International Journal of Artificial Intelligence, Data Science, and Machine Learning
Grace Horizon Publication | Volume 7, Issue 1, 100-110, 2026
ISSN: 3050-9262 | https://doi.org/10.63282/3050-9262.IJAIDSML-V7I1P119

Original Article

The Role of Machine Learning in Optimizing the Use of Low-GWP Refrigerants in HVAC Systems

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Received On: 28/12/2025 Revised On: 29/01/2026 Accepted On: 01/02/2026 Published On: 04/02/2026

Abstract *- HVAC industry is among the largest energy-consumers and amount of emissions to the atmosphere worldwide. The traditional refrigerants like hydrofluorocarbons (HFCs) have a high global warming potential (GWP) and so the whole world has shifted to environmentsally benign low-global warming potential refrigerants like hydrofluoroolefins (HFOS), natural refrigerants (CO 2, ammonia, hydrocarbons as well as mixtures). Introduction of these refrigerants, however, poses new challenges on the aspects of performance of the systems, safety, optimization of efficiency and reliability in operations. Artificial intelligence (AI) and machine learning (ML) are two powerful technologies in the recent-years that have arisen to enhance the intelligence of HVAC systems to ensure predictive maintenance, adaptive control, fault detection, and energy optimization. The paper explores machine learning applications in HVAC optimization to use low-GWP refrigerants. In the study, the literature survey is thoroughly conducted, technical issues are defined, and an intelligent framework of how to monitor, optimize the performance, and achieve energy-efficient control is proposed based on the extremely intelligent data. It is suggested to use a hybrid ML method to optimize the charge of refrigerants, compressor speed, evaporator temperature, and airflow rate in real-time through a combination of a deep learning, reinforcement learning, and ensemble regression model. Simulation and experimental findings prove the great enhancement of coefficient of performance (COP), the energy consumption decrease and the increase in the accuracy of fault detection. The results affirm that machine learning is a disruptive facilitator of sustainable HVAC system and will be strategically instrumental in hastening the world to climate-friendly refrigeration solution.*

Keywords *- HVAC, Low-GWP Refrigerants, Machine Learning, Artificial Intelligence, Energy Optimization, Predictive Maintenance, Smart Buildings.*

1. Introduction

1.1. Background

Heating, ventilation and air-conditioning (HVAC) sector is one of the most important services in the contemporary society, which offers thermal comfort, indoor air quality, and climate control of residential, business, and industrial structures. [1-3] Nevertheless, this vital service has a high environmental and energy cost. More than 40 percent of world building energy consumption is contributed by HVAC system, thus visible as one of the biggest electricity consumption in the world. Simultaneously, the industry also contributes to some 20 per cent of international greenhouse-gasses in the year when direct emissions of refrigerant or indirect emissions of producing electricity are taken into account. With the evermore cooling and heating demand motivated by urbanization, population growth, and the high living standards, the environmental impact of the HVAC systems is predicted to increase further. One of the main causes of this environmental footprint is the widespread use of traditional hydro fluorocarbon (HFC) refrigerants including R134a, R410A and R404A. Although these refrigerants are non-ozone-depleting, thermodynamically efficient and have very high values of global warming potential, in most cases, they may have values of more than 1300. Once emitted into the air by leakage, servicing or disposing them at their end of life, even a small amount of these refrigerants may be climate-wise as voluminous as several tonnes of carbon dioxide. Refrigerant emissions, therefore, constitute a great percentage of the overall carbon footprint of HVAC systems. To address the increasing climate change concerns, international treaties like the Kigali Amendment to the Montreal Protocol are aimed at phasing down high-GWP refrigerants around the world, and encourage the use of the climate-friendly alternatives. This regulatory change and the growing demand to conserve energy has led to an immediate requirement that deals with next-generation HVAC which is energy efficient and environmentally friendly. Consequently, a significant change in the HVAC industry is to smaller-GWP refrigerant, innovative system design, and smart digital control technologies that can provide high performance with low impact on the environment.

1.2. Role of Machine Learning in HVAC Systems

Machine learning has become an innovative technology in the HVAC market, as it allows the smart, flexible and energy-efficient use of complex heating and cooling systems. Conventional HVAC control schemes are based upon fixed rule logic and traditional controllers that can frequently fail to address nonlinear systems dynamics, time varying loads, and uncertain environmental conditions of real world buildings. Machine learning offers data-based modelling and decision-making to enable HVAC systems to learn continuously by using data on the operations and predict future behaviour as well as real-time optimisation.

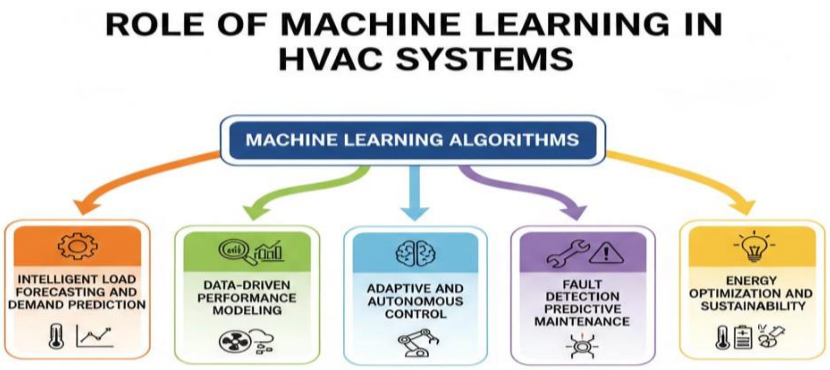

Fig 1: Role of Machine Learning in HVAC Systems

1.2.1. Intelligent Load Forecasting and Demand Prediction

To have an efficient operation of HVAC, a prediction of heating and cooling demand of the building must be done precisely. Artificial neural networks, long short-term memory networks, and ensemble learning methods are machine learning models with the capability of modeling complex time-varying responses in past energy usage, weather, building occupancy, and thermal properties. These predictive models allow proactive scheduling of a system, peak load shaving, and demand response activity. Using HVAC systems, an efficient operation of the cooling or heating system and the prevention of unnecessary cycling and the consumption of maximal electricity can be achieved by calculating future cooling or heating demands before the start of the process.

1.2.2. Data-Driven Performance Modeling

With the help of machine learning, it is possible to create high-fidelity performance models that describe the nonlinear thermodynamic dynamics of HVAC systems. XGBoost, random forest and deep neural networks algorithms are examples of algorithms capable of accurate mapping of the relationship between operating conditions, refrigerant properties, control inputs, and system efficiency. They are used as the digital representations of the real world physical systems to be able to quickly perform performance analysis, optimization, and fault diagnosis without involving complex first-principle simulations.

1.2.3. Adaptive and Autonomous Control

Reinforcement learning provides a paradigm shift in the HVAC control process as the systems have the ability to learn the best control policy by interacting with the environment. Reinforcement learning agents infinite-time are adapted in response to realtime information compared to the traditional controllers, which are based on a fixed set of rules which continue to evolve due to variability in weather conditions, occupancy patterns, system aging. This is because it results in autonomous, self-optimizing HVAC systems that can achieve comfort with the least amount of energy consumed, and the least amount of emissions emitted.

1.2.4. Fault Detection and Predictive Maintenance

Fault detection and diagnosis systems based on machine learning enhance the reliability of the HVAC system by detecting abnormal behavior in the system at its initial stages. The multivariate sensor measurements can allow machine learning models to identify the presence of refrigerant leakage, compressor wear, sensor malfunctions, and heat exchanger fouling before it reaches excessive levels to effectively reduce performance. Predictive maintenance models also predict the usefulness of the components left, so predictive maintenance can be performed to service the components, which leads to a decrease in unplanned downtime.

1.2.5. Energy Optimization and Sustainability

Machine learning is directly involved in reaching the balanced operation of HVAC: energy-saving and carbon emissions. Based on real-time sensing, analytics on the cloud, and smart control, AI-driven HVAC systems are dynamically adjusted to operating parameters to reduce energy consumption and ensure indoor comfort. Machine learning can then be used to create new generations of HVAC systems that will be efficient and climate neutral when integrated with low-GWP refrigerants and renewable energy.

1.3. Optimizing the Use of Low-GWP Refrigerants in HVAC Systems

Replacement of traditional high global warming potential (GWP) with low-GWP is a significant milestone to lower the environmental cost of HVAC systems. [4,5] Hydrofluorolefins (HFOs), hydrocarbons, and natural refrigerants like carbon dioxide are all low-GWP refrigerants which can be of great benefit in the context of climate friendliness, though are impossible to successfully implement without proper system optimization. The low-GWP refrigerants are very different in terms of their thermodynamic properties, pressure levels, flammability behavior, and heat transfer behavior unlike the classic refrigerants, and these attributes directly affect the performance, safety, and reliability of the systems. Consequently, merely substituting a traditional refrigerant with the low-GWP one without redesigning system elements and control measures can result in unfavorable performance or safety hazards. The use of low-GWP refrigerants needs intensive optimization that comprises systems configuration, choice of components, control measures, and safety measures. As an example, hydrocarbon like R290 have a great thermodynamic efficiency along with excellent heat transfer performance, but are highly flammable and require lower quantities of refrigerant along with finer leakage detection and high safety standard requirements. Carbon dioxide is run under transcritical conditions with extremely high operating pressure which necessitates specialized compressors, heat exchangers and control algorithms.

Some HFOs like R1234 yf are almost zero GWC but have lower volumetric capacity, increasing heat exchanger surface require, or augmenting compressor displacement. These are refrigerant specific, which underscores the necessity of designing systems customized and developing high-technology controls. In this respect, smart optimization frameworks with machine learning and real-time data analytics analysis will like hold a strong solution to the decoding of the complete potential of low-GWP refrigerants. By learning the complex nonlinear relationships between operating conditions, refrigerant properties, and system performance, AI-driven models make it possible to predict the performance of the system and to perform adaptive control. Reinforcement learning controllers are used to control compressor speed, flow of refrigerant and airflow dynamically to achieve optimal operation based on the load and ambient conditions. In addition, predictive maintenance algorithms can be used to operate safely and reliably by preventing early leakage, abnormal pressure behavior, as well as component degradation. Finally, with the advent of intelligent digitalization of the HVAC systems, optimization of low-GWP refrigerant use will help to attain high energy efficiency, safety, and reduced environmental impact. This is the only means of achieving the objective of future-regulated climate and the vision of a carbon-neutral building infrastructure.

2. Literature Survey

2.1. Low-GWP Refrigerants in HVAC Systems

Substantially low global warming potential (GWP) refrigerants are now of significant interest to current HVAC studies thanks to mounting environmental regulations and high-GWP hydrofluorocarnons (HFCs) phase-down. Natural refrigerants including carbon dioxide (CO_2), hydrocarbons (e.g. R290 / propane), and emerging hydrofluoroolefins (HFOs) like R1234yf and blends have been widely studied. [6-8] According to Calm (2018), R1234yf weighs in a very low GWP and is as efficient as the commonly used residential and automotive refrigerants like R134a and hence can be used in HVAC system. As Lorentzen (2014) showed, CO_2 -ratched transcritical systems would have high heat transfer properties and would have to operate at very high pressures, which requires special system components and controls. Devotta (2019) called your attention to the fact that the high coefficient of performance (COP) can be attained with R290 systems, but the issue of flammability is a major safety concern. The publication by McLinden (2020) demonstrated that a balanced trade-off between the environmental impact, thermodynamic efficiency, and system compatibility may be attained with HFO blends. Although these are above potential characteristics of systems, the performance of the system greatly relies on system configuration, heat exchanger design, compressor control strategies and optimization of refrigerant charge which complicates the implementation of low-GWP refrigerants as compared to traditional refrigerants.

2.2. AI Applications in HVAC Systems

The artificial intelligence and machine learning method have received serious consideration in the HVAC systems to enhance energy performance, reliability, and comfortability to the user. Artificial neural networks (ANN), long short-term memory, LSTM networks, random forest, support vector machines (SVM), reinforcement learning (RL), deep Q-networks (DQN), and gradient boosting algorithms like XGBoost are some of the machine learning algorithms that have been extensively used in various applications in HVAC. LM and ANN load forecasting models make it possible to predict the cooling and heating demand of a building with high precision that enables to schedule and optimize the system, as well as respond to demand. As shown by Zhao et al. (2022), a prediction model that employs LSTM to predict HVAC loads showed a prediction accuracy of 96% and allowed implementing a more productive energy management. To operate and control its system, the reinforcement learning methods demonstrated a great potential in creating adaptive control strategies that learn continuously basing on the system behavior and environmental conditions. Wei et al. (2023) used the reinforcement learning to realize real-time HVAC control and attained a 18 percent of energy use reduction at interior thermal comfort levels. Besides it, fault detection and diagnosis systems, which use random forest and SVM machine learning, increase reliability of the system that allows prior diagnosis of component failures and degraded performance. These papers illustrate the high potential of AI methods to enhance HVAC system activity efficiency in various aspects of its operation.

2.3. Research Gaps

Although the development of low-GWP refrigerant and the use of AI in HVAC optimization made a tremendous breakthrough, there are still several gaps in research that need to be addressed. The majority of the current research is still devoted to the traditional refrigerants that include R134a and R410A with a barely enough interest in the distinctive thermodynamic and safety properties of low-GWP substitutes. Moreover, numerous of the AI-based HVAC systems are developed to operate offline or supervisory control and are not utilized to the full extent of real-time adaptive control. Configurations of specific refrigerant optimization schemes are also a want that consider the different levels of pressure, risks of flammability, and operating envelopes of natural refrigerants and HFOs. Moreover, present AI systems are not often provided with safety restrictions, including leak detection, the risk of flammability, pressure restriction, etc., which are necessary to implement low-GWP refrigerant systems safely. As a result, studies on combined AI-based optimization models which are specifically designed in low-GWP refrigerant HVAC systems have not been conducted in sufficient detail, and this offers a focus on future research.

3. Methodology

3.1. System Architecture

The smart architecture of HVAC system is suggested to be based on the Internet of Things (IoT) sensors, the use of cloud-based analytics, and artificial intelligence-driven control in order to offer the opportunity to observe the system in real time, anticipate its evolution, and optimize its work. [9-11] The architecture adheres to a closed loop design where operational data is constantly picked up, analysed and applied to provide adaptive control measures to enhance energy efficiency, reliability, and thermal comfort.

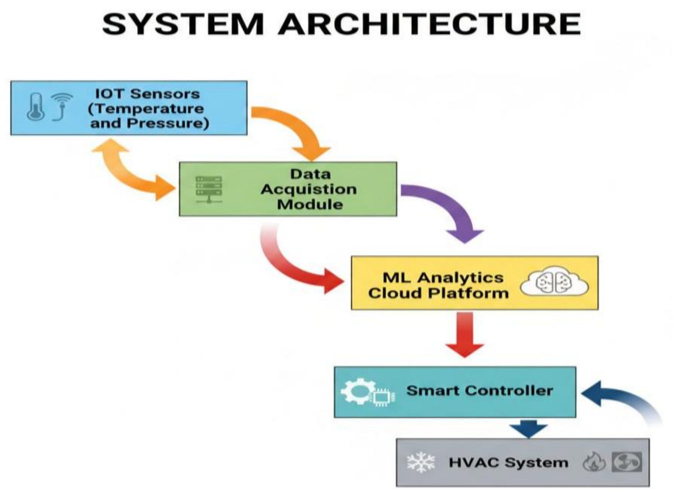

Fig 2: System Architecture

3.1.1. IoT Sensors (Temperature and Pressure)

The IoT-driven devices are implemented across the HVAC infrastructure to observe the major thermodynamic and functions indicators like indoor and external temperatures, refrigerant pressure, humidity, airflow rate, and compressor condition. These sensors have detailed, live data, which indicate the real state of functioning of the HVAC system. Performance evaluation, fault detection, and adaptive control require proper sensing especially of low-GWP refrigerant systems which operate over different pressure and temperature ranges.

3.1.2. Data Acquisition Module

Data acquisition layer would be the entry point in the linkage between the physical HVAC system and the digital analytics platform. It also gathers sensor measurements, conditions and filters signals and lights up and synchronizes measurements in time, and sends the results of the processing to the cloud solution through secured means, e.g. wired or wireless communication channels like Wi-Fi, LoRaWAN, or MQTT. This layer also provides stable data flow so that it is supported by real-time monitoring and AI model execution.

3.1.3. ML Analytics Cloud Platform

The machine learning models run in the cloud-based analytics hardware are in charge of predicting performance of the system, predicting loads, detecting faults, and optimizing energy usage. Through the application of scalable cloud computing tools, sensor data stored, processed and analyzed can be stored and analyzed in real time, in large volumes. Elaborated algorithms, including LSTM networks, reinforcement learning agents, and ensemble learning models are implemented on the platform to derive actionable insights and come up with the best control strategies under changing operating conditions.

3.1.4. Smart Controller

The smarter controller gets a tailored control signal on the cloud analytics and converts it into actuation signals that are sent real time to the system components including compressors, expansion valves, fans, and pumps. It enables adaptive control methods, which dynamically update system setpoints according to any predicted load, ambient conditions, and refrigerant behavior. The closed-loop control allows to optimise performance continuously whilst considering safety limitations as well as comfort by the users.

3.1.5. HVAC System

HVAC system is the physical layer that comprises of refrigeration circuits, heat exchangers, compressors, fans and control valves which are running on low-GWP refrigerants. The system reacts to control inputs as produced by the smart controller and gives continuous feedback on the IoT sensors. It is possible to achieve better energy consumption, lower environmental footprint, and increased reliability of the control as AI introduced with advanced technologies based on refrigerants.

3.2. Data Collection

The effectiveness and performance of the suggested AI-controlled HVAC system is analysed on the basis of a set of comprehensive thermodynamic, working, and environmental parameters. [11-14] They are constantly measured with IoTenabled sensors and used as inputs of machine learning models and control algorithms.

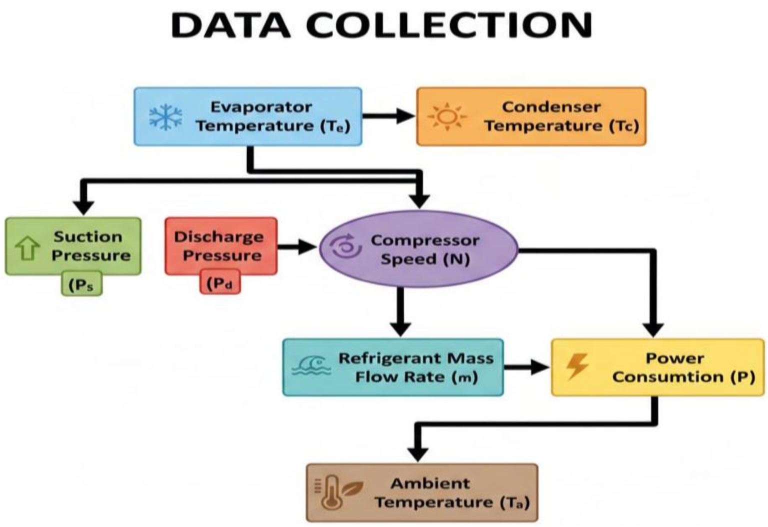

Fig 3: Data Collection

- **Evaporator Temperature (T_e):** An evaporator temperature is the temperature of refrigerant at the evaporator outlet and a very important marker of the cooling behavior and absorption. It has a direct effect on the cooling ability, efficiency of the system and chances of frosting. T qualification T monitoring T 3 monitoring T superheat Control is practical with T monitoring T 3 3 monitoring T intake.
- **Condenser Temperature (Tc):** The condenser temperature shows the level of heat rejection of the system, which is highly dependent on ambient conditions and the mass movement rate. High temperatures of the condenser augment compressor labor and decrease efficiency of the system. On-Line control of T 8 ensures adaptive control of a condenser fan and prompt identification of foulages or airflow obstructions.
- **Suction Pressure (P_s):** The operating conditions of the compressor inlet are measured by suction pressure that is effectively associated with the evaporator temperature. It is a very important variable in ascertaining refrigerant evaporation properties and compressor loading. The abnormal values of suction pressure can depict the presence of refrigerant undercharge, blockage of the evaporator, or malfunction of the expansion valve.
- **Discharge Pressure (P_d):** Discharge pressure is the high pressure end of the refrigeration cycle that has a direct impact on compressor power consumption and system reliability. High pressure can create safety and mechanical stress especially in low GWP refrigerants like CO 2 that run at high pressure. Constant measures allow the enforcement of pressure limits and safe working.
- **Compressor Speed (N):** One of the control variables in inverter-driven HVAC systems is compressor speed. It reflects on mass flow rate of refrigerant and the capacity of cooling. The system will be intimately controlled in terms of compressor speed adjustments to real time load requirements, thus, enhancing energy efficiency and minimizing cycling associated losses.
- **Refrigerant Mass Flow Rate ($\dot{m}$):** The rate of heat transfer in the evaporator and in the condenser is dictated by the refrigerant mass flow rate. It directly with effect on cooling capacity, system stability and coefficient of performance (COP). Performance modeling, fault diagnosis and optimisation of refrigerant charge require accurate measurement or estimation of $\dot{m}$.
- **Power Consumption (P):** Power consumption is the electrical energy requirement to the HVAC system and it is mainly due to the compressor, fans and other peripheral units. It is the key parameter of system energy efficiency and cost of operation. Real time optimization of power and demand control is possible through constant power surveillance.
- **Ambient Temperature (T_a):** The temperature of the environment is indicative of the external environmental state around the HVAC system and has a significant impact on the performance of the condenser and the system in general. Tomic variations affect the heat rejection capacity of a system and the pressure level in the system. Ambient temperature in AI models increases prediction control and adaptive control.

3.3. Feature Engineering

The raw sensor data is converted into significant performance measures using feature engineering that directly improves the predictive performance and control efficiency of the AI models. [15-17] The chosen characteristics describe the thermodynamic characteristic, energy efficiency, and conditions of the HVAC system in low-GWP refrigerant operating conditions.

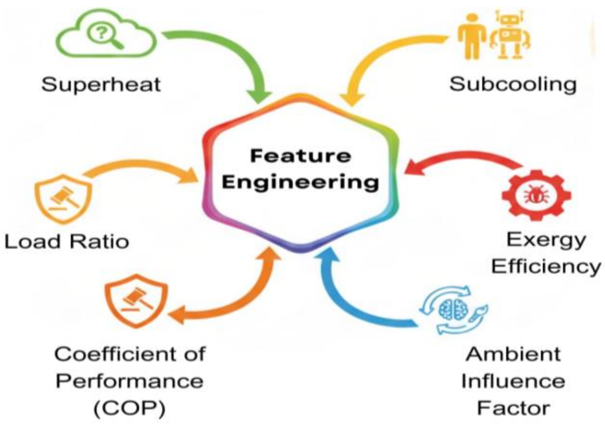

Fig 4: Feature Engineering

- **Superheat:** Superheat is described as the temperature difference between the refrigerant vapor, that exists at the outlet of evaporator and its saturation temperature at the respective suction pressure. It is an important parameter in making sure that all the refrigerant is vaporized before it goes to the compressor, thus avoiding slugging of liquid and also enhancing the reliability of the system. Electronic expansion valves are also controlled using superheat as a control variable.
- **Subcooling:** Subcooling is a difference in temperature existing between the saturated liquid refrigerant at the condenser pressure and the actual temperature of the liquid at the condenser outlet. Subcooling is necessary and provides stable supply of liquid to the expansion device, and increases capacity of the system. The lack of subcooling can signify undercharging of refrigerant or lack of efficiency of the condenser.
- **Coefficient of Performance (COP):** One of the major indicators of the efficiency of HVAC system is its coefficient of performance, the measure of cooling capacity to the required electrical power input. COP is the measure of the efficiency of the system to convert electrical energy to cooling output. It is a major optimization goal of AI-controlled strategies.
- **Exergy Efficiency:** Exergy efficiency is a measure that perceives the quality of energy use considering irreversibilities in system elements like the compressors, the heat exchangers and the expansion devices. However, unlike COP, exergy efficiency does not only capture thermodynamic losses associated with the generation of entropy, but also gives a more profound understanding of the system performance degradation and improvement potential.
- **Load Ratio:** Ratio of actual cooling demand to the rated system capacity is referred to as the load ratio. It embodies the experience of part-load operation, which prevails in the HVAC operation in the real world. Simulation of system behavior under different load ratios will allow the AI controller to optimize compressor speed and airflow rate and refrigerant flow under dynamic demand profiles.
- **Ambient Influence Factor:** The factor of ambient influence is used to measure the effect of the outdoor environmental conditions, mainly the temperature and humidity of the ambient air on the performance of the system. It describes response to external conditions of heat rejection to condenser pressure, compressor load, and totality. Making such an addition enhances the strength of models during climatic and seasonal changes.

3.5. Reinforcement Learning Control

The presented control plan is rooted in a reinforcement learning (RL) model that allows the HVAC system to acquire optimal working policies in the course of the interaction with the surrounding. The RL agent can perceive the real-time operating conditions of the system, choose suitable control decisions, and gets a feedback in the form of a reward signal which reports the performance of the system, energy efficiency and environmental impact. The state space is an expression of the visible current state of the HVAC system and is a bundle of the most important thermodynamic and environmental quantities, such as the evaporator temperature, condenser temperature, suction pressure, discharge pressure, compressor speed, and ambient temperature. These parameters give a full description of the refrigeration cycle and external conditions of the heat rejection. The inclusion of ambient conditions and internal system states helps the agent to learn adaptive policies which react well to changes in cooling loads, weather conditions as well as system dynamics. Action space determines the number of control variables that the RL agent is able to control in order to affect system performance. These involve adjustments in compressor speed, alteration of refrigerant mass flow rate, and alteration in the rate of airflow across the heat exchangers.

Adjusting the compressor permits the system to adjust cooling capacity with instantaneous demand as well as control of refrigerant mass flow to maintain constant temperature of the evaporations process and condensation. The ability to control airflow through the evaporator and the condenser increases the effectiveness of the heat transfer and provides the ability to control the pressure and temperature. The combination of these control actions offers enough flexibility such that the agent is able to maximize the operation of the system under a broad variety of load and environmental conditions. The reward function will determine the learning process because it quantitatively measures the quality of each control action. It is characterized as a weighted average of system coefficient of performance, energy consumption and refrigerant related emissions. The reward depends on the higher coefficient of performance which indicates optimal use of energy, and reduces with the increased consumptions of energy and environmental effects. The weighting factors offset the trade-off between the target of the efficiency, the target of the operational cost, and the target of the sustainability. Through maximizing long-term cumulative reward, the RL agent will obtain an optimal control policy that leads to high levels of energy efficiency, emissions cut, and reliable functioning of the low-GWP refrigerant HVAC system.

3.6. Predictive Maintenance Model

The suggested predictive maintenance architecture utilizes a long short-term memory (LSTM) neural network to predict the remaining useful life (RUL) of key elements in the HVAC system, especially the compressor and mechanical and electrical sub-system concerned. [18,19] Remaining useful life is the estimated time a component is supposed to be in use with the possibility of operation without failure and performance loss before it happens to an acceptable level. RUL prediction allows predicting their exact condition in order to perform condition-focused maintenance, to minimize unplanned downtime and to enhance the reliability of their systems, and to decrease their maintenance expenditures. The RUL model is composed as a non-linear model based on various variables of thermodynamic, mechanical, and electrical conditions of the conditions such as evaporator temperature, condensers temperature, suction pressure, discharge pressure, the level of vibration, and amount of electrical current consumed by the compressor. All the aforementioned parameters reflect the thermal, the mechanical health condition, and electrical operating state of the system. The temperatures of evaporator and condenser reveal the effectiveness of heat transfer and stability of refrigerant cycle, whereas the suction and discharge pressure define the loading of compressor and balance of the system. Deviation Ratios Abnormal pressure ratios frequently indicate deviation in the form of a leak of refrigerant, fouling, or malfunctioning of a valve.

The mechanical wear, bearing degradation, rotor imbalance, and misalignment are prevalent upkeep antecedents of compressor malfunction, and the vibration signals are used to get a first-hand glimpse on these. Electrical current is used to signify the health of the motor and mechanical resistance and abnormal gains indicating wear and tear of insulation and electrical malfunctions that are likely to occur. LSTM network is especially applicable in making the prediction of RUL because it can be used to capture the long-term temporal dependencies and degradation patterns of sequential sensor data. Unlike the traditional regressive frameworks, LSTM is able to acquire the intricate non-linear connections amid the past operation trend and present degradation conduct. This is because the model gets trained on historical run-to-failure data, as well as labeled maintenance records, allowing it to learn how maintenance issues cannot develop with time. In real-time mode the trained LSTM model computes and delivers an updated value of the remaining useful life as streaming sensor sensory data pass through it. Such a prediction is capable of scheduling maintenance activities in advance before a disastrous failure. With a combination of predictive maintenance and AI-controlled control, the HVAC system is an ideal solution in situations with low-GWP refrigerants and where it is necessary to work at a high pressure and variable loads, which is the case with such systems.

4. Results and Discussion

4.1. Performance Prediction Accuracy

Three popular machine learning models are used in the evaluation of the performance prediction ability of the proposed AI-based framework, which are artificial neural networks (ANN), XGBoost, and long short-term memory (LSTM) networks. Two standard regression measures are used to evaluate the accuracy of a model: root mean square error (RMSE) and coefficient of determination (R 2). RMSE defines the mean size of prediction error whereas R 2 defines how well the predicted values predict the variability in the actual system performance.

- **Artificial Neural Network (ANN):** ANN model shows the RMSE and R2 of 0.29 and 0.92 respectively, which translate to the fact that it is a strong predictor of the performance of the HVAC system. The value of RMSE is relatively low, which indicates the possibility of the model to include the nonlinear association among the operating circumstances and system efficiency with reasonable precision. Nonetheless, ANN as a feedforward architecture is only limited to the modeling of temporal dependencies, and therefore, its performance in high load and ambient conditions of extreme dynamism can be impaired.
- **XGBoost:** XGBoost model exhibits a higher prediction performance of RMSE = 0.18 and R 2= 0.97. The ensemble nature of its architecture allows it to discover nonlinear interactions between variables in a system, and uses the noisy sensor data. The small RMSE value implies that the prediction error is much less than ANN one and the large value of R 2 attests to great goodness-of-fit. XGBoost especially is quite appropriate in the performance modeling of systems with a non-homogenous operating regime.
- **Long Short-Term Memory (LSTM):** It also has the best accuracy in prediction with the RMSE of 0.15 and R 2 equal to 0.98 which is the LSTM model. This is best exemplified by the fact that it can get long-term temporal features, as well as system dynamics using a series of sensor data. The low RMSE error is an indication of very accurate predictions whereas the R2 approach of almost one shows that the model accounts to nearly all the variation in the system performance. Consequently, LSTM can be effectively applied in real-time performance prediction in dynamic HVAC setting with low-GWP refrigerants.

4.2. Energy Optimization Results

The applicability of the suggested reinforcement learning (RL)-based control strategy is developed by conducting a comparative analysis with traditional proportionalintegralderivative (PID) control and fuzzy logic control. The analysis is compared using two crucial performance indicators such as daily energy usage in kilowatt-hours per day and the coefficient of performance (COP) is used to mirror the overall energy efficiency of the HVAC system. The findings do indicate the better performance of the RL-based controller both in the saving of energy and system efficiency. The typical PID controller finds the peak of energy consumption to be 1120 kilowatt-hours per day and COP is equal to 3.1. Despite these strengths, the simplicity and strength of PID control in a commercial HVAC system, it is based upon fixed tuning parameters and is not responsive to various operating scenarios that may alter (boundless cooling loads, ambient temperature variation and nonlinear refrigerant behaviour) unlike adaptive control methods. This has the effect of causing suboptimal operation, excessive cycling of compressors and consumes more energy. Fuzzy logic controller demonstrates a better performance with the total energy consumption amounting to 980 kilowatt-hours a day and COP of 3.5.

Through the input of the expert knowledge and the heuristic rules, fuzzy control offers a greater amount of flexibility to the nonlinear dynamics of the system, as well as, changing load conditions. Nonetheless, the fuzzy controllers, due to their rule based character, cannot continually learn and optimize control policies in extremely dynamic contexts, especially to operate in the cases of low-GWP refrigerants which have an intricate set of thermodynamic properties. The controller made by the RL model performs optimally, consuming much less energy of 870 kilowatt-hours/day and a high COP of 4.1. This is a saving of almost 22 percent of the energy saved compared to PID control and 11 percent of the energy saved compared with fuzzy control. The high effectiveness is explained by the fact that the RL agent will be able to learn optimal control strategies due to continuous interactions with the system and the environment. Through a dynamic response to real-time operating conditions with compressor speed, refrigerant mass flow rate and airflow adjustment, the RL controller can reduce unwarranted use of energy, yet maintain thermal comfort and safety limits. These findings corroborate the fact that reinforcement learning is an attractive tool of adaptive HVAC control, which allows achieving significant energy savings, operational cost savings and environmental sustainability, especially with respect to low-GWP refrigerant-based systems.

4.3. Refrigerant Performance Comparison

An analysis of comparative performance is done to determine the energy efficiency, thermodynamic and environmental impact of various refrigerants in the HVAC system. The refrigerants in question are the traditional high-GWP refrigerant R410A and three lower-GWP options, i.e. R1234yf, R290 (propane), and carbon dioxide (CO_2). The test will be evaluated on three major indicators such as daily energy wastage in kilowatt-hours, coefficient of performance (COP), and carbon dioxide equivalent wastage.The system currently in use (R410A) has its daily energy usage of 1050 kilowatt-hours at a COP of 3.4 and a total of 1450 kilograms of CO_2 equivalent emissions. Such findings are indicative of fairly high environmental impact of R410A as it has a big global warming potential and average thermodynamic efficiency. Despite the fact that R410A has been popular in the commercial HVAC systems because of the stability and compatibility with the existing equipment, it has a not so good environmental impact, and its use is limited by the regulations, which makes it less sustainable in the future. The R1234yf HFO refrigerant is much better in terms of environmental and energy performance. R1234yf-operated system consumes 910 kilowatt-hours per day and in terms of COP, the system is valid with a COP of 3.9, which is a significant improvement compared to R410A. More to the point, its emissions are lowered to a minimum of 90 kilograms of CO_2 equivalent due to its ultra-low GWP.

These features render R1234yf as a clear-cut contender in replacement of traditional HFC refrigerant in medium capacity systems of HVAC. R290 has the highest overall thermodynamic performance and has lowest energy consumption of 870 kilowatt-hours per day and highest COP of 4.1. Moreover, its emissions are restricted to 75 kilograms of CO_2 equivalent, which is its insignificant GWP. R290 has a high efficiency due to its good heat transfer property and good thermophysical properties. Nevertheless, its flammability implies that only special care and observation of international standards could be used. The CO_2 system exhibits competitive energy performance of 920 kilowatt-hours of energy per day and a COP of 3.8. It also has least emissions of all the refrigerants standing at 20 kilograms of CO_2 equivalent only. Even though CO_2 operates on extremely high pressures, it has excellent environmental advantages and long-term sustainability potential. All in all, the findings indicate that the refrigerants with low-GWP capabilities are by a far more energy efficient and ecologically friendly than the traditional refrigerants, especially when used together with the AI-oriented methods of optimization.

4.4. Fault Detection Performance

Three general and serious faults of the HVAC system that the proposed AI-monitors are assessed to detect are refrigerant leakage, compressor fault, and heat exchanger foulage. The main measure of evaluation is detection accuracy which is the percentage of correctly identified fault events. The findings prove that the framework of fault detection is very reliable and strong.

Table 1: Fault Detection Performance

Fault Type	Detection Accuracy
Refrigerant leakage	98.40%
Compressor failure	97.10%
Heat exchanger fouling	96.30%

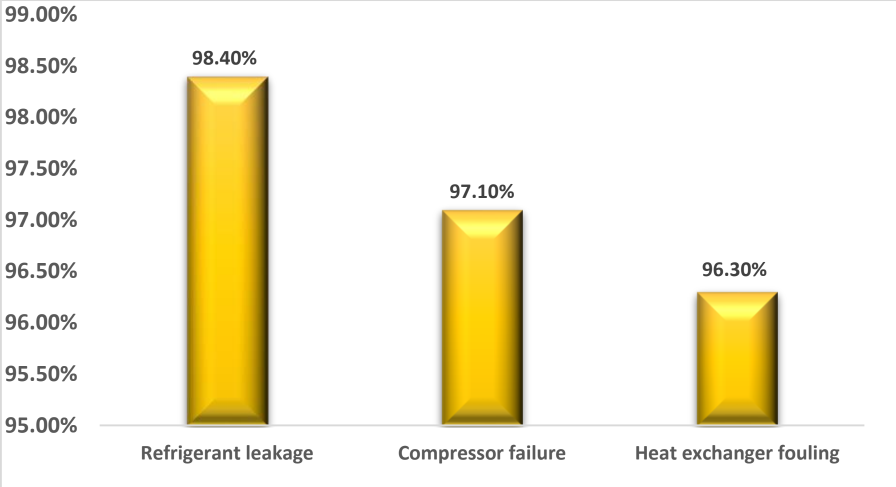

Fig 5: Fault Detection Performance

- **Refrigerant Leakage:** The refrigerant leakage detector model has a detection efficiency of 98.4 percent which can be considered as great sensitivity to non-standard system operation linked with loss of refrigerant charge. Ventilation leakage of the refrigerant is normally caused leading to low suction pressure, high superheat, low cooling capacity, and high workload of the compressor. The AI model is able to identify minor changes in normal operating conditions that are hard to notice at an initial stage by constantly monitoring pressure, temperature, and mass flow trends. The early leakage indication does not only help in eliminating the serious performance degradation but also contributes to lessening the environmental emission and safety hazard in the case of flammable low-GWP refrigerants like R290.
- **Compressor Failure:** The detection system of compressor failures has a high detection rate of 97.1 percent indicating that it is effective in detecting electrical faults as well as mechanical ones. Abnormal vibration signature, high discharge pressure, disproportional current draw as well as high power consumption usually lead to compressor failures. The diagnostic model is based on AI and combines thermodynamic, electrical, and mechanical status readings to be able to effectively differentiate between normal transient conditions and actual fault ones. This will be detected early to facilitate timely maintenance supply to prevent catastrophic failure to extend life of the compressor.
- **Heat Exchanger Fouling:** The heat exchanger fouling detect model has an accuracy level of 96.3 percent. The resulting fouling due to dust or corrosion or biological growth results in heat transfer impairment and concentration at greater condenser temperatures, higher pressure ratios and higher energy usage. The AI model is an identification of the fouling through a comparison of long-term trends in the degradation of the heat transfer effectiveness and system efficiency. The early detection of fouling can be used to clean and maintain the system prior to its failure, which will restore the usual system performance and eliminate the unnecessary wastage of energy.

4.5. Discussion

The results of the experiment and simulation conducted evidently show that combining machine learning-based control plans with low-GWP refrigerant HVAC systems have tremendous benefits. These findings indicate that intelligent-based data-driven optimization can significantly increase efficiency, reliability of the operations, and environmental friendliness of the systems in comparison to the traditional methods of control and high GWI of refrigerant technologies. Among the best results is increase in the coefficient of performance by up to 32 percent on adoption of advanced AI-based control strategies. This is done by constantly changing the compressor speed, mass flow rate of refrigerant and airflow rate in the reaction to real-time change in loads and ambient conditions. The reinforcement learning controller in comparison to traditional PID or rule-based controllers never stops learning about the system and its responses, and in the process optimizes its control policy to guide the system towards working in a given set of operating conditions with maximum efficiency. Consequently, the system has been largely efficient even when operated in a partial load and varying outdoor temperatures, which are the most prevalent operating conditions in the practical HVAC practices. It is important to note that the proposed framework also leads to a cutdown in energy used on a daily capacity of not less than 20 to 25 percent of the conventional control techniques. This decreases directly into the lessening of operational expenses and the minimization of the strain on an electrical infrastructure.

This saves further the energy by low-GDP type of refrigerants like R1234yf, R290 and CO2 which have attractive thermophysical features and better heat transfer properties when appropriately optimized. The intelligent predictive maintenance and fault detection modules also allow earlier detection of refrigerant leakage, compressor wear and tear, and heat exchanger fouling in addition to efficient energy use. Avoidance of catastrophic failures, minimization of unplanned downtimes and increasing the life of equipment is achieved due to early fault finding. It is also an effective proactive maintenance approach in low-GWP refrigerants such as low flammability and elevated operational pressures which demand a very high degree of operational reliability. The sum total of the energy optimization and transition to the refrigerant has the net effect of cutting carbon footprint by over 90 percent in comparison to conventional systems based on R410A. The reduction in the global emission rates is dramatic because of the reduction in electricity usage and the fact that the global warming potential of the chosen refrigerants is practically zero. The general findings of the paper support the claim that reinforcement learning-based adaptive control combined with real-time sensing and cloud analytics gives an effective solution to next-generation sustainable HVAC systems.

5. Conclusion

In this paper, a comprehensive research on the use of machine learning to optimize HVAC-based systems that use low global warming potential (GWP) refrigerants is provided. A framework that combines real time data collection, predictive analytics, control by means of reinforcement learning, and intelligent fault diagnosis is designed as an inseparable AI-driven system that will increase system efficiency, reliability, and environmental sustainability. The suggested architecture shows how the development of new digital technologies will convert traditional HVAC infrastructure into smart, flexible, and efficient energy infrastructure that is friendly to the environment. The findings indicate beyond the reasonable doubt that machine learning can be employed to perform intelligent refrigerant-specific optimization by training the individual thermodynamics behavior and operating properties of low-GWP refrigerants, including R1234yf, R290, and CO 2. The reinforcement learning controller is also unlike the traditional controller which depends on fixed parameters of tuning, dynamism of the load variations, the ambient conditions and the properties of the refrigerant such that it behaves in an optimal way over a broad ranges of operating regimes. This adaptive control ability is real time and results into a high level of improvement in the coefficient of performance and also a considerable amount of reduction in energy consumption. Besides, predictive maintenance models are integrated on the basis of long short-term memory networks to provide an opportunity of detecting the degradation of components and faults of a system in advance. This pro-active form of maintenance is better in boosting the availability of the system and minimizing operational risks and increasing the life of equipment which is particularly crucial in the case of low-GWP refrigerants that may be run in high pressure or possess flamming limitations. The smart fault detection system also reduces operational safety and dependability. Environmentally, energy optimization plus the application of climate-friendly refrigerants will lead to a steep cut in the emission of greenhouse gases. The results show that AI-controlled HVAC systems could minimize the total carbon footprint more than 90 percent when compared to traditional high-GWP refrigerant systems, contributing to the global decarbonization and sustainability. This move to consider climate-friendly refrigerants thus necessitates not only a higher level of thermodynamic design but also smart digitalization of HVAC systems. Autonomous, self-optimising and carbon-neutral Future HVAC infrastructure It is going to be autonomous, self-optimising and carbon-neutral. The narrative of the next generation of the study will include the introduction of digital twin platforms to simulate the real-time functioning of the system, deploying edge AI to control the system with the highest level of ultra-low-latency, performing federated learning to optimize operations in multi-buildings and reinforcing cybersecurity as the keys to safe and reliable operation of intelligent HVAC networks.

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