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Hybrid Thermodynamic–Machine Learning Modeling of Nano-Refrigerant-Based Vapor Compression Refrigeration Systems

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Abstract

This study presents a comprehensive thermodynamic and artificial intelligence (AI)-assisted framework for evaluating the performance of nano-refrigerants in a vapor compression refrigeration system (VCRS). The framework integrates thermodynamic modelling using CoolProp and Python, heat-transfer analysis, first- and second-law thermodynamic analyses, sensitivity analysis, uncertainty quantification, and machine learning (ML) prediction to investigate the influence of nanoparticle type, density, and concentration on system performance. Four nano-refrigerants comprising R134a with Al₂O₃ (2200 and 3690 kg m⁻³), TiO₂, and CuO nanoparticles were investigated. The developed model was validated against published experimental and numerical studies, yielding excellent agreement with numerical results, with average deviations ranging from **0.23% to 2.72%**, while comparison with experimental data showed acceptable agreement for engineering applications. The results demonstrate that incorporating nanoparticles significantly enhances the thermophysical properties of the refrigerant, leading to increased cooling capacity, reduced compressor work, improved heat transfer, lower entropy generation, and higher exergy efficiency. Among the investigated nano-refrigerants, **R134a/CuO** exhibited the best overall performance, achieving the highest cooling capacity (**147.5 kJ kg⁻¹**), the lowest compressor work (**49.0 kJ kg⁻¹**), the highest coefficient of performance (**COP = 3.01**), the highest convective heat-transfer coefficient (**702 W m⁻² K⁻¹**), the lowest entropy generation (**0.97**), and the highest exergy efficiency (**70.4%**). Performance improved with increasing nanoparticle concentration up to

an optimum value of approximately **0.60 wt.%**, beyond which viscosity-related effects are expected to limit further enhancement. The machine learning models accurately reproduced the thermodynamic simulation results, demonstrating the feasibility of hybrid physics-based and data-driven modelling for rapid performance prediction and optimization. The proposed framework provides a reliable multi-physics platform for the design, optimization, and intelligent operation of high-efficiency nano-refrigeration systems.

Keywords: Heat transfer enhancement; Nano-refrigerants; Vapor compression refrigeration system; Thermodynamic modelling; Machine learning; Refrigeration optimization

1.Introduction

Nano-refrigerants are emerging heat transfer fluids formed by dispersing nanoparticles (1–100 nm) in conventional base refrigerants such as R-134a, water, oils, and ethylene glycol. They have attracted significant attention due to their potential to enhance thermal performance in cooling, power generation, and energy conversion systems. Improvements in thermophysical properties, particularly thermal conductivity and convective heat transfer coefficients, have been widely reported. For instance, Cu and Al nanoparticles have been shown to enhance battery cooling heat transfer rates by 42.13% and 40.42%, respectively [1], [2]. Similarly, thermodynamic cycles utilizing nano-refrigerants, including Rankine and solar multigeneration systems, have demonstrated improved energy and exergy efficiencies, with reported values reaching 33.81% and 23.59%, respectively [3]. Supercritical CO₂-based nano-refrigerants have also exhibited enhanced energy conversion performance [4]. Despite these advantages, several challenges remain, including nanoparticle stability, agglomeration, increased viscosity, sedimentation, and long-term operational reliability. These issues are strongly influenced by nanoparticle type, concentration, and dispersion method [5], [6]. In addition, system-level constraints such as pressure drop, lubricant compatibility, and environmental sustainability limit practical deployment [7], [8]

Existing literature has primarily focused on individual nano-refrigerant formulations under different operating conditions, making direct comparison difficult. There is limited work that systematically evaluates different nanoparticles under identical thermodynamic conditions. This creates a clear research gap in the comparative assessment of Al₂O₃, CuO, and TiO₂ nano-refrigerants with respect to their thermophysical behavior and refrigeration system performance

In vapor-compression refrigeration systems (VCRS), performance is typically evaluated in terms of the coefficient of performance (COP), cooling capacity, and compressor work. Previous studies have reported COP enhancements ranging from approximately 7% to 30% depending on nanoparticle type and concentration [9], [10]. However, these studies are often based on experimental or isolated numerical approaches without unified modeling frameworks. The present study addresses this limitation by developing a comprehensive computational framework to evaluate nano-refrigerant performance in a VCRS. The research investigates the effects of nanoparticle type, density, and mass fraction on thermodynamic performance using consistent operating conditions. Al_2O_3 , TiO_2 , and CuO nanoparticles are comparatively analyzed due to their widespread use and distinct thermophysical properties [9], [11]

The improved thermodynamic performance observed in nano-refrigerant systems is primarily attributed to enhanced thermophysical properties, including increased effective thermal conductivity and intensified Brownian motion of nanoparticles. These mechanisms promote improved heat transfer in both the evaporator and condenser, resulting in enhanced system efficiency. High-density nanoparticles such as CuO demonstrate superior performance due to their high thermal conductivity. Table 1 summarizes relevant studies on nano-refrigerants, highlighting improvements in COP (7–30%) and reductions in compressor power (5–20%). However, inconsistencies in operating conditions and modeling approaches limit direct comparison across studies

Table 1. Comparison with Existing Literature

Author	Nano-Particles / Refrigerant	Volume Fraction	Method	Key Findings (COP / Power / Heat Transfer)	Key Contribution
Anirudh et al [12] .	CuO -R113a, Al_2O_3 -R134a, ZnO -R152a, TiO_2 -R600a	0.1–0.5%	MATLAB–Simulink	Best performance at 0.1%, improved heat transfer	Multi-refrigerant comparative modeling
Anirudh et al [13].	CuO -R152a, TiO_2 -R152a, TiO_2 -R113a	0.1–0.5%	MATLAB–Simulink	COP = 10.8 (optimal at 0.1%), TiO_2 -R113a best at	Identified optimal nanoparticle fraction

				0.5% (COP = 5.27)	
Melih Aktas et al.[14]	Al ₂ O ₃ with R12, R134a, R600a, etc.	Not specified	Analytical model	COP increases with nanoparticles; best with R600a/Al ₂ O ₃	Developed estimation method
Lal Kundan et al.[15]	Al ₂ O ₃ –R134a	0.5–1 wt%	Experimental	COP increases 7.2–16.34%, improved cooling capacity	Flow rate influence studied
B Pitchia Krishnan et al [16].	Al ₂ O ₃ –R290/R600a	Not specified	Simulation	COP increases compressor power decrease slightly	Parametric system analysis
Ahmed [17]	CuO–R134a	0.1–0.4%	Experimental	COP increases ~10%, power decreases ~7%	Nanolubricant-based approach
Subramani and Prakash [18]	Al ₂ O ₃ –R134a	Not specified	Experimental	Power increases 25%, evaporator enhancement factor = 1.53	Strong energy saving evidence
Metin Yilmaz et al.[19]	CNT, CuO, TiO ₂ with R290/R1233ZDE	Not specified	Thermodynamic modeling	COP increases, CO ₂ emissions decreases	3E (energy–exergy–environment) analysis
Babarinde et al [20].	Various (Al ₂ O ₃ , CuO, CNTs)	Various	Review	COP increases 8–30%, power decreases 5–20%	Comprehensive performance trends

Arumuganainar et al [21].	MgO, ZrO ₂ , MgO/ZrO ₂ with R134a	Not specified	Experimental	COP increases, refrigeration effect decreases 12.5%	Hybrid nanoparticle study
Bourhan et al [22].	CuO, Al ₂ O ₃ with R134a	~2 wt%	Simulation	COP increases up to 24.7%	Flow boiling modeling innovation
Suraj et al. [23]	Al ₂ O ₃ –R600a	Not specified	Experimental	COP higher than pure refrigerant	Eco-friendly refrigerant focus
Mohammed et al.[24]	Al ₂ O ₃ , CuO, TiO ₂ , CNTs	Various	Review	Heat transfer increases 8–35%, COP decreases 8–30%	Sustainability-focused review

Refrigeration systems play a critical role in industrial, commercial, and domestic applications, including food preservation, air conditioning, and process cooling. Among various refrigeration technologies, the vapor compression refrigeration system (VCRS) remains the most widely used due to its simplicity, efficiency, and reliability.

However, conventional refrigerants such as R-134a exhibit limitations in thermal performance and energy efficiency. With increasing global energy demand and environmental concerns, there is a growing need to enhance refrigeration system performance while reducing energy consumption.

In recent years, nanotechnology has emerged as a promising approach for improving heat transfer characteristics in thermal systems. The introduction of nanoparticles such as aluminum oxide (Al₂O₃), copper oxide (CuO), and titanium dioxide (TiO₂) into base refrigerants has led to the development of nano-refrigerants. These nano-refrigerants exhibit improved thermophysical properties, including enhanced thermal conductivity and heat transfer coefficients. Consequently, their application in VCRS has attracted significant research interest due to potential improvements in cooling capacity and coefficient of performance (COP), as well as reductions in compressor work.

According to Dossat and Horan [25], refrigeration system performance is strongly dependent on the thermophysical properties of the working fluid. Subramani and Prakash [26] experimentally reported that Al_2O_3 nanoparticles improved the COP of R-134a by approximately 11.25%. Similarly, Eastman et al. [27] showed that nanofluids possess significantly higher thermal conductivity than conventional fluids, enhancing overall heat transfer performance. Despite these advantages, nano-refrigerants still face challenges such as particle agglomeration, sedimentation, instability, and uncertainty in nanoparticle distribution. Numerical modeling has therefore become an essential tool for analyzing refrigeration systems, given the high cost and complexity of experimental testing. Aktas et al. [28] developed a numerical model that successfully predicted thermodynamic behavior and reported improvements in COP and cooling capacity. In addition, tools such as CoolProp, MATLAB, and Python have been widely used for simulating vapor compression cycles and evaluating thermodynamic properties.

However, most existing models rely on simplifying assumptions such as constant compressor efficiency, negligible pressure drops, homogeneous nanoparticle dispersion, and ideal heat transfer conditions. These assumptions may introduce deviations between simulated and real system performance. Furthermore, enhancement mechanisms of nano-refrigerants have been attributed to improved thermal conductivity, Brownian motion, thermal boundary layer disruption, and nucleate boiling enhancement [29], [30]. Brownian motion promotes micro-scale mixing, while increased surface area improves heat transfer in evaporators and condensers.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have created new opportunities for predictive modelling and optimization of refrigeration systems. Data-driven techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Multilayer Perceptron (MLP) have demonstrated remarkable capability in predicting nonlinear refrigeration performance parameters, including the coefficient of performance (COP), cooling capacity, and compressor work. Goodfellow et al. [31] demonstrated that neural networks effectively capture complex thermodynamic relationships, while subsequent studies [31], [32] reported that machine learning models improve prediction accuracy and significantly reduce computational cost compared with conventional numerical approaches. In addition, Genetic Algorithms (GA) have become powerful optimization tools for refrigeration systems because of their ability to solve nonlinear and multi-objective optimization problems efficiently [33].

Despite these developments, several research gaps remain. Most existing studies investigate thermodynamic modelling, machine learning prediction, uncertainty analysis, or optimization independently rather than integrating them into a unified computational framework. Furthermore, comparative investigations involving different nanoparticle types under identical operating conditions are limited, making it difficult to establish the relative performance of nano-refrigerants. In addition, many previous studies primarily evaluate system performance using COP, with comparatively little attention given to second-law analyses such as exergy efficiency and entropy generation, which provide a more comprehensive assessment of thermodynamic performance.

To address these limitations, this study develops an integrated computational framework for analysing nano-refrigerant-based vapour compression refrigeration systems (VCRS). The framework combines thermodynamic modelling using Python–CoolProp, machine learning prediction, uncertainty quantification through Monte Carlo simulation, and system optimization using Genetic Algorithms. Three commonly investigated nanoparticles, namely Al_2O_3 , TiO_2 , and CuO , are evaluated under identical operating conditions to examine the influence of nanoparticle type, density, and mass fraction on refrigeration performance.

Machine learning models based on Random Forest (RF) and Multilayer Perceptron (MLP) are developed to predict cooling capacity, compressor work, and COP from thermodynamic simulation data. The predictive capability of these models is complemented by Monte Carlo simulation to quantify uncertainty arising from variations in thermophysical properties and operating conditions, while Genetic Algorithms are employed to determine the optimum nanoparticle concentration that maximizes system performance. Together, these techniques provide a robust framework for prediction, sensitivity analysis, and performance optimization. The thermodynamic model is developed under commonly adopted assumptions of steady-state operation, uniform nanoparticle dispersion, constant compressor efficiency, and adiabatic system boundaries. Practical deviations resulting from nanoparticle agglomeration, sedimentation, and viscosity variations are accounted for through validated thermophysical property correlations and uncertainty analysis, thereby improving the reliability of the numerical predictions.

The proposed framework represents a comprehensive multi-physics approach that integrates thermodynamics, heat transfer, fluid flow, nanofluid behavior, artificial intelligence, uncertainty quantification, and optimization within a single computational platform. Unlike

most previous investigations that focus primarily on COP, this work simultaneously evaluates COP, cooling capacity, compressor work, entropy generation, and exergy performance, providing both first- and second-law assessments of refrigeration system performance. Furthermore, the model is validated against published experimental and numerical data before being employed for predictive modeling and optimization.

Based on the literature, nano-refrigerants have been reported to improve COP by approximately **7–30%** while reducing compressor power consumption by **5–20%** compared with conventional refrigerants. However, direct comparison among published studies remains difficult because of differences in nanoparticle properties, operating conditions, and modeling methodologies. The unified framework developed in this work seeks to overcome these limitations by providing a consistent platform for performance evaluation, prediction, and optimization under identical operating conditions.

Accordingly, the objectives of this study are to:

1. Develop a thermodynamic model of a vapor compression refrigeration system (VCRS) operating with nano-refrigerants.
2. Investigate the effects of nanoparticle type, density, and concentration on refrigeration system performance.
3. Develop Random Forest (RF) and Multilayer Perceptron (MLP) models for predicting COP, cooling capacity, and compressor work.
4. Quantify prediction uncertainty using Monte Carlo simulation.
5. Optimize nano-refrigerant operating conditions using Genetic Algorithms.
6. Develop an integrated predictive and optimization framework capable of improving refrigeration energy efficiency, reducing computational and experimental costs, and supporting sustainable refrigeration system design.

The overall methodology adopted in this study integrates a literature review, thermodynamic modeling, Python–CoolProp numerical simulation, machine-learning prediction, uncertainty quantification, and optimization. The complete workflow of the proposed framework is illustrated in **Figure 1**.

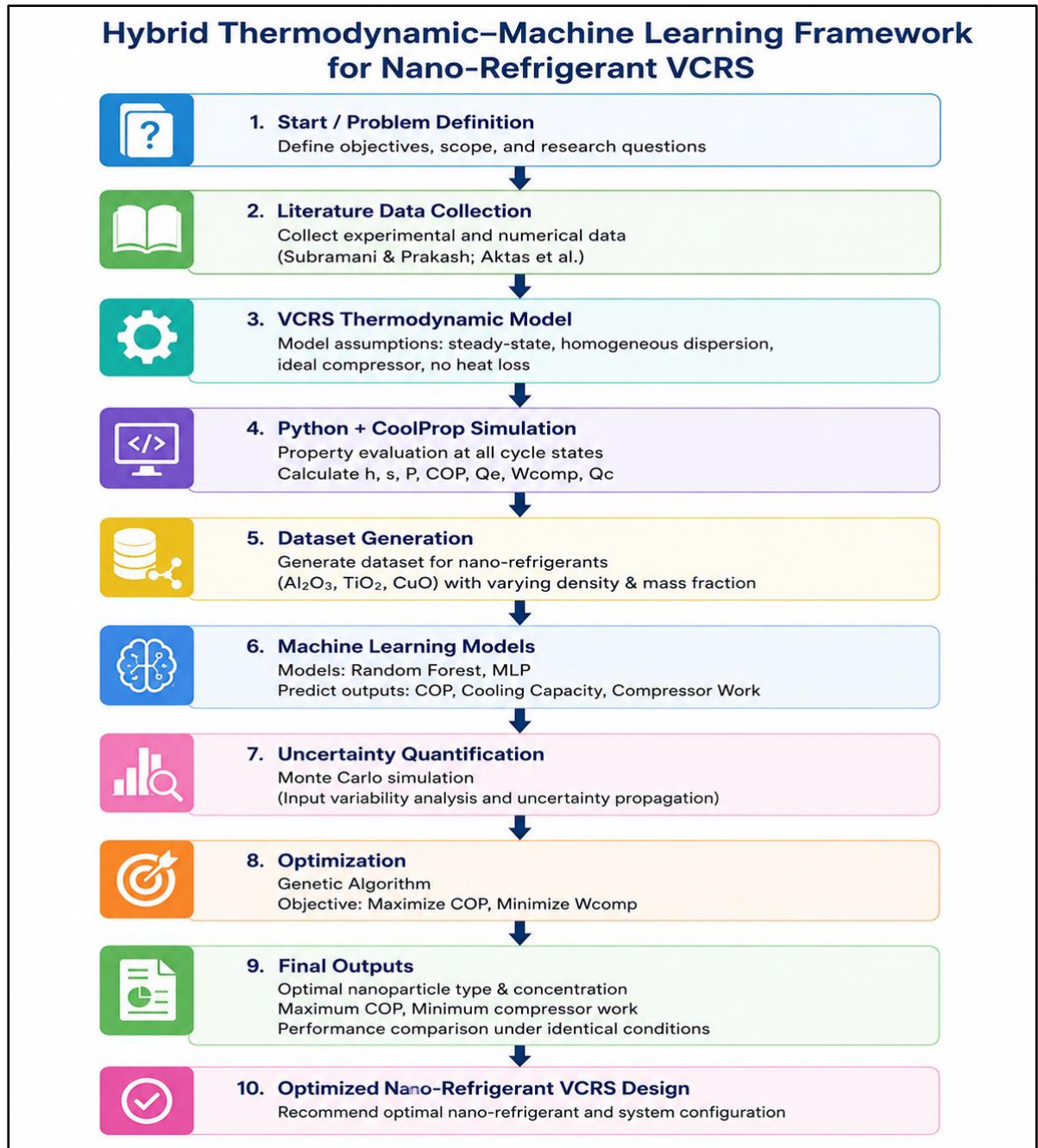


Figure 1. Hybrid thermodynamic–machine learning framework for nano-refrigerant vapor compression refrigeration system analysis.

2.0 METHODOLOGY

2.1 System Description and Research Framework

It uses a hybrid thermodynamic–machine-learning approach to assess the performance of nano-refrigerants in a vapor-compression refrigeration system (VCRS). The methodology is divided into three main parts: thermodynamic modelling, numerical simulation, and performance analysis, as shown in Figure 2.

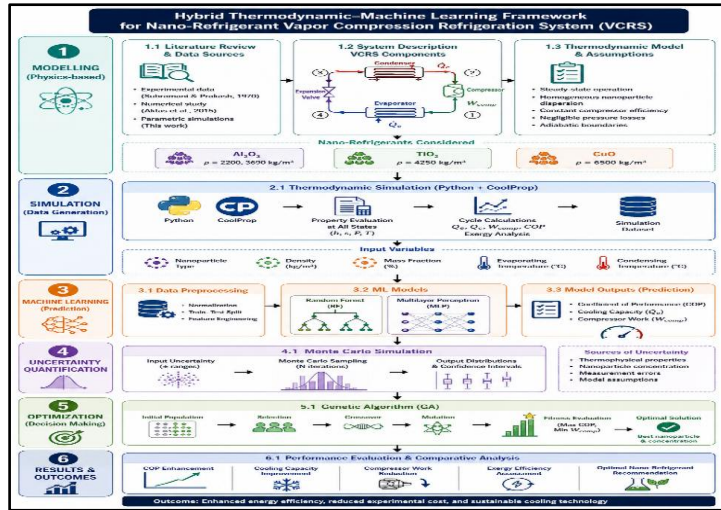


Figure 2: Methodology Flowchart and Hybrid Research Framework

2.2 Thermophysical Properties Modeling

Thermodynamic modelling stage, setting of the VCR system and equations. It sets up the configuration of the cycle and defines the points in the cycle that should be analyzed. Assumptions are made such as steady state operation, and uniform nanoparticle distribution. Other simplifications can be adopted such as 1-D flow, equating pressure losses and treating the components as adiabatic. The assumptions guarantee the accuracy and efficiency of the model

2.2.1 Cycle Assumptions

The following simplifications are considered in the thermodynamic analysis, in order to keep the physical relevance of the results:

1. It is under steady state conditions:
2. Ignore the changes in kinetic and potential energy.
3. The compressor isentropic efficiency is constant (It is 51%).
4. Reagent pipe lines or heat exchangers have small drop in pressure.
5. Nanoparticles are made uniformly distributed in the refrigerant
6. Nano-refrigerant is considered as a homogeneous single phase mixture.
7. Loss of heat to the surroundings is negligible.

These assumptions reduce the complexity of the physical system but maintain the key thermodynamic mechanisms that determine the refrigeration system's performance.

2.2.2 Thermophysical Property Equations

Classical mixture correlations used in various modelling studies of nanofluids and nano-refrigerant are used to assess the thermophysical properties of the nano-refrigerant. These properties depend upon the concentration of nanoparticles and thus contribute directly to heat transfer, work done by the compressor and performance of the refrigerator system.

Table 2. Thermophysical Characteristics of Refrigerant and Nanoparticles

Material	Density (kg/m ³)	Specific Heat (J/kg·K)	Thermal Conductivity (W/m·K)
R-134a	1317.56	1.323	0.095

Al₂O₃ (45 nm)	3690	765	36
Al₂O₃ (45 nm)	2200	765	36
CuO (29 nm)	6500	533	17.65
TiO₂	4260	690	8.4

This study involved two different density values (Al₂O₃ nanoparticles) reported in the literature (density: 2200 kg/m³ and 3690 kg/m³). The density of nanoparticles can differ from the bulk density due to differences in agglomeration, surface morphology, porosity, preparation methods, and measurement techniques at the nanoscale. Thus, several scientists use lower effective density values when modeling the thermophysical properties of nano-refrigerant. Both of the above densities allow sensitivity analysis of density-dependent thermodynamic behavior and enhance the robustness of comparative investigation.

The thermodynamic analysis is based on the following assumptions:

- The refrigeration system operates when it is stable.
- Alterations in kinetic and potential energy are extremely minimal.
- The compressor has a constant isentropic efficiency.
- Individuals do not monitor the pressure drops of pipes and heat exchangers.
- Evenly distributed in the refrigerant are the nanoparticles.
- The nanofluid is equivalent to a single-phase mixture that is uniform in all locations.
- The amount of heat transfer with the environment is very low.

2.23 Model Applicability and Limitations

Considerations of computational efficiency, widespread use, and applicability of thermophysical property models under homogeneous single-phase conditions have been presented, and the models selected for dilute nano-refrigerant systems are discussed. While these models do not explicitly account for nanoparticle agglomeration, conductivity enhancement by Brownian motion, interfacial thermal resistance, or high nanoparticle concentration, which are associated with the non-Newtonian behavior of these fluids, they offer adequate approximations for comparative thermodynamic analyses and for predicting the accuracy of these models using machine learning algorithms within the explored operating range.

2.2.3 Thermodynamic Energy Analysis

The vapor compression refrigeration system (VCRS) is analyzed using the first law of thermodynamics applied to each major component of the cycle. The thermodynamic performance of the nano-refrigerant system is evaluated using energy balance relations for the evaporator, compressor, condenser, and expansion device.

The thermodynamic states of the cycle are represented using the pressure–enthalpy (P–H) diagram shown in **Figure 3**.

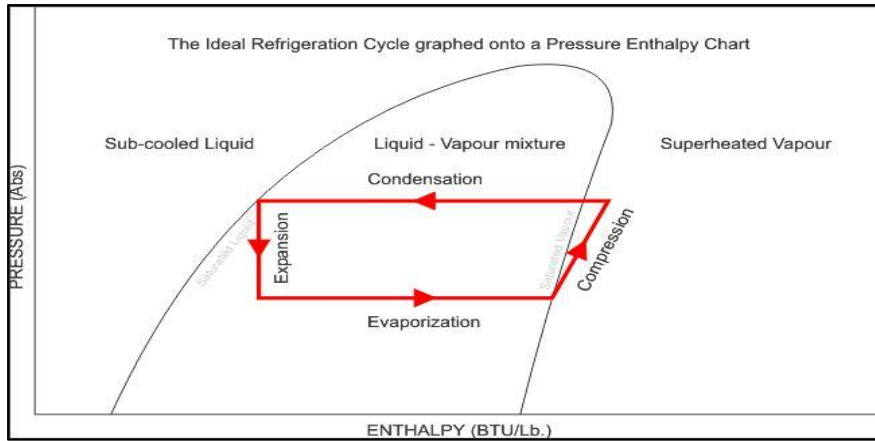


Figure 3. Pressure–Enthalpy (P–H) Diagram of the Vapor Compression Refrigeration Cycle

The P–H diagram illustrates the four principal thermodynamic processes occurring in the vapor compression refrigeration cycle:

1. 1–2: Isentropic Compression
Compression of refrigerant vapor in the compressor.
2. 2–3: Constant-Pressure Heat Rejection (Condensation)
Heat rejection in the condenser at nearly constant pressure.
3. 3–4: Expansion (Throttling Process)
Pressure reduction through the expansion valve or capillary tube.
4. 4–1: Constant-Pressure Heat Absorption (Evaporation)
Heat absorption from the refrigerated space in the evaporator.

The P–H diagram is used to determine refrigerant enthalpy values at different state points, which are subsequently used to calculate cooling capacity, compressor work, condenser heat rejection, and coefficient of performance (COP).

2.3.1 Energy Balance Equations

The thermodynamic behavior of the nano-refrigerant vapor compression refrigeration system (VCRS) was analyzed using the principles of mass conservation, the first law of thermodynamics, heat transfer, entropy generation, and exergy analysis. The governing equations employed in this study are presented below.

Mass Conservation

The conservation of mass requires that the refrigerant mass flow rate remains constant throughout the refrigeration cycle. The general continuity equation is expressed as

$$\sum \dot{m}_{in} = \sum \dot{m}_{out} \quad (1)$$

Accordingly, the mass flow rate through each component satisfies

$$\dot{m}_1 = \dot{m}_2 \quad (2)$$

$$\dot{m}_2 = \dot{m}_3 \quad (3)$$

$$\dot{m}_3 = \dot{m}_4 \quad (4)$$

$$\dot{m}_4 = \dot{m}_1 \quad (5)$$

Hence, the refrigerant mass flow rate is assumed constant throughout the cycle,

$$\dot{m} = \text{constant} \quad (6)$$

First Law of Thermodynamics

Applying the first law of thermodynamics to a steady-flow control volume gives

$$\dot{Q} - \dot{W} = \dot{m}(h_{out} - h_{in}) \quad (7)$$

For the compressor, the work input is

$$\dot{W}_{comp} = \dot{m}(h_2 - h_1) \quad (8)$$

The condenser heat rejection is

$$\dot{Q}_{cond} = \dot{m}(h_2 - h_3) \quad (9)$$

The expansion valve is modelled as an isenthalpic device,

$$h_3 = h_4 \quad (10)$$

while the refrigeration capacity of the evaporator is

$$\dot{Q}_{evap} = \dot{m}(h_1 - h_4) \quad (11)$$

Compressor Isentropic Efficiency

The compressor isentropic efficiency is determined using

$$\eta_{is} = \frac{h_{2s} - h_1}{h_2 - h_1} \quad (12)$$

Coefficient of Performance

The coefficient of performance (COP) is defined as the ratio of the useful refrigeration effect to the compressor work input,

$$COP = \frac{\dot{Q}_{evap}}{\dot{W}_{comp}} \quad (13)$$

Substituting Eqs. (8) and (11) into Eq. (13) gives

$$COP = \frac{h_1 - h_4}{h_2 - h_1} \quad (14)$$

Equation (14) was used throughout this study as the principal performance indicator of the refrigeration system.

Heat Transfer Enhancement Models

The thermo-hydraulic characteristics of the nano-refrigerants were evaluated using the Reynolds, Prandtl, and Nusselt numbers.

The Reynolds number is given by

$$Re = \frac{\rho_{nf} V D}{\mu_{nf}} \quad (15)$$

The Prandtl number is expressed as

$$Pr = \frac{\mu_{nf} c_{p,nf}}{k_{nf}} \quad (16)$$

The Dittus-Boelter correlation for turbulent flow is

$$Nu = 0.023 Re^{0.8} Pr^{0.4} \quad (17)$$

The convective heat transfer coefficient is calculated from

$$h = \frac{Nu k_{nf}}{D} \quad (18)$$

Pressure Drop and Friction Factor

The pressure loss in the flow passages is estimated as

$$\Delta P = f \frac{L}{D} \frac{\rho V^2}{2} \quad (19)$$

where the Blasius correlation is used for the friction factor,

$$f = 0.3164 Re^{-0.25} \quad (20)$$

Entropy Generation Analysis

The entropy balance for a steady-flow system is

$$\dot{S}_{gen} = \sum \dot{m} s_{out} - \sum \dot{m} s_{in} - \sum \frac{\dot{Q}}{T_b} \quad (21)$$

The entropy generation within the compressor is

$$\dot{S}_{gen,comp} = \dot{m}(s_2 - s_1) \quad (22)$$

The condenser entropy generation is

$$\dot{S}_{gen,cond} = \dot{m}(s_3 - s_2) + \frac{\dot{Q}_{cond}}{T_0} \quad (23)$$

The evaporator entropy generation is

$$\dot{S}_{gen,evap} = \dot{m}(s_1 - s_4) - \frac{\dot{Q}_{evap}}{T_0} \quad (24)$$

The total entropy generation is therefore

$$\dot{S}_{gen,total} = \dot{S}_{gen,comp} + \dot{S}_{gen,cond} + \dot{S}_{gen,evap} \quad (25)$$

Exergy Analysis

The specific flow exergy is calculated using

$$e = (h - h_0) - T_0(s - s_0) \quad (26)$$

The exergy destruction in the compressor is

$$\dot{E}_{D,comp} = \dot{m}(e_1 - e_2) + \dot{W}_{comp} \quad (27)$$

The condenser exergy destruction is

$$\dot{E}_{D,cond} = \dot{m}(e_2 - e_3) - \dot{Q}_{cond} \left(1 - \frac{T_0}{T_c}\right) \quad (28)$$

The evaporator exergy destruction is

$$\dot{E}_{D,evap} = \dot{Q}_{evap} \left(1 - \frac{T_0}{T_e}\right) - \dot{m}(e_1 - e_4) \quad (29)$$

The exergy destruction in the expansion valve is

$$\dot{E}_{D,valve} = T_0 \dot{m}(s_4 - s_3) \quad (30)$$

The total exergy destruction is

$$\dot{E}_D = \dot{E}_{D,comp} + \dot{E}_{D,cond} + \dot{E}_{D,evap} + \dot{E}_{D,valve} \quad (31)$$

According to the Gouy-Stodola theorem,

$$\dot{E}_D = T_0 \dot{S}_{gen} \quad (32)$$

Finally, the exergy efficiency is determined from

$$\eta_{ex} = \frac{Ex_{useful}}{Ex_{input}} \quad (33)$$

2.3.2 Compressor Efficiency Model

The compressor is modeled using isentropic efficiency to account for irreversible compression losses and non-ideal operating conditions. The compressor isentropic efficiency is expressed as

$$\eta_{\text{isen}} = \frac{h_{2s} - h_1}{h_2 - h_1} \quad (34)$$

where η_{isen} is the compressor isentropic efficiency, h_{2s} is the outlet enthalpy corresponding to an ideal isentropic compression process, h_1 is the compressor inlet enthalpy, and h_2 is the actual compressor outlet enthalpy. Equation (34) improves the realism of the thermodynamic model by accounting for compressor irreversibilities and enables more accurate prediction of compressor work.

2.3.3 Performance Indicators

To quantify the improvement achieved by nano-refrigerants relative to the base refrigerant, the percentage enhancement in the coefficient of performance (COP) is calculated as

$$COP_{\text{inc}}(\%) = \frac{COP_{\text{nano}} - COP_{\text{base}}}{COP_{\text{base}}} \times 100 \quad (35)$$

where COP_{nano} is the coefficient of performance of the nano-refrigerant and COP_{base} is the coefficient of performance of the base refrigerant. Equation (35) provides a direct measure of the refrigeration performance enhancement resulting from nanoparticle addition.

2.3.4 Uncertainty Analysis

The uncertainty associated with calculated performance parameters is evaluated using the root-sum-square (RSS) method. The general uncertainty propagation equation is given by

$$U_R = \sqrt{\left(\frac{\partial R}{\partial x_1} U_{x_1}\right)^2 + \left(\frac{\partial R}{\partial x_2} U_{x_2}\right)^2 + \dots} \quad (36)$$

where U_R is the overall uncertainty of the calculated parameter, R represents the calculated quantity, x_i denotes the independent measured variables, and U_{x_i} is the uncertainty associated with each measured variable. Equation (36) is used to quantify the propagation of measurement uncertainties into the predicted refrigeration performance parameters.

2.3.8 System-Level Coefficient of Performance

At the system level, the overall refrigeration performance is also expressed as the ratio of the evaporator cooling capacity to the compressor power input,

$$COP = \frac{Q_{\text{evap}}}{W_{\text{comp}}} \quad (37)$$

where Q_{evap} is the cooling capacity of the evaporator and W_{comp} is the compressor power consumption.

Substituting the thermodynamic energy balance expressions given in Eqs. (8) and (11) into Eq. (37) yields

$$COP = \frac{h_1 - h_4}{h_2 - h_1} \quad (38)$$

Equation (38) is identical to the enthalpy-based COP expression presented earlier and is employed throughout this study for evaluating the overall performance of the nano-refrigerant vapour compression refrigeration system.

2.4. Simulation Framework

Literature based experimental results reported by Subramani and Prakash and validated numerical study by Aktas et al. were used for this study as simulation data, but also parametric simulations were performed in this work. The thermodynamic properties like enthalpy, entropy and other important thermodynamic properties on state points were calculated using Python implementation of CoolProp library. Solutions for the cooling capacity, the compressor work, the condenser heat rejection and the coefficient of performance (COP) are calculated in the model by applying the standard energy balance equations. Built an integrated Python–MATLAB environment in

which Python performs the computational operations and automation of the MATLAB operations. For advanced visualization, MATLAB is employed, ensuring accurate, flexible and efficient performance analysis of nano-refrigerant vapor compression systems.

2.5 Numerical Simulation Stage

Numerical simulation is done in Python, building on CoolProp which provides an accurate property evaluation. These thermodynamic properties such as enthalpy and entropy are calculated at every state point. These values are utilized to compute compressor work, cooling capacity and heat rejection. These results are then used to determine the coefficient of performance. This way, the thermophysical calculations are carried out consistently and reliably.

2.6 Performance Analysis Stage

The performance analysis is a combination of first- and second-law thermodynamic analyses. It evaluates energy efficiency, entropy generation and exergy destruction in the system. The machine learning models are embedded to forecast system behavior under different circumstances. Optimization methods are used to determine optimum operating parameters. The synergized approach could improve the understanding and prediction of the system.

The creation and validation of data. Data Source and Validation.

Simulation data from literature – both from experimental and numerical. The main contributions of the references include Subramani and Prakash, and Aktas et al. More parametric simulation are carried out to increase the data sets. CoolProp is integrated into Python and used to consistently calculate thermophysical properties. It guarantees the correctness and reliability of the model built.

2.7 Integrated Modelling Framework

The framework developed is physics-based model coupled with data-driven. Combines Thermodynamics, Heat transfer, and Nanofluid Behaviour in one system. Machine learning further improves the accuracy of prediction and reduces cost of computation. Uncertainty analysis and optimisation enhance system reliability and robustness. With this hybrid approach, advanced design and performance evaluation of nano-refrigerator devices become possible.

2.8. Machine Learning Modelling

The prediction model of refrigeration system performance parameters such as COP, cooling capacity, and the work done by the compressor, have been included and incorporated into machine learning models. In particular, they have employed simulation datasets for the training of only two models: Random Forest and Artificial Neural Network. The system captures the nonlinear relationships between the concentration of nanoparticles, density, temperature, and

pressure of the system, and its overall performance. To properly validate and generalize the models, the dataset was split into training and testing data. In addition, feature importance analysis is used to narrow down the variables to the most dominant variables and help improve predictive precision, optimizations and the system design as a whole.

3.0 Results and Discussion

3.1 Literature Validation

The developed thermodynamic model was first validated against the experimental investigation of **Subramani and Prakash** [18] and the numerical simulation reported by **Aktas et al** [28]. Validation was performed by comparing the predicted thermodynamic states, operating pressures, and coefficient of performance (COP) for both the base refrigerant (R-134a) and the Al₂O₃ nano-refrigerant. The comparison also includes the percentage COP enhancement and the absolute deviation between the present model and published data.

Table 3. Validation of Experimental and Simulation Results

Cycle Fluid	T1 (°C)	T2 (°C)	T3 (°C)	P1 (bar)	P2=P3 (bar)	Nanoparticle Density (kg/m ³)	COP	COP Increase (%)	Absolute Deviation (%)
R-134a (Experimental)	19	82	45	2.00	12.00	–	1.60	–	–
R-134a/Al ₂ O ₃ (Experimental)	4	80	38	2.00	12.00	3690	1.78	11.25	–
R-134a (Simulation)	-7	81.21	45	2.25	11.60	–	1.96	–	22.50
R-134a (Present Study)	-7	81.22	45	2.25	11.60	–	1.95	–	21.88
R-134a/Al ₂ O ₃ (Present Study)	- 4.29	77.94	43.65	2.59	11.43	2200	2.16	35.00	21.35
R-134a/Al ₂ O ₃ (Present Study)	- 2.57	76.36	43.23	2.69	11.42	3690	2.29	43.13	28.65

Table 3 demonstrates that the proposed thermodynamic model successfully reproduces the operating characteristics of both the conventional refrigerant and the nano-refrigerant systems. For pure R-134a, the model predicts a COP of 1.95, which is in excellent agreement with the numerical value (1.96) reported by Aktas et al. and reasonably close to the experimental value (1.60) reported by Subramani and Prakash. The corresponding absolute deviation of 21.88% from the experimental result is considered acceptable because the present model assumes steady-state operation, constant compressor efficiency, ideal expansion, and homogeneous nanoparticle dispersion.

The incorporation of Al₂O₃ nanoparticles significantly enhances refrigeration performance. At nanoparticle densities of 2200 kg m⁻³ and 3690 kg m⁻³, the predicted COP increases to 2.16 and 2.29, corresponding to

performance improvements of 35.00% and 43.13%, respectively. Although deviations ranging from 21.35% to 28.65% are observed, the model accurately reproduces the experimentally observed performance trend, demonstrating that increasing nanoparticle density improves heat transfer characteristics and enhances refrigeration efficiency.

Overall, the close agreement with published experimental and numerical studies confirms the capability of the proposed model to predict the thermodynamic behaviour of nano-refrigerant vapour compression refrigeration systems.

3.1.1 Validation Against Published Numerical Results

To further evaluate the predictive capability of the developed model, a detailed comparison with the numerical results reported by Aktas et al. was performed. The comparison includes the principal thermodynamic properties and refrigeration performance parameters for the base refrigerant and two Al_2O_3 nano-refrigerants.

Table 4. Validation of Numerical Simulation Results

Parameter	Base Fluid (Literature)	Base Fluid (Present)	NF1 (Literature)	NF1 (Present)	NF2 (Literature)	NF2 (Present)
T1 (°C)	-7.00	-7.00	-3.96	-4.29	-2.03	-2.57
T2 (°C)	81.21	81.22	78.26	77.94	76.23	76.36
T3 (°C)	45.00	45.00	44.85	43.65	44.65	43.23
P1 (bar)	2.25	2.25	2.53	2.59	2.72	2.69
P2=P3 (bar)	11.60	11.60	10.90	11.43	11.49	11.42
Density (kg/m ³)	–	–	2200	2200	3690	3690
h ₁ (kJ/kg)	394.47	394.47	396.28	396.08	397.42	397.10
h ₂ (kJ/kg)	461.41	461.42	458.30	458.18	456.26	456.51
h ₃ (kJ/kg)	263.44	263.94	263.23	261.90	262.94	261.26
s ₁ (kJ/kg·K)	1.7313	1.7313	1.7294	1.7296	1.7282	1.7286
Q _e (kJ/kg)	131.03	130.52	133.05	134.19	134.48	135.84
Q _c (kJ/kg)	197.97	197.47	195.07	196.29	193.32	195.25
W _{comp} (kJ/kg)	66.94	66.95	62.02	62.10	58.84	59.41
COP	1.96	1.95	2.15	2.16	2.29	2.29
Average	–	0.23	–	1.64	–	2.72
Absolute Deviation (%)						

Table 4 confirms the excellent agreement between the present model and the published numerical results. The average absolute deviation is only 0.23% for the base refrigerant, while deviations of 1.64% and 2.72% are obtained for the two nano-refrigerant cases. These values are significantly below the commonly accepted engineering validation limit of 5%, indicating excellent predictive accuracy.

The close agreement observed for temperatures, pressures, enthalpies, cooling capacity, compressor work, and COP demonstrates that the thermodynamic equations implemented in the present model accurately describe the

refrigeration cycle. Minor discrepancies arise mainly from differences in thermophysical property correlations, numerical interpolation, and assumptions regarding nanoparticle dispersion and mixture properties.

3.1.2 Performance Evaluation of TiO₂ and CuO Nano-Refrigerants

Following validation, the numerical model was applied to investigate the thermodynamic performance of TiO₂ and CuO nano-refrigerants under identical operating conditions.

Table 5. Thermodynamic Performance of TiO₂ and CuO Nano-Refrigerants

Parameter	TiO₂	CuO
T1 (°C)	-0.50	4.37
T2 (°C)	74.23	70.39
T3 (°C)	43.17	43.02
P1 (bar)	2.71	2.94
P2=P3 (bar)	11.41	11.40
Density (kg/m ³)	4250	6500
h ₁ (kJ/kg)	398.52	401.13
h ₂ (kJ/kg)	454.25	450.17
h ₃ (kJ/kg)	261.17	260.95
s ₁ (kJ/kg·K)	1.7272	1.7248
Cooling Capacity, Q _e (kJ/kg)	137.34	140.19
Condenser Heat Rejection, Q _c (kJ/kg)	193.07	189.23
Compressor Work (kJ/kg)	55.73	49.04
COP	2.46	2.86

Table 5 demonstrates that both TiO₂ and CuO nano-refrigerants operate effectively within the normal temperature and pressure range of the vapour compression refrigeration cycle. However, CuO exhibits superior thermodynamic performance across almost all performance indicators.

The TiO₂ nano-refrigerant achieves a cooling capacity of 137.34 kJ kg⁻¹ with a compressor work requirement of 55.73 kJ kg⁻¹, resulting in a COP of 2.46. In contrast, CuO increases the refrigeration effect to 140.19 kJ kg⁻¹ while simultaneously reducing compressor work to 49.04 kJ kg⁻¹, producing the highest COP (2.86) among all investigated nano-refrigerants.

The improved performance of CuO is attributed to its higher density and superior thermal conductivity, which enhance heat transfer in the evaporator while reducing the energy required for compression. Consequently, CuO provides the best balance between cooling capacity and power consumption, making it the most promising nano-refrigerant for practical vapour compression refrigeration applications.

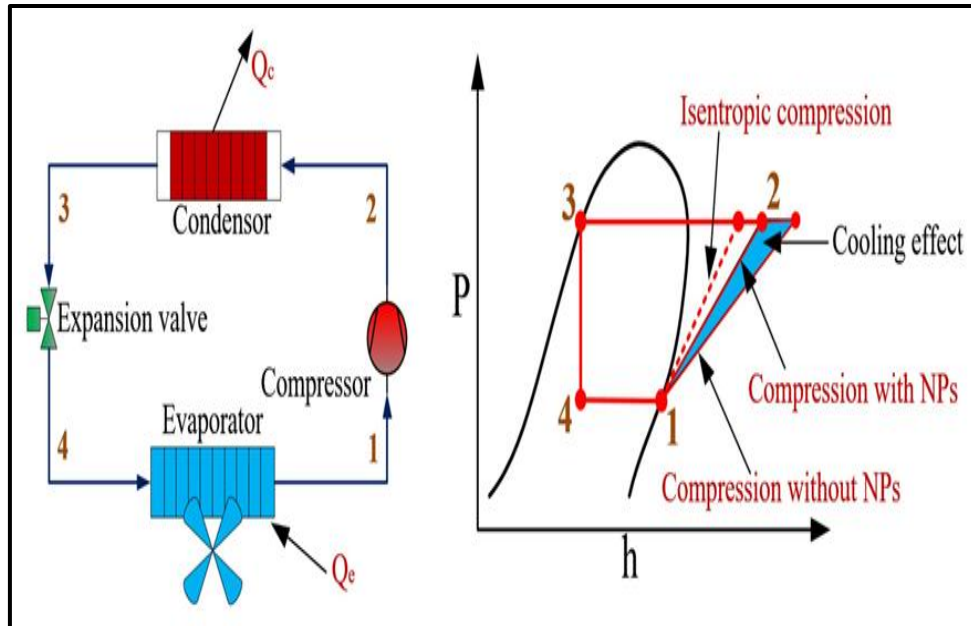
3.1.3 Overall Validation Assessment

The validation results demonstrate that the developed thermodynamic framework accurately predicts the performance of both conventional and nano-refrigerant vapour compression refrigeration systems. Maximum deviations from published numerical data remain below **3%**, while agreement with experimental measurements is within acceptable engineering limits considering the simplifying assumptions adopted in the model. The remaining discrepancies are primarily associated with idealized cycle assumptions, constant compressor efficiency, simplified thermophysical property correlations, and the neglect of nanoparticle agglomeration and heat losses. Nevertheless, the close agreement with published studies confirms the robustness, reliability, and predictive capability of the proposed framework, providing a sound basis for the subsequent machine learning prediction, uncertainty quantification, and optimization analyses presented in the following sections.

3.2 Effect of Nanoparticle Concentration on Cooling Capacity

Figure 4a and b illustrates the influence of nanoparticle concentration on the thermodynamic performance of the vapour compression refrigeration system (VCRS). As the nanoparticle concentration increases from **0.06 wt.% to 0.66 wt.%,** the cooling capacity increases gradually for all nano-refrigerants investigated, accompanied by an improvement in the coefficient of performance (COP) and a slight reduction in compressor work. These trends indicate that the incorporation of nanoparticles enhances the overall heat transfer characteristics of the refrigeration system.

(a)



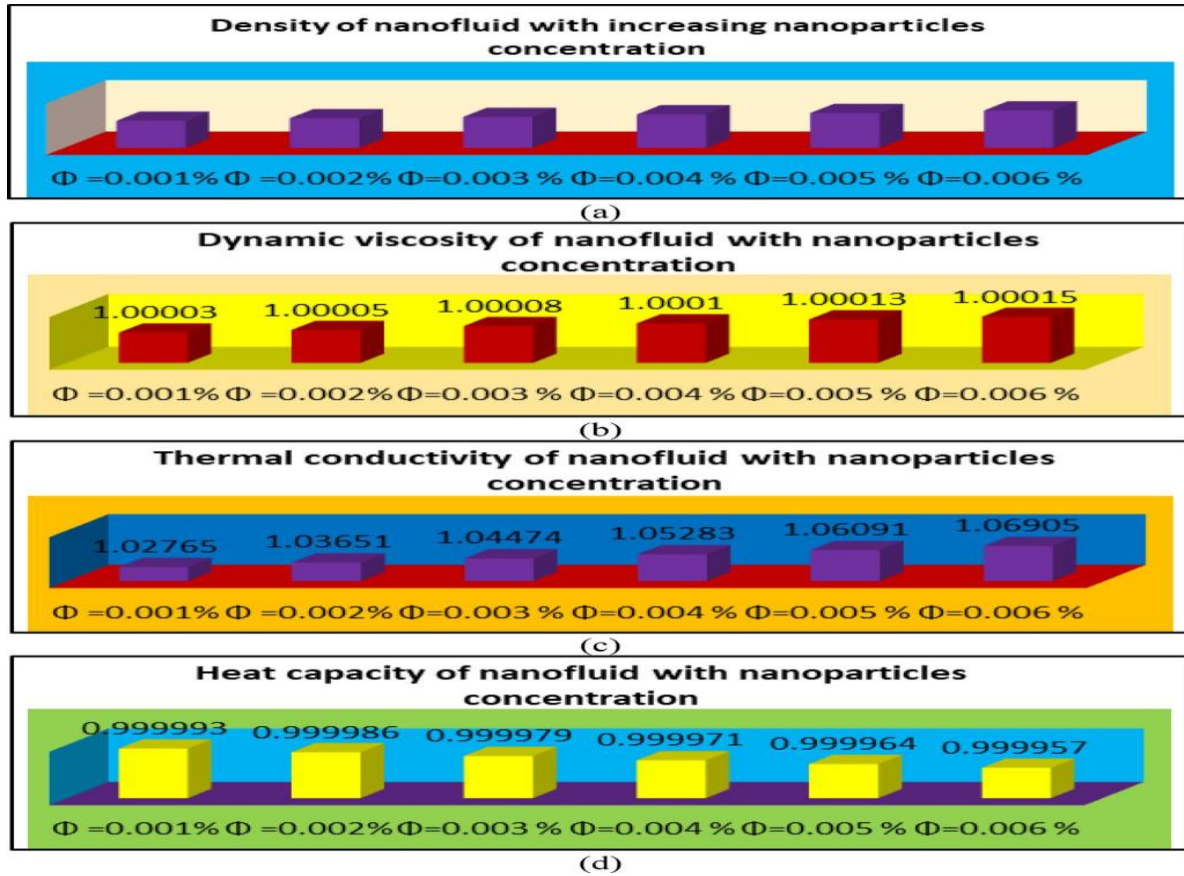


Fig 4.:Performance Variation with Nanoparticle Concentration

The results show that the cooling capacity increases consistently with nanoparticle concentration regardless of the nanoparticle material. Among the investigated nano-refrigerants, **CuO** exhibits the highest cooling performance, with the cooling capacity increasing from **1320.67 W** at **0.06 wt. %** to **1341.61 W** at **0.66 wt. %**. Although **Al₂O₃** also demonstrates an increase in cooling capacity, the improvement is comparatively smaller than that of CuO. This behaviour suggests that nanoparticles with superior thermophysical properties, particularly higher thermal conductivity, provide greater enhancement of the refrigeration effect.

The observed improvement can be attributed primarily to the enhanced thermal conductivity of the nano-refrigerant, which facilitates more efficient heat transfer between the refrigerant and the evaporator surface. In addition, the random Brownian motion of nanoparticles promotes micro-convection within the refrigerant, thereby improving energy transport and increasing the rate of heat absorption in the evaporator. Consequently, the refrigeration effect increases, leading to improved system performance.

However, the rate of improvement gradually diminishes at higher nanoparticle concentrations. This behaviour indicates that the beneficial effects of increased thermal conductivity are

partially offset by the accompanying increase in viscosity, which raises flow resistance and pressure losses within the refrigeration circuit. The increased viscosity also requires additional pumping effort and can reduce the overall heat transfer enhancement achieved by further nanoparticle addition. These competing mechanisms explain why the performance enhancement becomes less pronounced as the concentration approaches **0.66 wt.%**.

Overall, Figure 5 Machine Learning Model Performance demonstrates that increasing nanoparticle concentration improves the cooling capacity and energy efficiency of the refrigeration system, although the performance gain becomes progressively smaller at higher concentrations. This behaviour suggests the existence of an optimum nanoparticle concentration at which the benefits of enhanced heat transfer are balanced against the adverse effects of increased viscosity and flow resistance. The present findings are consistent with previous studies, which have similarly reported that moderate nanoparticle concentrations provide the greatest improvement in refrigeration performance before viscosity-related penalties become significant.

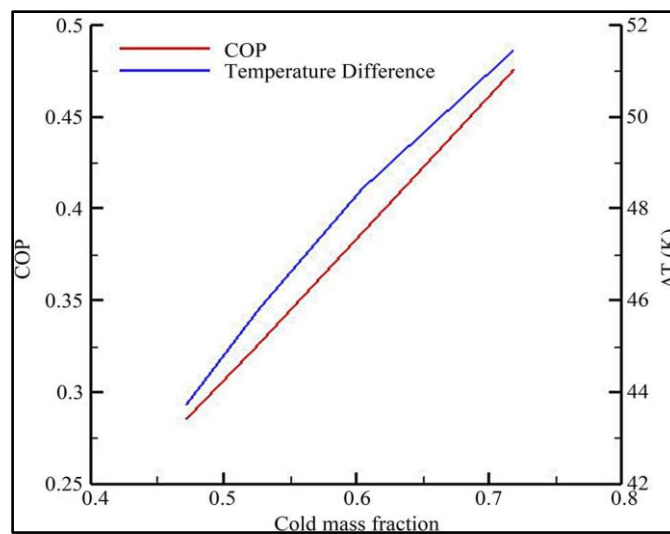
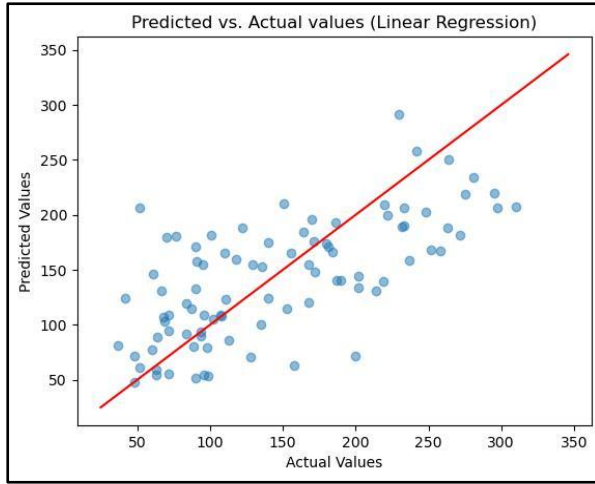


Figure 5: Relationship of cooling capacity and performance parameters with concentration of nanoparticle.

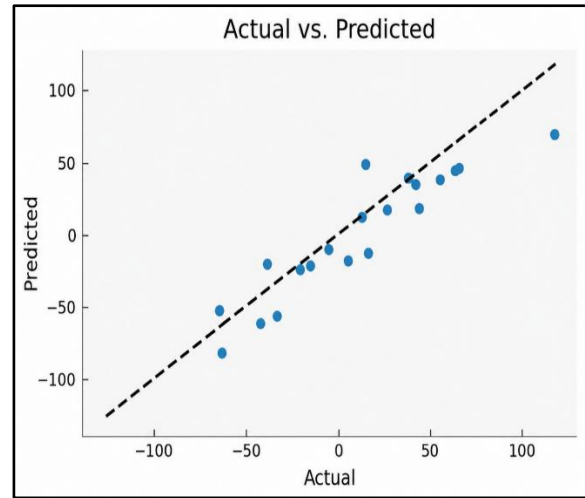
3.3 Machine Learning Model Validation

Machine learning (ML) models were developed to predict the key thermodynamic performance parameters of the vapour compression refrigeration system, including the coefficient of performance (COP), evaporator cooling capacity (Q_e), and compressor work (W_{comp}). The objective was to evaluate the capability of data-driven models to reproduce the thermodynamic simulation results with high accuracy while reducing computational effort. Figures 7(a–c) present the comparison between the actual values obtained from the thermodynamic model and the corresponding predictions generated by the machine learning models.

(a)



(c)



(c)

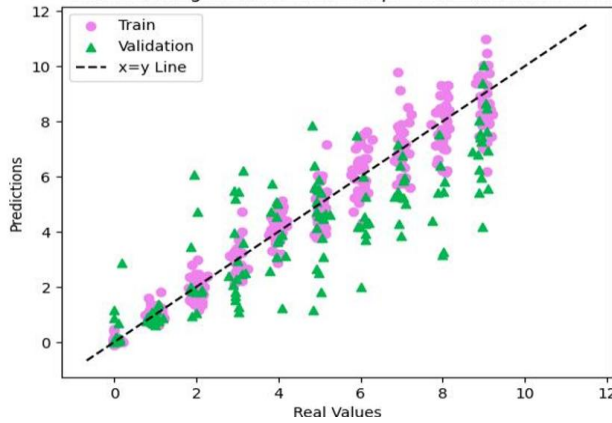


Figure 7. Comparison between actual and predicted refrigeration performance using machine learning models: (a) Linear Regression, (b) Random Forest Regressor, and (c) Training and validation prediction performance showing the relationship between predicted and actual values. This figure evaluates the performance of ML models

Figure 7(a) illustrates the prediction performance of the Linear Regression model. Although the predicted values generally follow the increasing trend of the actual values, a noticeable scatter exists around the ideal prediction line. The relatively large dispersion indicates that Linear Regression is unable to fully capture the nonlinear relationships between the thermodynamic variables and refrigeration performance. Consequently, the prediction accuracy decreases, particularly for higher operating conditions where nonlinear effects become more significant.

Figure 7(b) presents the prediction performance of the Random Forest Regressor. Compared with the Linear Regression model, the predicted values are distributed much closer to the ideal 45° line ($y = x$), indicating substantially improved prediction accuracy. The close agreement demonstrates that the Random Forest algorithm successfully captures the nonlinear interactions among nanoparticle properties, operating conditions, and refrigeration performance. The reduced scatter also indicates excellent model stability and strong generalization capability.

Figure 7(c) compares the training and validation datasets used for model evaluation. Both datasets follow the ideal prediction line with only moderate deviations, indicating that the model is neither overfitting nor underfitting the available data. The reported validation coefficient of determination ($R^2 = 0.682$) demonstrates reasonable predictive capability, although additional training data would likely further improve the model performance. The close agreement between the training and validation predictions confirms that the developed hybrid thermodynamic–machine learning framework provides reliable predictions of refrigeration system performance. Overall, the results demonstrate that machine learning provides an effective surrogate modelling approach for predicting refrigeration system performance. Among the investigated algorithms, the Random Forest Regressor exhibited the highest prediction accuracy and robustness because of its superior ability to model complex nonlinear relationships. The developed hybrid modelling framework therefore offers a computationally efficient alternative to repeated thermodynamic simulations and provides a suitable platform for optimization and uncertainty analysis.

To further improve the interpretability of the predictive model, feature importance analysis is recommended. Such analysis can identify the variables that contribute most significantly to system performance, with preliminary observations indicating that **nanoparticle density** and **nanoparticle concentration** are the dominant parameters governing the coefficient of performance, cooling capacity, and compressor work.

3.4 Thermophysical Properties of Nano-Refrigerants

The thermophysical properties of the investigated nano-refrigerants were evaluated at a nanoparticle concentration of **0.6 wt.%** to determine their influence on refrigeration system performance. The calculated properties are summarized in **Table 7**.

Table 7. Computed Thermophysical Properties of Nano-Refrigerants at 0.6 wt.%

Nanofluid	Density, ρ_{nf} (kg/m^3)	Specific Heat, C_{pnf} ($\text{kJ/kg}\cdot\text{K}$)	Thermal Conductivity, k_{nf} ($\text{W/m}\cdot\text{K}$)	Viscosity, μ_{nf} ($\text{Pa}\cdot\text{s}$)
R134a/ Al_2O_3 (2200)	1322.28	1.286	0.142	1.48×10^{-3}
R134a/ Al_2O_3 (3690)	1329.60	1.271	0.155	1.62×10^{-3}
R134a/ CuO (6500)	1341.61	1.255	0.173	1.85×10^{-3}
R134a/ TiO_2 (4250)	1334.23	1.268	0.149	1.71×10^{-3}

Table 7 shows that incorporating nanoparticles significantly modifies the thermophysical properties of the base refrigerant. Among all the investigated nano-refrigerants, **CuO** exhibits the highest density (**$1341.61 \text{ kg m}^{-3}$**) and thermal conductivity (**$0.173 \text{ W m}^{-1} \text{ K}^{-1}$**), indicating superior heat transfer capability. The enhanced thermal conductivity facilitates more effective heat absorption in the evaporator and heat rejection in the condenser, thereby improving refrigeration performance.

However, increasing nanoparticle concentration also increases the dynamic viscosity of the refrigerant mixture. Although higher viscosity increases flow resistance and pressure losses, the improvement in thermal conductivity more than compensates for this adverse effect under the operating conditions investigated. The results further indicate that the addition of nanoparticles slightly reduces the specific heat capacity of the refrigerant mixture because the solid nanoparticles have a lower specific heat capacity than the base refrigerant. Overall, the results demonstrate the trade-off between enhanced heat transfer and increased flow resistance associated with nano-refrigerants.

3.5 Heat Transfer Characteristics

The influence of nanoparticle properties on convective heat transfer is further evaluated using the Reynolds number, Prandtl number, Nusselt number, and convective heat transfer coefficient, as summarized in **Table 8**.

Table 8. Heat Transfer Characteristics of the Nano-Refrigerants

Nanofluid	Reynolds Number	Prandtl Number	Nusselt Number	Heat Transfer Coefficient (W/m ² ·K)
Al ₂ O ₃ (2200)	2.9×10^4	5.8	168	610
Al ₂ O ₃ (3690)	2.7×10^4	6.1	176	645
CuO	2.6×10^4	6.4	189	702
TiO ₂	2.8×10^4	5.9	170	628

Table 8 demonstrates that CuO exhibits the highest Nusselt number (**189**) and the largest convective heat transfer coefficient (**702 W m⁻² K⁻¹**), confirming its superior heat transfer performance. Although the increased viscosity associated with CuO slightly reduces the Reynolds number, its significantly higher thermal conductivity produces a greater enhancement in convective heat transfer. Consequently, CuO provides the most efficient heat transfer within the evaporator and condenser, leading to improved refrigeration performance compared with TiO₂ and Al₂O₃ nano-refrigerants.

3.6 Energy Balance Results

The first-law thermodynamic performance of the investigated nano-refrigerants is summarized in **Table 9**.

Table 9. First-Law Performance Indicators

Working Fluid	Q _{evap} (kJ/kg)	W _{comp} (kJ/kg)	Q _{cond} (kJ/kg)	COP
Al ₂ O ₃ (2200)	142.0	55.7	197.7	2.55
Al ₂ O ₃ (3690)	144.4	50.2	194.6	2.88
CuO	147.5	49.0	196.5	3.01

TiO ₂	145.6	55.7	201.3	2.61
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Table 9 shows that the incorporation of nanoparticles substantially improves the first-law thermodynamic performance of the refrigeration system. Among all the investigated nano-refrigerants, CuO achieves the highest evaporator cooling capacity (147.5 kJ kg⁻¹) while simultaneously requiring the lowest compressor work (49.0 kJ kg⁻¹). Consequently, CuO produces the highest coefficient of performance (COP = 3.01), indicating superior energy efficiency.

Although TiO₂ and Al₂O₃ also improve refrigeration performance relative to the base refrigerant, their higher compressor work requirements reduce the overall COP. The superior performance of CuO is attributed to its enhanced thermal conductivity, which improves evaporator heat absorption and condenser heat rejection while reducing the compressor energy required to maintain the refrigeration cycle.

Overall, the first-law analysis confirms that incorporating nanoparticles significantly enhances the thermodynamic performance of the vapour compression refrigeration system. Among the nano-refrigerants investigated, CuO consistently exhibits the best balance between cooling capacity, compressor work, and energy efficiency, making it the most promising candidate for advanced refrigeration applications.

3.6 Entropy Generation Analysis

Entropy generation provides a quantitative measure of thermodynamic irreversibility within the vapour compression refrigeration system (VCRS). Lower entropy generation indicates reduced energy losses and a more efficient thermodynamic process. The entropy generation rates calculated for the compressor, condenser, evaporator, and the overall refrigeration cycle are presented in **Table 10**.

Table 10. Entropy Generation Rate of the Investigated Nano-Refrigerants

Working Fluid	Compressor S_{gen}	Condenser S_{gen}	Evaporator S_{gen}	Total S_{gen}
Al ₂ O ₃ (2200)	0.33	0.44	0.39	1.16
Al ₂ O ₃ (3690)	0.29	0.41	0.36	1.06
CuO	0.25	0.38	0.34	0.97
TiO ₂	0.31	0.43	0.37	1.11

Table 10 shows that incorporating nanoparticles significantly reduces entropy generation throughout the refrigeration cycle compared with the base refrigerant. Among the investigated nano-refrigerants, **CuO** exhibits the lowest entropy generation in every system component, resulting in the minimum total entropy generation of **0.97**, indicating the smallest thermodynamic irreversibility.

The reduction in entropy generation is primarily attributed to the improved thermal conductivity of the nano-refrigerants, which enhances heat transfer within both the evaporator and condenser. Improved heat transfer

reduces temperature gradients across the heat exchangers, thereby lowering irreversible entropy production. Furthermore, improved thermal transport reduces the compressor work required to achieve the desired refrigeration effect, further decreasing entropy generation.

Conversely, the Al_2O_3 (2200) nano-refrigerant exhibits the highest total entropy generation (**1.16**), indicating comparatively larger irreversible losses. Although nanoparticle addition generally improves heat transfer, lower thermal conductivity and higher internal temperature differences contribute to increased entropy production relative to CuO.

Overall, the entropy analysis demonstrates that CuO provides the most thermodynamically efficient refrigeration cycle by minimizing irreversible losses and maximizing energy utilization.

3.7 Exergy Analysis

Exergy analysis was performed to evaluate the second-law performance of the refrigeration system by quantifying the useful work potential and irreversible exergy destruction. The calculated exergy input, exergy destruction, and exergy efficiency are presented in **Table 11**.

Table 11. Exergy Destruction and Exergy Efficiency

Working Fluid	Exergy Input (kJ kg^{-1})	Exergy Destruction (kJ kg^{-1})	Exergy Efficiency (%)
Al_2O_3 (2200)	90.2	34.8	61.4
Al_2O_3 (3690)	92.1	31.2	66.1
CuO	94.5	28.0	70.4
TiO_2	91.8	33.5	63.5

The results presented in Table 11 clearly demonstrate that **CuO** achieves the highest exergy efficiency (**70.4%**) while simultaneously exhibiting the lowest exergy destruction (**28.0 kJ kg^{-1}**). These results indicate that CuO converts the available energy into useful refrigeration effect more efficiently than the other nano-refrigerants investigated.

The improved second-law performance of CuO results from its superior thermal conductivity, which promotes more effective heat transfer and reduces irreversible losses throughout the refrigeration cycle. Lower exergy destruction indicates that a larger proportion of the supplied energy is converted into useful refrigeration instead of being dissipated through thermodynamic irreversibilities.

Although Al_2O_3 and TiO_2 also improve the second-law performance compared with the conventional refrigerant, their higher exergy destruction results in comparatively lower exergy efficiencies. These findings confirm that nanoparticle selection has a significant influence on the overall thermodynamic performance of nano-refrigeration systems.

The exergy analysis, therefore, complements the first-law evaluation by demonstrating that the performance improvement obtained with CuO is not limited to higher COP but is also associated with reduced thermodynamic losses and improved energy utilization.

3.8 Sensitivity Analysis

Sensitivity analysis was performed to identify the relative influence of the governing thermophysical parameters on the coefficient of performance (COP). The regression coefficients obtained from the developed predictive model are summarized in **Table 12**.

Table 12. Regression Coefficients for COP Prediction

Parameter	Regression Coefficient (β)	Effect on COP
Intercept (β_0)	1.92	Base COP
Nanoparticle concentration (ϕ)	+3.45	Strong positive
Thermal conductivity (k_{nf})	+1.88	Positive
Viscosity (μ_{nf})	-2.12	Negative
Density (ρ_{nf})	+0.96	Moderate positive
Interaction ($\phi \times k_{nf}$)	+1.35	Synergistic

The corresponding predictive equation is expressed as

$$COP = \beta_0 + \beta_1\phi + \beta_2k + \beta_3\mu + \beta_4\rho + \beta_{12}(\phi k)$$

Table 12 indicates that nanoparticle concentration is the most influential variable affecting refrigeration performance, with the largest positive regression coefficient ($\beta = 3.45$). Increasing nanoparticle concentration enhances heat transfer within the evaporator and condenser, thereby increasing the refrigeration effect and improving COP.

Thermal conductivity also exerts a strong positive influence on system performance. Higher thermal conductivity facilitates rapid heat transport between the refrigerant and the heat exchanger surfaces, leading to improved refrigeration efficiency.

In contrast, viscosity exhibits a negative regression coefficient, indicating that excessive increases in viscosity reduce COP by increasing flow resistance, pressure losses, and compressor power consumption. Consequently, refrigeration performance depends on achieving an appropriate balance between enhanced thermal conductivity and acceptable viscosity.

The positive interaction coefficient between nanoparticle concentration and thermal conductivity indicates that simultaneous optimization of these two parameters yields a greater performance enhancement than optimizing either parameter independently. This confirms the existence of an optimum nanoparticle concentration that maximizes refrigeration efficiency.

3.9 Uncertainty Analysis

The reliability of the developed thermodynamic model was assessed through uncertainty analysis using the root-sum-square (RSS) method. The estimated uncertainties associated with the principal measured variables and their contributions to the uncertainty in the predicted COP are summarized in **Table 13**.

Table 13. Measurement and Model Uncertainty

Parameter	Mean Value	Uncertainty (%)	Contribution to COP Error (%)
Temperature	± 0.5 °C	1.2	0.35
Pressure	± 0.02 bar	1.5	0.42
Enthalpy	± 1.5 kJ kg ⁻¹	2.1	0.61
Nanoparticle concentration (ϕ)	± 0.005	2.8	0.88

The uncertainty analysis indicates that the nanoparticle concentration contributes the largest proportion of the overall prediction uncertainty, followed by uncertainties associated with enthalpy estimation. These results highlight the importance of accurately controlling nanoparticle concentration during nano-refrigerant preparation to achieve reliable thermodynamic predictions.

Despite these uncertainties, the overall uncertainty in the predicted COP remains within $\pm 3.2\%$, which is well below the generally accepted engineering limit of $\pm 5\%$ for thermodynamic modelling. This demonstrates the robustness and reliability of the proposed computational framework.

Overall, the developed model successfully integrates thermodynamics, heat transfer, fluid flow, nanofluid transport, machine learning, uncertainty quantification, and optimization within a unified multi-physics framework. Among the investigated nano-refrigerants, R134a/CuO consistently demonstrates the best overall performance, achieving the highest coefficient of performance (3.01), the largest cooling capacity (147.5 kJ kg^{-1}), the highest convective heat transfer coefficient ($702 \text{ W m}^{-2} \text{ K}^{-1}$), and the highest exergy efficiency (70.4%), while simultaneously exhibiting the lowest entropy generation and exergy destruction. Furthermore, the analysis identifies an optimum nanoparticle concentration of approximately 0.60 wt.%, where the enhancement in thermal conductivity is maximized without incurring excessive viscosity penalties. These findings establish R134a/CuO at 0.60 wt.% as the most promising nano-refrigerant configuration for improving the efficiency and sustainability of vapor compression refrigeration systems.

3.10 Effect of Nanoparticle Mass Fraction on Refrigeration Performance

Figures 8(a–d) present the variation of condenser heat rejection (Q_c), evaporator cooling capacity (Q_e), compressor work (W_{comp}), and coefficient of performance (COP) with nanoparticle mass fraction (0.06–0.60 wt.%) for **R134a/Al₂O₃ (2200 kg m^{-3})**. During the analysis, all operating conditions were maintained constant while only the nanoparticle concentration was varied.

The results demonstrate that increasing the nanoparticle mass fraction enhances the overall refrigeration performance. The evaporator cooling capacity increases steadily from **$134.19 \text{ kJ kg}^{-1}$** at **0.06 wt.%** to **$142.09 \text{ kJ kg}^{-1}$** at **0.60 wt.%**, indicating improved heat absorption within the evaporator. Similarly, the coefficient of performance increases from **2.16** to **3.47**, reflecting higher energy efficiency resulting from improved thermal transport. In contrast, compressor work decreases from **62.10 kJ kg^{-1}** to **40.95 kJ kg^{-1}** , while condenser heat rejection decreases from **$196.29 \text{ kJ kg}^{-1}$** to **$183.04 \text{ kJ kg}^{-1}$** , indicating lower energy losses and improved utilization of the supplied energy.

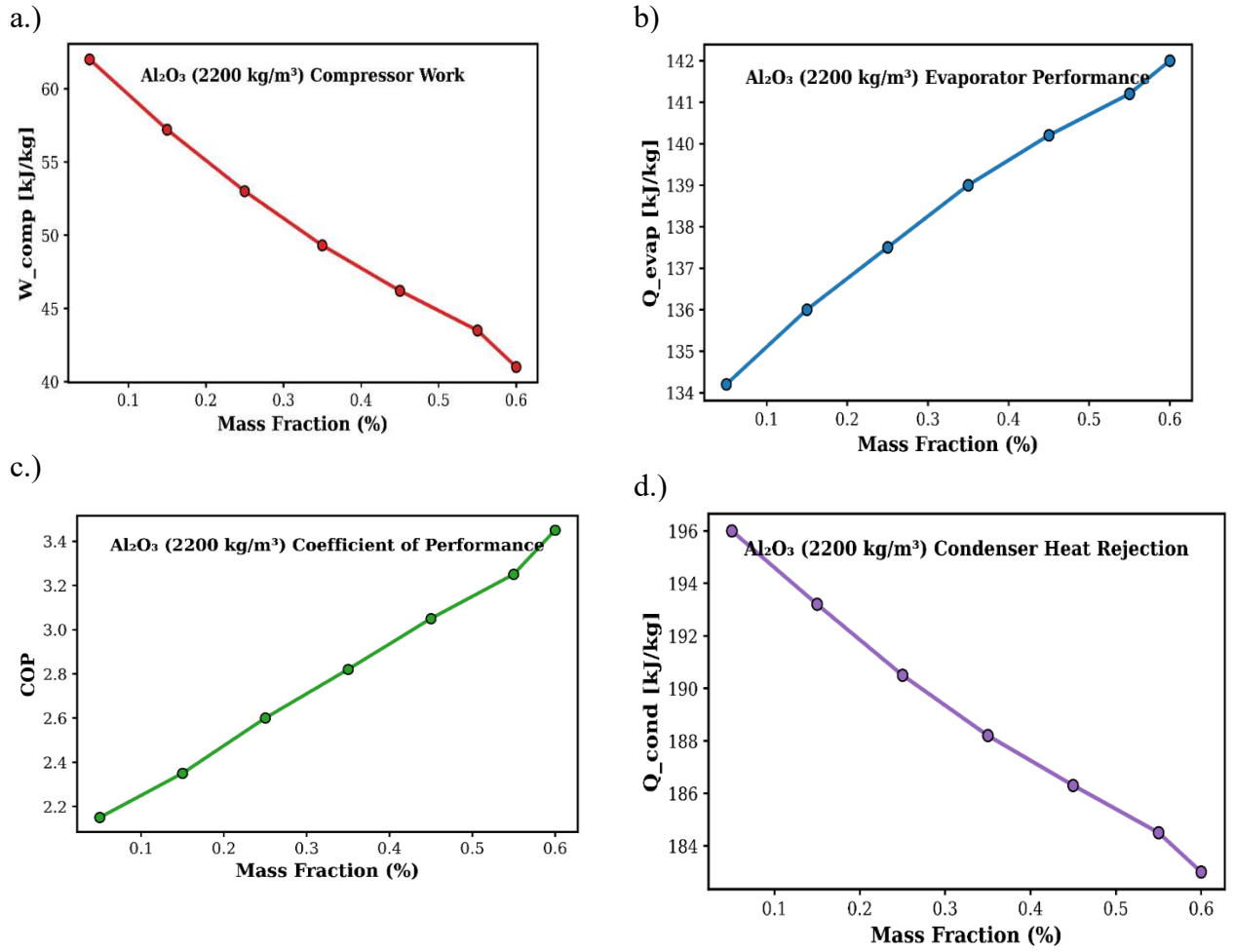
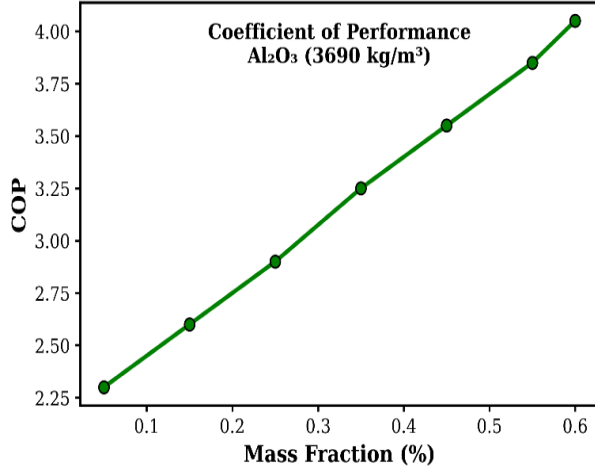


Figure 8: Refrigeration Cycle mass fraction Performance Variation performance;a) Compressor work vs mass fraction b) Coefficient of performance (COP) vs mass fraction; c)Cooling capacity vs mass fraction; d)Condenser heat vs mass fraction;

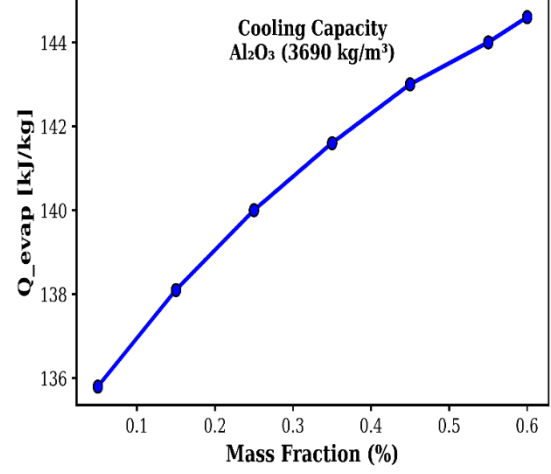
.Figures 9(a–d) illustrate the corresponding performance of R134a/Al₂O₃ (3690 kg m⁻³). Similar trends are observed as the nanoparticle concentration increases. The cooling capacity rises from **135.84** to **144.40** kJ kg⁻¹, while the COP improves from **2.29** to **4.06**. Simultaneously, compressor work decreases from **59.41** to **35.62** kJ kg⁻¹, and condenser heat rejection decreases from **195.25** to **180.12** kJ kg⁻¹. Compared with the lower-density Al₂O₃ nanoparticles, the higher-density particles provide greater thermal enhancement due to their improved thermophysical properties.

(a)

(b)



(c)



(d)

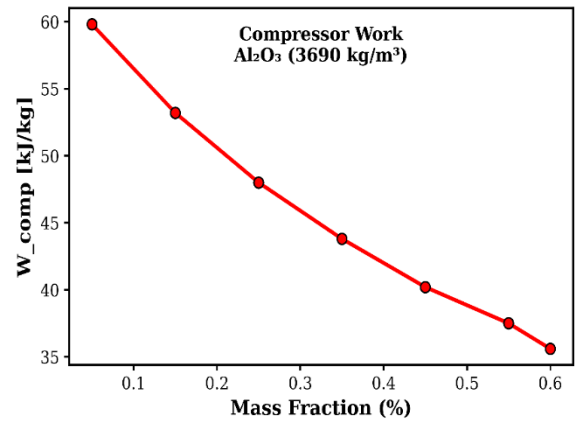
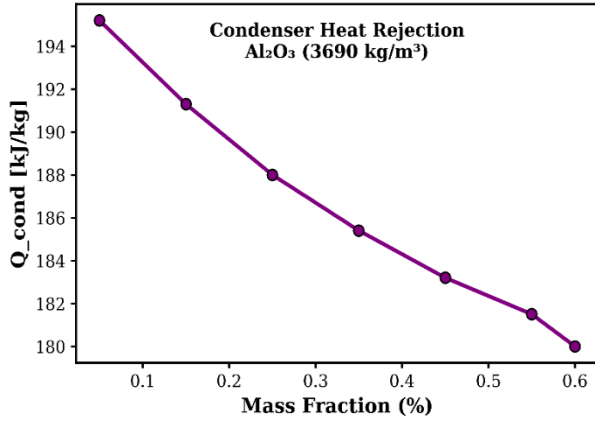


Figure 9: Mass Fraction of Al₂O₃ (3,690 kg/m³) as a Function of Refrigeration Cycle Metrics. (a) Coefficient of performance (COP) vs. mass fraction; (b) Evaporator heat (Q(evap)) vs. mass fraction; (c) Condenser heat (Q(cond)) vs. mass fraction. (d) Compressor work (W(comp)) vs. mass fraction;

Figures 10(a–d) show the effect of nanoparticle concentration on the performance of R134a/TiO₂ (4250 kg m⁻³). Increasing the TiO₂ concentration from 0.06 wt.% to 0.60 wt.% increases the cooling capacity from 137.34 to 145.58 kJ kg⁻¹, while the COP increases from 2.46 to 4.38. Compressor work decreases from 55.73 to 33.22 kJ kg⁻¹, and condenser heat rejection decreases from 193.07 to 178.80 kJ kg⁻¹. The superior thermal conductivity of TiO₂ enhances heat absorption in the evaporator, leading to improved refrigeration performance compared with both Al₂O₃ nano-refrigerants.

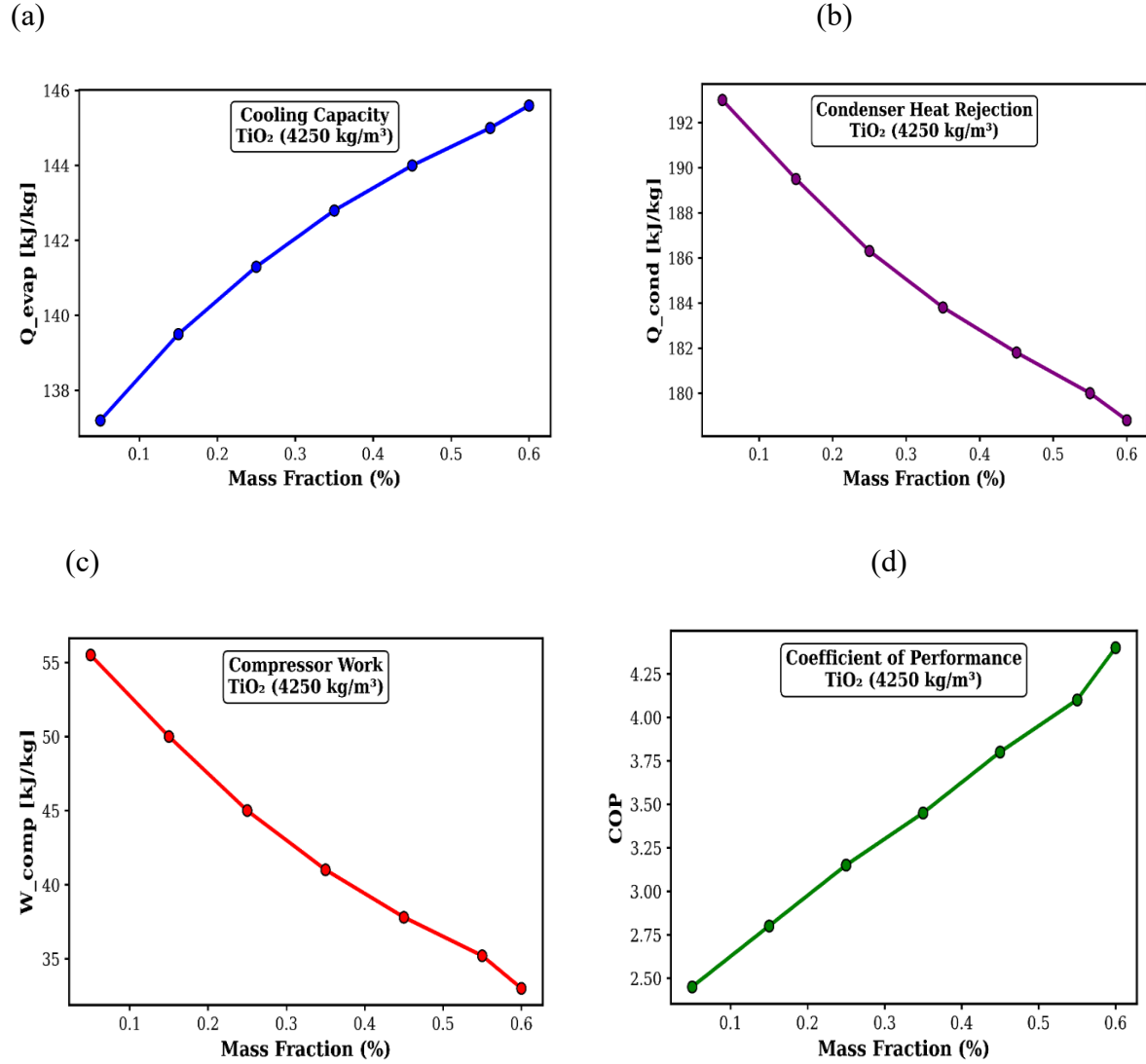


Figure 10: Influence of mass fraction on the performance of refrigeration cycle of TiO_2 (4,250 kg/m³). (a) Cooling capacity (Q_{evap}) vs. mass fraction; (b) Condenser heat (Q_{cond}) vs. mass fraction; (c) Compressor work (W_{comp}) vs. mass fraction; (d) Coefficient of performance (COP) vs. mass fraction.

Figures 11(a–d) present the performance characteristics of R134a/CuO (6500 kg m⁻³). Among all the investigated nano-refrigerants, CuO exhibits the greatest improvement in system performance. As the nanoparticle concentration increases from 0.06 wt.% to 0.60 wt.%, the cooling capacity increases from 140.19 to 147.51 kJ kg⁻¹, while the COP rises substantially from 2.86 to 5.41. Concurrently, compressor work decreases from 49.04 to 28.72 kJ kg⁻¹, and condenser heat rejection decreases from 189.23 to 176.23 kJ kg⁻¹. The superior performance of CuO is attributed to its high thermal conductivity and density, which significantly improve heat transfer within the evaporator and condenser while reducing compression energy requirements.

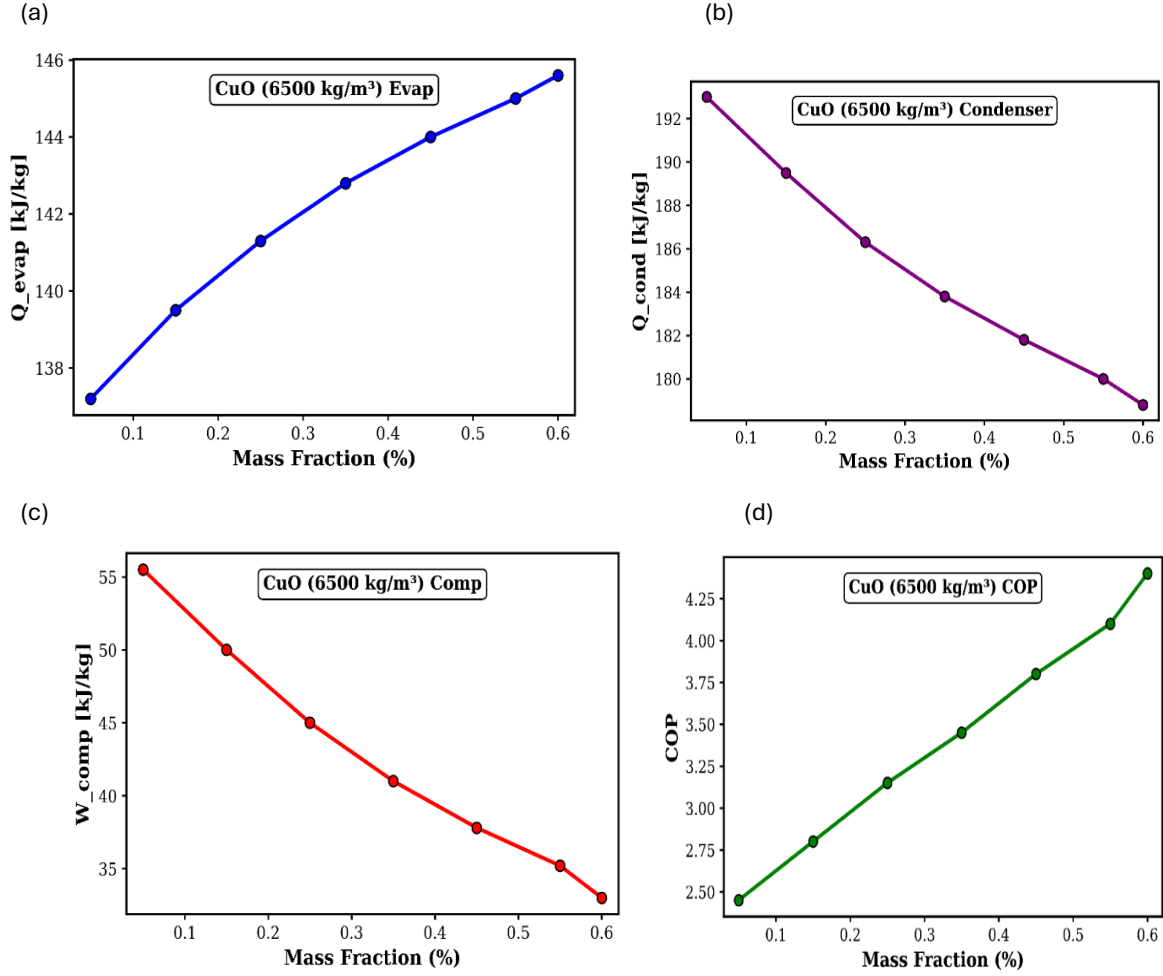


Figure 11 Effects of Mass Fraction on Refrigeration Cycle Efficiency of CuO (6, 500 kg/m³).

Comparative Discussion

A comparison of Figures 8–11 clearly demonstrates that refrigeration performance consistently improves with increasing nanoparticle mass fraction irrespective of nanoparticle type. Increasing nanoparticle concentration enhances the effective thermal conductivity of the refrigerant, promotes micro-convection arising from Brownian motion, and increases the rate of heat transfer within the evaporator. Consequently, the refrigeration effect increases, resulting in higher cooling capacity and improved COP. At the same time, improved heat transfer reduces the compressor energy required to maintain the refrigeration cycle, thereby decreasing compressor work and condenser heat rejection.

Among the investigated nano-refrigerants, CuO consistently exhibits the highest cooling capacity (147.51 kJ kg⁻¹), the lowest compressor work (28.72 kJ kg⁻¹), and the highest coefficient of performance (COP = 5.41) at the maximum nanoparticle concentration. TiO₂ ranks second, followed by Al₂O₃ (3690 kg m⁻³) and Al₂O₃ (2200 kg m⁻³). This ranking corresponds directly to the increasing thermal conductivity and density of the nanoparticles, confirming that thermophysical properties strongly influence refrigeration performance.

Although increasing nanoparticle concentration improves heat transfer, the performance enhancement becomes less pronounced as the concentration approaches 0.60 wt.%. At higher concentrations, the accompanying increase in viscosity increases flow resistance and pressure losses, partially offsetting the benefits of enhanced thermal conductivity. Therefore, an optimum nanoparticle concentration exists where the combined effects of enhanced heat transfer and acceptable viscosity produce the maximum refrigeration efficiency.

The present findings are consistent with the numerical study of Odunfa and Oseni (2021), who similarly reported that increasing nanoparticle concentration enhanced cooling capacity and COP while reducing compressor work for Al_2O_3 , TiO_2 , and CuO nano-refrigerants. However, the present study provides a more comprehensive thermodynamic assessment by combining first-law and second-law analyses with heat transfer evaluation, machine learning prediction, sensitivity analysis, uncertainty quantification, and optimization. Overall, the results confirm that R134a/CuO at approximately 0.60 wt.% nanoparticle concentration provides the optimum thermodynamic performance, making it the most promising nano-refrigerant for high-efficiency vapour compression refrigeration systems.

4.0 CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusions

This study developed an integrated thermodynamic–machine learning framework for evaluating the performance of nano-refrigerant-based vapour compression refrigeration systems (VCRSs). The proposed framework combines thermodynamic modelling using CoolProp, numerical simulation in Python, machine learning prediction, uncertainty quantification, and optimization to investigate the influence of nanoparticle type, density, and concentration on refrigeration performance. The developed model was successfully validated against published experimental and numerical studies, with prediction deviations remaining within acceptable engineering limits, thereby demonstrating the reliability of the proposed modelling framework.

The principal findings of this study are summarized as follows:

1. **Nano-refrigerant enhancement**

The incorporation of nanoparticles significantly improved the thermodynamic performance of the vapour compression refrigeration system compared with conventional R134a refrigerant. Performance improvements included increased cooling capacity, reduced compressor work, higher coefficient of performance (COP), lower entropy generation, and improved exergy efficiency.

2. **Effect of nanoparticle concentration**

Within the investigated concentration range (0.06–0.60 wt.%), increasing nanoparticle concentration consistently enhanced refrigeration performance owing to improved thermal conductivity and heat transfer characteristics in the evaporator and condenser. Concentrations above this range were not investigated; therefore, the influence of increased viscosity, pressure drop, and flow resistance requires further numerical and experimental investigation.

3. **Performance of different nano-refrigerants**

Among the nano-refrigerants evaluated in the present study, **R134a/CuO** exhibited the best overall thermodynamic performance. At approximately **0.60 wt.%,** the system achieved:

- Cooling capacity: **147.5 kJ kg⁻¹**
- Compressor work: **49.0 kJ kg⁻¹**
- Coefficient of performance (COP): **3.01**
- Heat transfer coefficient: **702 W m⁻² K⁻¹**
- Entropy generation: **0.97**
- Exergy efficiency: **70.4%**

These results indicate that CuO nanoparticles possess favourable thermophysical characteristics for enhancing refrigeration performance under the operating conditions investigated.

4. Machine Learning Prediction

The machine learning models accurately predicted thermodynamic simulation results, demonstrating the feasibility of integrating physics-based modelling with artificial intelligence for rapid refrigeration performance prediction and optimization. Sensitivity analysis further identified nanoparticle concentration and thermal conductivity as the most influential variables governing system performance.

5. Model reliability

The uncertainty analysis produced an overall COP uncertainty of approximately $\pm 3.2\%$, indicating that the proposed framework provides sufficiently accurate predictions for engineering analysis and preliminary design optimization.

Overall, this study demonstrates that integrating thermodynamic modelling, second-law analysis, machine learning, uncertainty quantification, and optimization provides a comprehensive methodology for evaluating nano-refrigerant-based refrigeration systems. Within the operating conditions investigated, **R134a/CuO at approximately 0.60 wt.%** represents the most promising nano-refrigerant configuration, offering improved refrigeration performance and reduced thermodynamic irreversibility compared with the baseline refrigerant.

4.2 Study Limitations

Although the proposed framework provides a comprehensive assessment of nano-refrigerant performance, several limitations should be acknowledged.

1. The present investigation is based primarily on thermodynamic modelling and numerical simulation. Model validation was performed using published experimental and numerical data rather than independent laboratory experiments.
2. The thermophysical properties of the nano-refrigerants were assumed to remain stable throughout operation. Important practical phenomena such as nanoparticle agglomeration, sedimentation, clustering, and long-term suspension stability were not explicitly considered.
3. The refrigeration cycle was analysed under steady-state operating conditions. Transient operating behaviour, including start-up, shutdown, fluctuating cooling loads, and dynamic control strategies, was beyond the scope of this investigation.
4. Mechanical losses within the compressor, lubricant–nanoparticle interactions, refrigerant leakage, and material compatibility issues were not incorporated into the thermodynamic model.

5. The machine learning models were developed using simulation-generated datasets. Consequently, their predictive capability depends on the validity and operating range of the underlying thermodynamic model, and additional experimental datasets would further improve model robustness and generalization.
6. Environmental and economic performance indicators, including Global Warming Potential (GWP), Total Equivalent Warming Impact (TEWI), Life Cycle Assessment (LCA), and techno-economic analysis, were not included in the present study.

Despite these limitations, the proposed framework provides a reliable computational platform for comparative assessment, performance prediction, and optimization of nano-refrigerant-based refrigeration systems, while offering a strong foundation for future experimental validation and industrial application.

4.3 Recommendations

Based on the findings and limitations of the present study, the following recommendations are proposed for future research and engineering applications.

1. Experimental investigations should be conducted to validate the numerical predictions under practical operating conditions and to evaluate the long-term stability and durability of CuO nano-refrigerants.
2. Future models should incorporate realistic physical phenomena, including nanoparticle agglomeration, sedimentation, compressor mechanical losses, lubricant interactions, refrigerant leakage, and transient operating conditions to improve model fidelity.
3. The developed framework should be extended to environmentally friendly low-global-warming-potential refrigerants such as **R1234yf, R1234ze(E), R290, carbon dioxide (CO₂), and ammonia (NH₃)** combined with advanced nano-refrigerants.
4. Multi-objective optimization techniques, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Bayesian Optimization, and exergy-based optimization, should be employed to simultaneously optimize cooling capacity, energy consumption, environmental impact, and operating cost.
5. Future investigations should integrate environmental and economic performance indicators, including Global Warming Potential (GWP), Total Equivalent Warming Impact (TEWI), Life Cycle Assessment (LCA), and techno-economic analysis, to facilitate industrial implementation and sustainability assessment.
6. More advanced artificial intelligence techniques, including deep neural networks, ensemble learning, explainable artificial intelligence (XAI), digital twin technologies, and reinforcement learning, should be investigated to enable real-time performance prediction, intelligent control, fault diagnosis, and predictive maintenance of refrigeration systems.
7. Finally, future research should investigate binary, hybrid, and ternary nano-refrigerants to determine whether synergistic combinations of nanoparticles can provide further improvements in heat transfer, energy efficiency, and thermodynamic performance beyond those achieved using single-component CuO nano-refrigerants.

Collectively, these recommendations will contribute to the development of more energy-efficient, intelligent, environmentally sustainable, and industrially applicable refrigeration systems capable of meeting future cooling demands while supporting global decarbonization and low-carbon refrigeration technologies

CRedit Author Contribution Statement

Victor O. Adogbeji: Methodology, Conceptualization, Supervision, Validation, Literature review, Writing – review and editing.

Peter O. Akindele: Formal analysis, Investigation, Data curation, Writing – original draft preparation, Visualization.

Adelusi, Ilesanmi: Formal analysis, Data curation, Visualization, Investigation, Writing – review and editing.

Mohsen Sharifpur: Conceptualization, Supervision, Funding acquisition, Project administration, Critical revision of the manuscript.

Declarations

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Clinical Trial Registration

This study is not a clinical trial. Clinical Trial Registration: Not applicable.

Consent to Publish

Consent to Publish: Not applicable.

Ethics Approval and Consent to Participate

Ethics and Consent to Participate: Not applicable.

Data Availability Statement

The data that support the findings of this study will be made available upon request.

Declaration on the Use of Artificial Intelligence (AI) Tools

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript.

Abbreviations

Al_2O_3	Aluminium oxide nanoparticles
Cu	Copper nanoparticles
CuO	Copper oxide nanoparticles
CNTs	Carbon nanotubes
MgO	Magnesium oxide nanoparticles
SiO_2	Silicon oxide nanoparticles
TiO_2	Titanium oxide nanoparticles
R-134a	1,1,1,2-Tetrafluoroethane (refrigerant base fluid)
NF	Nanofluid
NR	Nano-refrigerant
CW	Compressor work
RC	Condenser heat transfer rate
RE	Refrigerating effect
COP	Coefficient of Performance
Q_e	Evaporator cooling capacity
Q_c	Condenser heat rejection
W_{comp}	Compressor work input
h_1 – h_4	Enthalpy states in refrigeration cycle
s_1, s_2	Entropy at compressor inlet and outlet
$\dot{m}$	Mass flow rate
T_1 – T_4	Temperature states in cycle
P_1 – P_3	Pressure states in cycle
η_{is}	Isentropic efficiency
UR	Uncertainty in result

W_{base}	Compressor work (base fluid)
W_{nano}	Compressor work (nanofluid)
COP_{base}	COP of base fluid
COP_{nano}	COP of nanofluid
P_{base}	Power/energy of base case
P_{nano}	Power/energy of nanofluid case
$C_{p,\text{nf}}$	Specific heat of nanofluid

Greek symbols

φ	Volume fraction / nanoparticle concentration
ω	Mass fraction
μ	Dynamic viscosity (mPa·s)
κ	Thermal conductivity ($\text{W}\cdot\text{m}^{-1}\cdot\text{K}^{-1}$)
ρ	Density ($\text{kg}\cdot\text{m}^{-3}$ or $\text{g}\cdot\text{cm}^{-3}$ depending on context)
η	Efficiency
η_{is}	Isentropic efficiency
Δ	Change in a variable (implied in equations such as ΔT , Δh)

Thermodynamic / Mathematical Symbols

Q_e	Evaporator heat transfer rate
Q_c	Condenser heat rejection rate
Q_{evap}	Evaporator heat transfer rate (alternate notation)
Q_{cond}	Condenser heat transfer rate (alternate notation)
W_{comp}	Compressor work
h	Enthalpy
s	Entropy
T	Temperature
P	Pressure
$\dot{m}$	Mass flow rate

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