Development of a Low-Cost IOT Device Focused on Protection and Monitoring Compressors in Refrigeration and Air-Conditioning Applications

Nelson Sierra[1,*], Felipe Gonzalez[2]

[1]Department of Electrical and Electronics Engineering, National University of Colombia Bogota DC, Colombia
[2]Department of Mechanics and Mechatronics Engineering, National University of Colombia Bogota DC, Colombia
*Corresponding author: nasierras@unal.edu.co

Abstract   This project addresses the problem of correctly diagnosing compressors for air conditioning and refrigeration systems. The aim is to use readily available instrumentation from the global market to create a low-cost, accessible, and easy-to-assemble diagnostic solution for all types of users. In this work, we propose the use of an Espressif ESP32 controller, compatible with Arduino language, connected to Microsoft Azure. Additionally, we introduce algorithms based on trends that provide both basic and advanced users with real-time knowledge of relevant variables and detected failures in the refrigeration process. This enables users to anticipate and prevent failures through an enhanced condition-based maintenance scheme. The proposed solution aims to reduce incorrect diagnoses, minimize system downtime, and enhance troubleshooting capabilities, spare parts control, and product preservation. Furthermore, to expand the reach of this solution, the device can be utilized as an input for system data to generate valuable information for a recurrent neural network. This network can diagnose not only compressors but also the entire system, considering two significant variables: coefficient of performance and mass flow.

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1. Introduction

Refrigeration and air conditioning systems play a crucial role in various sectors, including food storage, transportation, and industrial processes. These systems are energy-intensive and require reliable and efficient operation to reduce energy consumption and greenhouse gas emissions. However, they are complex and can experience various faults and malfunctions that lead to decreased efficiency, increased energy consumption, and costly downtime.

To tackle these challenges, there has been a growing emphasis on developing sustainable and energy-efficient solutions for refrigeration and air conditioning systems. International initiatives, such as the Montreal Protocol signed in 1987 [1] and the Kigali Amendment that came into force in 2019 [2], aim to phase out or reduce the use of harmful refrigerants with high global warming potential and ozone depletion potential.

As a result of these initiatives, natural refrigerant solutions such as carbon dioxide and hydrocarbons have gain popularity. However, the use of natural refrigerants

presents its own challenges, including safety concerns and the need for specialized equipment and training. It is also important to identify that not all systems cannot afford retrofit practices, therefore, increasing confidence in the actual systems that use common refrigerants such as HFC (hydrofluorocarbon) and HCFC (hydrochlorofluorocarbon) is a crucial aspect. This development also works with a specific approach, that incorporates CO_2 and vibration measurement.

With specific instrumentation for measuring and correlating variables, it is important to review past approaches and trends that some companies still employ. These approaches tended to have a more reactive approach to maintenance (corrective maintenance), where the failure of any equipment affected the entire process, resulting in higher costs not only for the equipment itself but also for the losses and waste generated by equipment downtime and process interruption. This approach later evolved into scheduled maintenance (preventive maintenance), where routines were established that could randomly coincide with failures or with events preceding them to reduce associated costs. Since not all equipment failures were fatal, it was possible (based on schedules) to choose the optimal moment for operation. Finally, the

trend is shifting towards condition-based maintenance (CBM+) [3], which utilizes specific field instrumentation to take a series of measurements to predict the behavior of the machine and generate trends that help determine the best time to intervene based on operational performance.

This is where expert systems become increasingly relevant, as they enable the analysis of a large volume of data by other systems or subsystems to determine operating parameters in real time. Define operating limits, or determine optimal operating conditions based on historical data or time series. [4]. However, this is not always a reality in underdeveloped countries due to the high import costs and the lack of technical knowledge among personnel. Consequently, systems must continue to function with substances that deplete and damage the ozone layer and operate under dangerous and unreliable conditions, posing a risk to food safety due to the loss or waste of refrigerated items (food or vaccines) and increase the cost associated with energy.

Proper preservation of inputs involves avoiding breaks in the cold chain at various points or stages in the production process. It is important to note that each input requires specific temperature and humidity conditions, and incorrect control of these conditions can lead to health problems for consumers or potential loss of goods due to poor storage [5]. From a social perspective, the loss and waste of food due to refrigeration equipment failures are closely related to food safety issues. The purpose of the cooling process is to prevent or reduce the rate of bacterial growth by removing heat, creating unfavorable conditions. As a significant statistic (see Figure 1), 1.3 billion tons of food are lost or wasted worldwide every year [6]. This not only involves resources associated with the cold chain but also non-renewable resources such as farmland (1400 million hectares) and has a direct impact on water usage (250 km^3) [6] [7].

2. Methodology

Afterconducting research about maintenance techniques in air conditioning and refrigeration systems, it was possible to determine critical variables that affects optimal performance in key components, specifically the compressor, have been identified.

The following are the critical variables and parameters that need to be monitored:

- **Electrical values:** The compression system is coupled to an electric motor that is often cooled by the refrigerant substance. The following parameters should be monitored:
  - Power supply parameters, such as voltage.
  - Consumption parameters, such as current.
  - Efficiency measurement, including Power and power factor.
- **Thermodynamical values:** The compressor increases the pressure of the refrigerant gas by reducing its volume and transport it through the pipeline. The following variables are crucial:
  - Measurement of superheat to ensure a pressure/temperature drop across the thermostatic or electronic expansion valve (TXV/EXV).
  - Prevention of liquid returns or migrations to the compressor.
  - Efficiency of the compressor based on the COP/EER (Coefficient of Performance/Energy Efficiency Ratio).
- **Vibration and CO$_2$ levels:** Monitoring excessive vibration and CO2 levels can help detect potential refrigerant leakage in the compressor or surrounding systems.
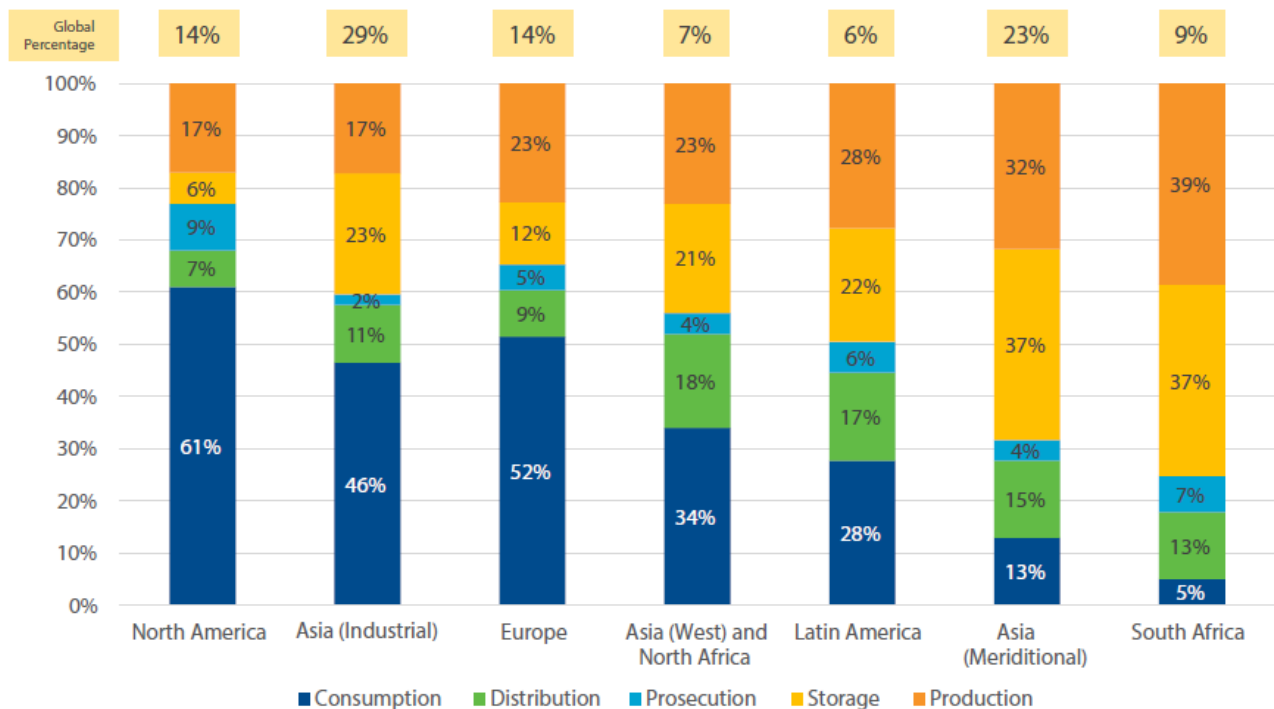

Figure 1. Food loss and spoilage [8]

To facilitate further understanding, flow diagrams, codes, and thermodynamic assumptions are available in the GitHub repository [9].

Based on these considerations, the following modules have been developed for monitoring and taking actions to protect the system (refer to Figure 3):

A. Operational Module Development

Each module defined below addresses a specific problem and provides a solution. Each module is further divided into sub-modules with specific inputs, outputs, and routines. These sub-modules are supported by declared functions and procedures, ensuring higher readability and clarity.

Sensor input modules offer user-predefined configurations, such as unit preferences for temperature and pressure. The compressor technology allows for a specific set of failures based on nominal horsepower, electrical parameters, and temperature application, which adjust the linear regression parameters for electrical monitoring and protection.

All the code implemented in this project has been developed in the Arduino IDE and for the Espressif ESP32 microcontroller device. Therefore, the development work and future works are "Arduino Compatible."

1. Superheat Module: The superheat (SH) is a critical variable in vapor compression refrigeration systems as the system requires that the input state be in gas form to prevent liquid refrigerant from entering the compressor.\\

The mathematical relationship is given by:

$$SH = T_{mea} - T_{sat} \qquad (1)$$

This equation relates the measured temperature T_{mea} at the compressor inlet with the saturated temperature T_{sat}, obtained from the pressure. Since the superheat value

varies as a normal effect of the refrigeration system (due to loads, inputs, expansion mechanism adjustment, etc.), implementing an ON/OFF controller with hysteresis would be inadequate. Instead, this module utilizes interconnected blocks that determine the outputs based on the known input variables. The modules and their relationships are shown in Figure 4.
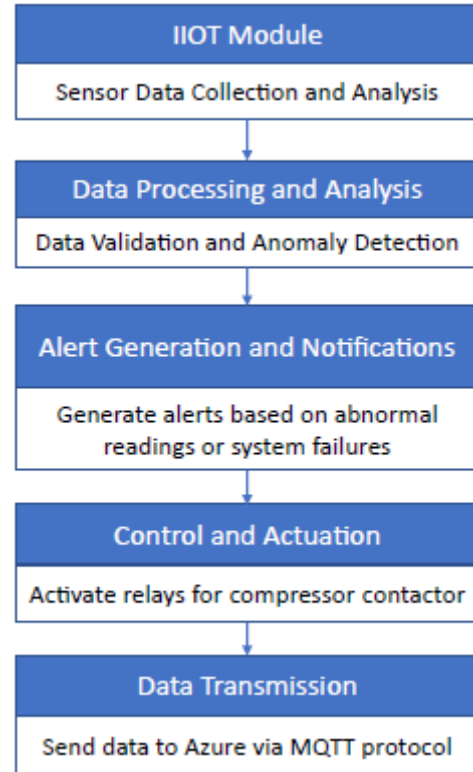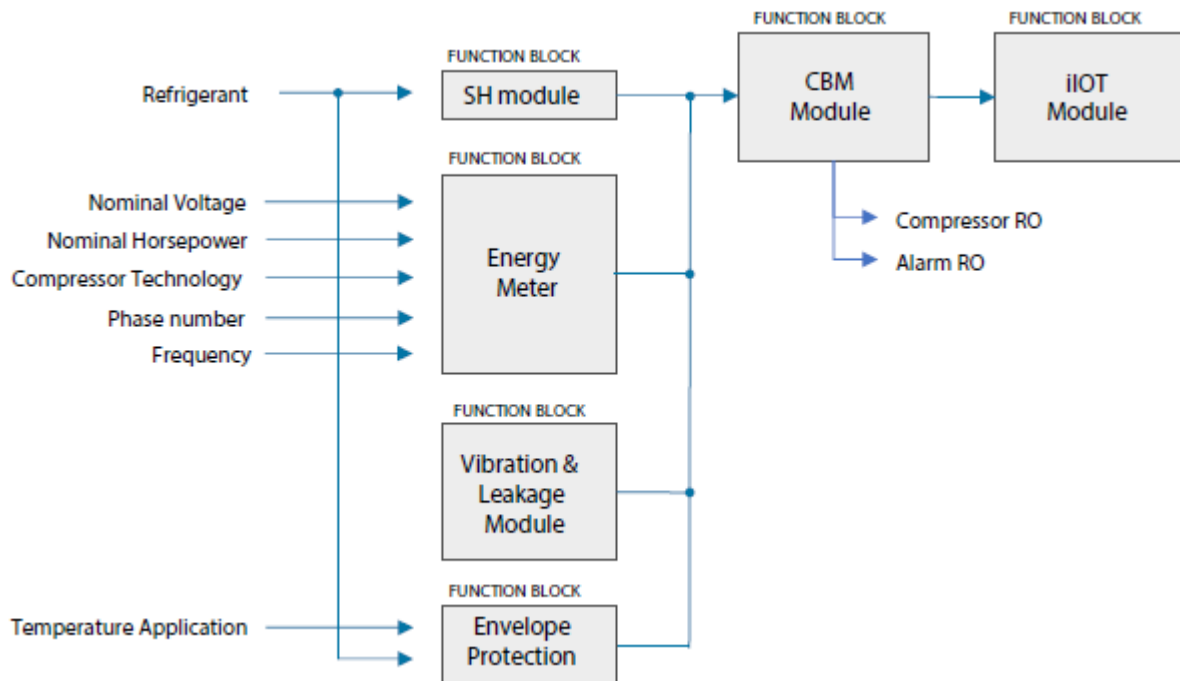

Figure 2. Device flow diagram
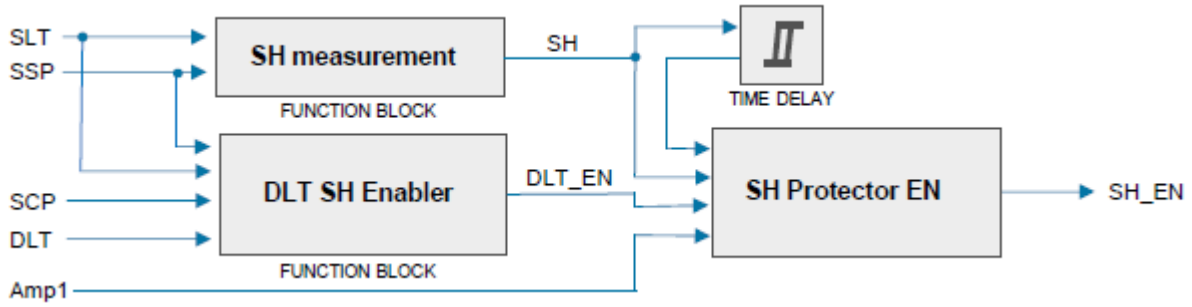

Figure 3. User inputs
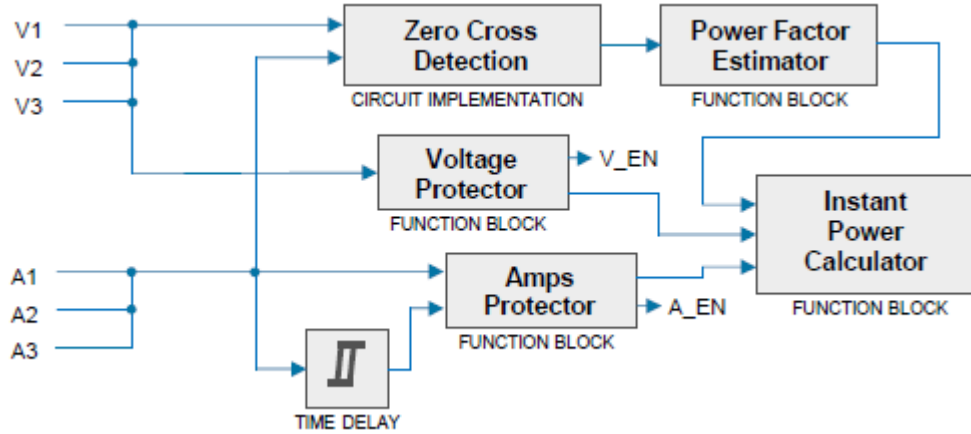
Figure 4. Superheat Module

Figure 5. Electrical Module

The refrigerant is selected through a menu, and each selected refrigerant will load a specific set of coefficients stored in the device's EEPROM. The calculated superheat is stored and delayed in time to observe trends and behavior for more accurate protection. The DLT SH enabler module estimates the compression isentropic discharge temperature per compressor (DLT) based on the absolute compression ratio and suction temperature, and compares it to the real DLT.

Each compressor manufacturer [10] determines a minimum level of superheat for their RAC compressors. This value is used as the lower limit for an ON/OFF hysteresis controller, which includes an output time delay implemented through code.

After confirming all the necessary actions mentioned above, the global module activates the relay outputs and the error counter.

2. Electrical Protection Module: The data acquisitions performed by the Electrical Module (see Figure 5) are directly related to voltages and currents. However, since the electrical motor is coupled to a vapor compression system, its nominal values differ from those of a standard electrical motor. This section provides a description to determine if the equipment is operating at nominal conditions or if its behavior is contributing significantly to an increased rate of wear.

Working currents are estimated based on the nominal power of the compressor's electrical motor. This estimation utilizes a linear regression model developed using data published by different manufacturers under various nominal working conditions [10]. The baseline established through this model provides the microcontroller with a solid foundation for performing calculations to identify

the average or expected current drawn by the electric motor based on the technology, application, and nominal horsepower.

3. Envelope/Temperature Module: The operating envelope of the compressor allows maintenance personnel to identify failures in system components that may be affecting equipment performance during operation or causing production losses associated with the cold room. The Envelope Module (see Figure 6) enables the identification of four main conditions, and the interaction between these conditions can provide further information to maintenance personnel.
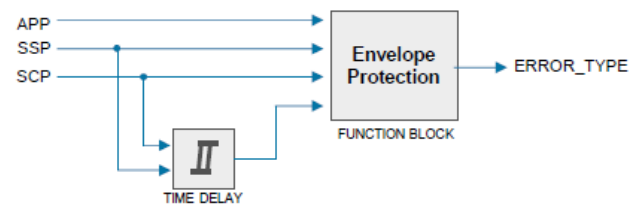

Figure 6. Envelope Protection Module

The code determines the vector to be loaded based on the application temperature and refrigerant. Then, it compares the operating point to a boundary (set point and hysteresis) for both evaporation and condensation. The code assigns a value of +1 if the operating point is higher than the boundary, -1 if it is lower, and 0 if it is within the boundary.

The optimal conditions (boundaries) were determined by conducting extensive searches in public manufacturing databases and cross-referencing that information to establish an average protection zone.

4. Vibration and Leakage Module: Vibration analysis is widely recognized for accurately diagnosing rotating parts and provides acceptance values based on operational guidelines. The primary purpose of these alarms is to make timely decisions about the machine. By analyzing historical data, machine downtime can be reduced, minimizing the impact on the overall process. The referential values for vibration analysis are based on data provided by the ISO 20816-8 standard, which specifically pertains to reciprocating machines.

While Fourier analysis (FFT) is commonly used in vibration analysis, its implementation complexity and the number of operations required by the microcontroller when acquiring other variables and activating outputs make it less suitable for this application. Instead, histogram analysis is utilized [11]. This analysis estimates the probability distribution of acceleration magnitude based on the physical location where the module is installed [12].

5. Navigation Module: To enhance user-friendly navigation, parameter input, and parameter display in the field, a physical input interface has been implemented.

To facilitate data entry, four main parameter inputs have been arranged as follows:

- **Mechanical menu [A]:** This menu allows for setting compressor powers as integer values to predict the current consumption. It also enables the selection of compression technology to account for model-specific faults.
- **Electrical menu [B]:** This menu allows for entering the nominal electrical parameters. Since the calculations are based on 460V/3Ph/60Hz, it is necessary to make the appropriate correction for accurate predictions.
- **Refrigerant menu [C]:** This menu enables the selection of the refrigerant. Upon selection, the system automatically configures the probes and adjusts the application to the protection limits of the compressor's operating framework.
- P**rotections menu [D]:** This menu allows for enabling the compressor relay outputs based on voltage, current, and temperatures (three inputs).

3. ΠοΤ Module

The following procedure is a modification of the one published by Microsoft Corporation in Azure SDK Development for Arduino [13].

The IIoT (Industrial Internet of Things) module is based on the MQTT (Message Queuing Telemetry Transport) protocol, which is a lightweight, publish-subscribe-based messaging protocol. The ESP32 device sends JSON-formatted (JavaScript Object Notation) data, including voltages, currents, pressures, temperatures, superheat, vibration, CO2 levels, and failure counters, to Microsoft Azure.

To enhance communication with the user through social media, a real-time feedback bot has been developed on the device using Twilio and ThingESP [14].

A. Data Validation

After defining and characterizing the data acquisition methods, monitoring, and protection modules, it is crucial to evaluate the device's relevance in the field.

As systems become more complex and involve a greater level of electronics for control, monitoring, and measurement of key parameters, it is essential for the workforce to be aware of the new set of skills required to leverage intelligent systems in efficiently diagnosing systems and subsystems. It is also important to understand the high dependence on various variables in the refrigeration cycle [15].

B. Prototype assembly and testing

While the render provides a reasonably accurate representation of the final design, it is important to note that the manufacturing stage does not account for some natural movements of the operator when making device connections.

During the prototype design stage, an estimated investment of 260 man-hours is anticipated. This includes programming work, PCB design, assembly, and testing. For an end-user, it is estimated to take approximately 4 to 5 hours to assemble and calibrate the device.

Figure 7. Device Assembly

4. Results

After implementing the measurement logic and error codes in the device, it is now possible to provide recommendations based on the measurements obtained from the device.

A. Measurement and Protections

Protection flow diagrams are valuable tools for ensuring the correct operation and safety of refrigeration compressor diagnostic systems. These systems, in turn, serve as input for a Recurrent Neural Network (RNN) in the diagnosis of refrigeration compressor systems.

1) Electrical Values: This protection mechanism allows for internal device-level protection and the transmission and storage of data with a percentage error (ε). The analysis is based on NEMA (National Electrical Manufacturers Association) criteria [16].

Unbalances in electrical values can have various side effects, including [17]:

1) Reduced motor performance
2) Uneven stress on motor winding

3) Increased energy consumption
4) Overheating and thermal stress
5) Reduced power factor

These values will be documented as references for using the device. Additionally, they will serve as inputs for a separate RNN that focuses on providing the user with a more comprehensive understanding of the system's internal workings.

B. Device Data as Input for a RNN

To propose an automatic system and obtain a more comprehensive set of characteristics from the acquired variables, a Recurrent Neural Network (RNN) is recommended. RNNs possess specific characteristics that make them suitable for this problem [18]:

1) Time Series: Refrigeration systems are dynamic processes, and their variables, such as temperature and pressure, change over time. RNNs are specifically designed to handle temporal sequences and capture relationships over time.
2) Short- and Long-Term Memory: RNN variants, such as LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit), have the ability to remember information from past events and utilize it to improve predictions of future events. This capability is particularly useful for analyzing complex systems like refrigeration systems.
3) Flexibility in Input Structure: RNNs can handle sequences of variable length, making them well-suited for working with data from refrigeration systems, which can vary in duration and frequency.
4) Generalization: RNNs can generalize better from limited data and are often more robust to noise and changes in the operating environment compared to other types of neural networks, such as Artificial Neural Networks (ANNs).

By utilizing an RNN, it becomes possible to analyze and interpret the acquired data in a more sophisticated manner, allowing for improved diagnosis and prediction of system behavior.

1) COP Values and Mass Flow: As previously mentioned, the device is capable of autonomously generating measurements. However, in order to provide data to an intelligent system that can analyze variables beyond the physical limitations of the microcontroller (such as memory and activation of outputs), two additional outputs are proposed. These outputs can be computed by external computer systems using historical data analysis.

- COP (Coefficient of Performance): This is a crucial metric used to assess the efficiency of a refrigeration system. It represents the ratio of the useful cooling effect achieved by the system to the amount of energy consumed (typically electrical energy) to operate the system. Essentially, the COP indicates how much cooling is achieved per unit of energy input.
- Mass flow: This refers to the quantity of refrigerant passing through the system per unit of time. Mass flow is an important parameter that directly affects the performance and efficiency of a refrigeration system.

By incorporating COP values and mass flow into the intelligent system, it becomes possible to gain further insights and make more informed decisions regarding system performance and optimization.

Coefficient of Performance: To determine the Coefficient of Performance (COP) with improved accuracy, it is recommended to generate a percentage error between "ideal" conditions and real conditions. This approach allows the intelligent system to infer better results by considering the energy invested and the outputs in terms of compressor capacity and net refrigerant effect (evaporator capacity) [19].

To calculate the COP accurately, it is beneficial to compute the enthalpy values at four specific points in the refrigeration cycle. These points include:

1) Enthalpy value at the liquid line temperature before entering the thermostatic expansion valve (TXV), at the discharge pressure.
2) Enthalpy value at the evaporator outlet, which is determined by measuring the saturated suction temperature plus a useful fraction of superheat at the suction pressure.
3) Enthalpy value at the compressor inlet, obtained by measuring the compressor return gas temperature at the suction pressure.
4) Enthalpy value at the compressor outlet, determined by measuring the compressor discharge line temperature at the suction pressure.

The "ideal" conditions can be calculated based on known values, such as the isentropic efficiency of the compressor and set points for control, as well as temperatures from the liquid line and outlet for the evaporators.

By comparing the enthalpy values under real conditions to the calculated values under "ideal" conditions, it becomes possible to calculate the COP more accurately, providing valuable insights into the system's performance and efficiency.

Mass flow: For the mass flow, it becomes handy to use the public data for the compressors available in software and technical web pages and calculate the mass flow according to the AHRI-540 standard [10] and AHRI-571 [20].

This give to the algorithm a point to evaluate a good approach to a real condition of mass flow without installing any more instrumentation such a flow meter. The mass flow $\bar{m}$ by the compression group (formed by k compressors) is calculated according to the product of the fraction of power (P_i) and the activation signal obtained from the compressor state (ON/ OFF). To estimate the actual value in the system, simple modelling of the evaporator is used [21]. The mass flow $\bar{m}$ required by the p evaporators in the suction group is calculated according to the product of the fraction of load (Q_i), the sensible heat ratio (SHR) and the activation signal obtained from the solenoid state (ON/ OFF).

Side effects of the error in the mass flow, system will face [22]:

- Changes in cooling capacity: A high mass flow rate generally results in a higher cooling capacity, but without a good system to handle liquid floodback in

the compressor inlet, it would be increase rate of wearing of the compression sets. But, A low mass flow rate can result in reduced cooling capacity, as less refrigerant circulates through the system, limiting heat absorption and transfer.

- Risk of freezing: In some cases, a low mass flow rate can lead to the risk of evaporator coil freezing, as the refrigerant may not adequately absorb heat from the air or process being cooled.

C. RNN results

With a dataset consisting of more than 28,000 records from a real system and simulated values, the intelligent system based on Recurrent Neural Networks (RNNs) demonstrates promising results in terms of predictive capabilities. These results suggest the potential of coupling this solution with the generated device to enhance diagnostic accuracy.

By calculating the relative frequency of failure events in a system, it is possible to estimate the likelihood of specific events occurring compared to others. This information can aid in identifying the most probable events and implementing appropriate risk mitigation strategies. However, it's important to note that relative

frequency is based on historical data and may fluctuate due to changes in system conditions or external factors.

The RNN results, as shown in Figure 8, exhibit an error histogram, prediction error, median square error across epochs, and training and validation loss. The coefficient of determination of the RNN model is 0.7039, indicating that the model can explain approximately 70.39% of the variation in the observed data. While this suggests a good performance, it is important to consider that the model may still miss or misdiagnose certain problems. Therefore, it is crucial to incorporate additional sources of information and expert knowledge when making decisions based on the model's output [23].

5. Conclusions

The integration of various sensors in the device and the utilization of the Microsoft Azure application enable real-time access to updated data from refrigeration systems. This comprehensive monitoring capability facilitates accurate and timely decision-making, enabling predictive actions and preventing system downtime that could impact production and food safety.
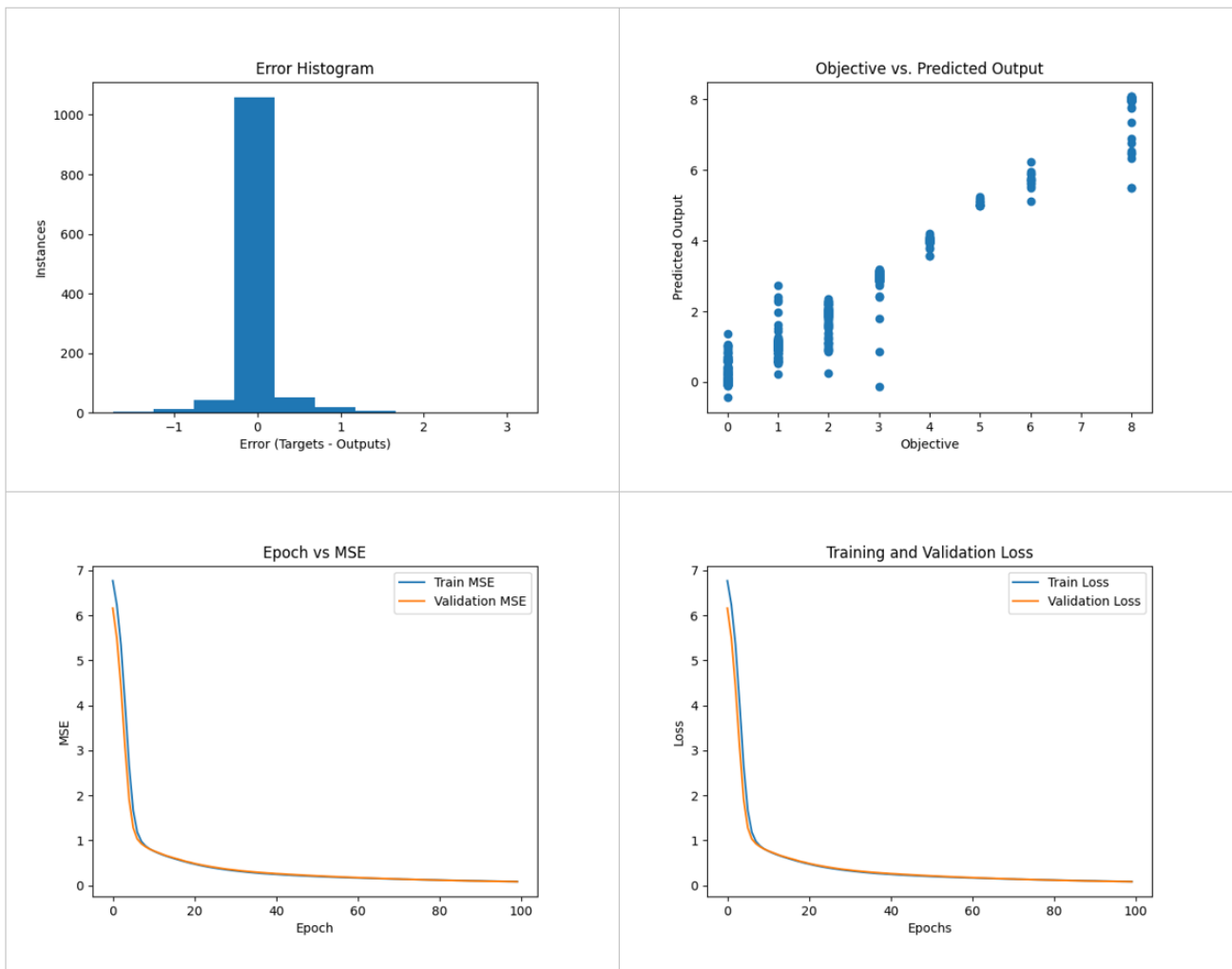

Figure 8. RNN results. (a) Error-Histogram (b) Prediction Error (c) Median Suquare Error across epochs (d) Training and Validation Loss

The described device proves to be a cost-effective and versatile tool for monitoring refrigeration systems. Priced at around 200 USD, it outperforms expensive alternatives available in the market. Unlike brand-specific devices, it can be deployed in a wide range of refrigeration systems regardless of size or compressor brand. In addition to measuring variables such as voltage, amperage, temperature, and pressure, it also monitors vibration, CO_2 ppm, and estimates power consumption, power factor, leakage percentage, superheat, and suction and discharge temperatures. With these capabilities, it provides a comprehensive analysis of refrigeration system conditions, ensuring their protection.

The use of Recurrent Neural Networks (RNNs) in refrigeration systems proves to be an effective method for diagnostic support and predictive maintenance. RNNs excel in analyzing time series data, making them suitable for examining the collected data from additional sensors in the cooling system. By identifying complex patterns and relationships, RNNs improve fault classification accuracy and can adapt to new data, continuously improving their performance over time. However, training RNNs requires substantial data and computational resources, and the quality of input data can affect their performance. Additionally, the interpretability of RNNs presents challenges, which can impact confidence and explainability in the model's conclusions and results.

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