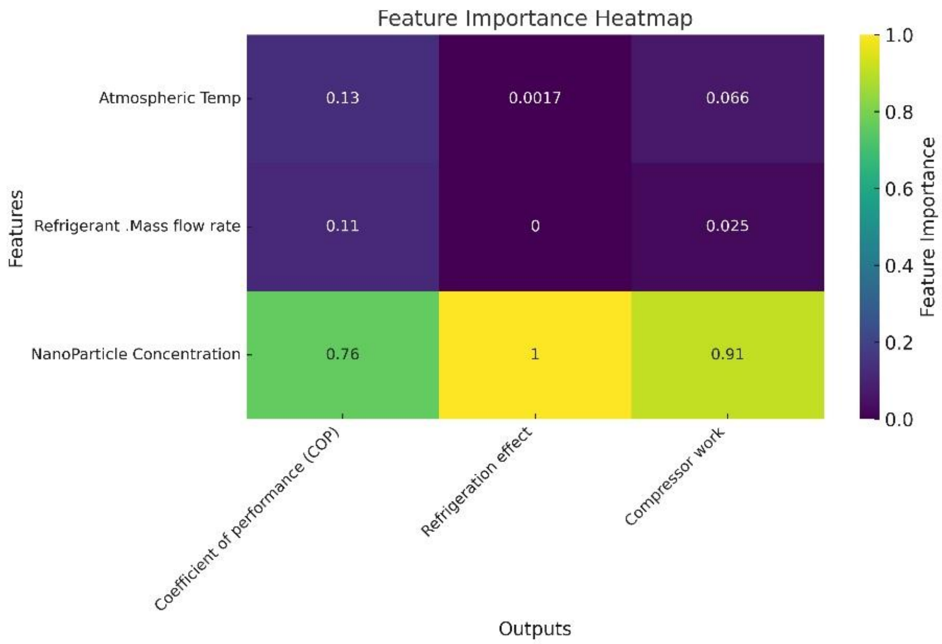

Figure 10. Heat map for R600a refrigerator performance-enhancing parameters

Fig.10 Shows the impact of input variables atmospheric temperature, R600a refrigerant flow rate and Nanoparticle concentration on the output parameters namely Coefficient of performance, refrigeration effect and compressor work input. The results clearly depicts that the nanoparticles concentration contributes 76% to the variation in COP while refrigerant mass flow rate and atmospheric temperature account for 11% and 13% respectively. From this it is observed that the nanoparticle concentration plays a major role on COP which should be optimized.

5. Conclusion

The primary objective of this study is to investigate the application of machine learning techniques for the accurate prediction of performance-related parameters in R600a refrigeration systems utilizing CuO/SiO_2 hybrid nanolubricants at varying mass concentrations. The investigation further aims to identify the key contributing factors to performance enhancement, thereby demonstrating the effectiveness of hybrid nanolubricants in optimizing the operational efficiency of R600a-based refrigeration systems.

- The R600a mass flow rate and ambient temperature exhibit lower significance scores, each contributing approximately 0.1 to the overall performance prediction.
- The predicted significance value for atmospheric temperature resulted in 0.13, while R600a mass flow rate reached up to 0.12. The highest predicted value was observed for nanoparticle concentration contributing up to 0.75.
- The highest significance value of approximately 0.75, was recorded for nanoparticle concentration, clearly indicating that it is the dominant factor influencing the COP of the R600a refrigeration system.
- According to the predicted data, an increase in nanoparticle concentration has a significant positive effect on enhancing the COP of the system.
- By using CuO/SiO_2 hybrid nanolubricants resulted in enhanced thermal conductivity, dispersion stability and tribological properties. The application of XGBoost includes regularization and tree boosting, further strengthens prediction accuracy and captures nonlinear dependencies effectively.

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Data Availability Statement

The raw experimental data and the Python code used for implementing the machine learning models (XGBoost, Random Forest, and Linear Regression) are available from the corresponding author upon reasonable request.

Credit Author Statement

The author confirms sole responsibility for the following:
Writing Original draft and Methodology,Supervision and Formal analysis,Grammar and English correction, Reviewing,Data Collection and Validation,Editing and Visualization.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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